Sectoral Endogenous Growth by Education in a System Dynamics Model

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for my family

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Ich versichere wahrheitsgemäß, die Dissertation bis auf die in der Abhandlung angegebene Hilfe selbständig angefertigt, alle benutzten Hilfsmittel vollständig und genau angegeben und genau kenntlich gemacht zu haben, was aus Arbeiten anderer und aus eigenen Veröffentlichungen unverändert oder mit Abänderungen entnommen wurde.
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Chapter overview

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Chapter 1

Introduction

The effect of an increase of the education level of the population on innovation and economic growth appears as an important topic in current political discussions. This thesis quantifies the effect with an empirically grounded system dynamics model distinguishing 30 economic sectors in Germany. This model is currently implemented without any connection to other models, but is designed technically to be able to be integrated in a larger analysis framework - *ASTRA*.

Because of the central challenges of our time climate protection, preservation of biodiversity, security of water supply and health protection we need to develop and to implement a large set of innovations in many different technological fields. Among these technological fields, energy conversion is one of the largest sources of problems, especially when it comes to the emission of climate changing CO_2 and the shortage of resources. Therefore, major transformations of the transport sector in particular as well as the energy conversion sector as a whole have to be undertaken in the coming decades. These include the mass deployment of new, low carbon technologies. In order to asses the impacts of these changes, the system dynamics model *ASTRA* was developed by Schade (2005b). It forms a tool for the analysis of impacts on the economy, the ecology and the society of climate protection policies in the transport and energy sector for all Europe. *ASTRA* is maintained within the workgroup of which I am part of at the *Fraunhofer Institute for Systems and Innovation Research* in Karlsruhe.

The work presented within this thesis constitutes the theoretical and empirical basis for an extension of the existing *ASTRA* model, incorporating economic effects of changes in education spending. Therefore, the model *SEGESD* - **S**ectoral **E**ndogenous **G**rowth driven by **E**ducation in **S**ystem **D**ynamics - was developed.

Starting point for this thesis was the question *in what way could the* *concepts of the broad field of 'endogenous growth theory' be included into a system dynamics simulation model on a sectoral level for all European Countries.*

Therefore, first (→ chap. 2) an overview of the existing *endogenous growth theory* literature is developed and the possibilities and limitations of the implementation of this theory into a quantitative framework are discussed along with the question to what aspects the empirical analysis should be reduced. This discussion results in the decision for the application of the theory for the implementation of one aspect of the theory - *the economic impact of education investments.* Also, it is argued that the empirical implementation is kept to one country - Germany - in order to demonstrate the modelled effects on one side but to avoid the highly repetitive tasks of the implementation for all EU countries on the other side. For this reason, *SEGESD* is not yet part of *ASTRA* technically, as *ASTRA* covers the EU27 countries. Therefore, the results of *SEGESD* currently are not connected to the *ASTRA* results. This technical connection has to be implemented in future projects.

After the theory, the methodological approach is described (→ chap. 3). Two methodological concepts were applied, system dynamics on the one hand and econometrics on the other. These two concepts were combined in order to develop a simulation model. During the implementation process the data availability was of crucial importance for the decisions on the design of the model, therefore the implementation work can be seen as *data-driven approach.* It determined the scope of the model, since from the beginning it was clear that the result of this work should be strictly grounded on an empirical basis. This approach led to a system dynamics model, in which the shortest possible causal links - determined by data availability - were statistically estimated and combined to form a simulation model. As will be shown later, in this way the long link between education spending and economic growth, which can only be estimated econometrically *in cross-country analyses*, can be modelled as a chain of short links for which direct relations can be estimated statistically *for Germany only.*

Then, the model *SEGESD*, implemented based on this approach, is described (→ chap. 4). It covers the time between 1970 and 2100. 130 years of simulation time are needed in order to completely cover the long time lags of the education system and to enable a comparison of costs and benefits. *SEGESD* quantifies changes in gross output growth for 30 sectors in Germany dependent on changes in the expenditures for education. This *long link* is implemented as a chain of four *short links:*

1. The relation between education spending and graduation probability was estimated statistically with simple regressions on different educa-

tion levels.

2. That link drives changes in the distribution of education levels within the population, calculated in a population cohort model which distinguishes the German population by 3 education levels (low, medium, high) and by sex in 85 age cohorts.

3. These changes in the population lead to changes in the labour input on sectoral level according to a simple regression model analysed for 540 relations between the population education structure (i.e. the labour supply) and the sectoral labour input (i.e. the labour demand).

4. And finally, that change of sectoral labour input *ceteris paribus* leads to a change of gross output within the sectoral growth accounting framework implemented in *SEGESD* based on the *EUKLEMS* project. Within that framework economic growth is decomposed into the growth of the input factors capital, labour, energy, materials and services.

The quantitative behaviour of this chain of effects implemented in *SEGESD* is laid out afterwards (→ chap. 5). Therefore, the results of the model are described from various perspectives. First, the complete chain of effects - the *long link* - is analysed, from the first to the last element, i.e. the effect of a change in education spending on the sectoral gross output. After that, in order to document the models behaviour and to explain the results of the *long link*, the complete set of permutations of partial analyses of this chain is described. This contains analyses of each one of the four *short links* as well as all combinations of two or three of them. This results in a complete picture of the complex results produced by *SEGESD*. They are disaggregated in each partial analysis according to the particular focus in order to explain the relevant mechanisms.

Finally, this thesis closes with a summary, policy recommendations and an outlook on further research in chapter 6.

This work, according to my knowledge of the existing literature, has not been undertaken so far. Many studies exist analysing the link between education spending and gross output in cross country analysis, a few even on sectoral level. Analysing the effects on sectoral level for one country within a long term simulation model constitutes a new contribution to the field of endogenous growth theory.

Chapter 2

Theory

This chapter compiles the theoretic background for a system dynamics model of the effects of education investments on economic growth. That model is described in detail in chapter 4. The process of developing that model included the conceptualisation of a broader endogenous growth model, taking into account various drivers of economic growth. That multifactor model was then reduced to the single factor which was actually implemented and which is described in chapter 4. Therefore, in this chapter, a broad picture of *endogenous growth theory* is given, and the reasons that led to the reduction of the model to one factor only - education investments - are laid out.

It starts with an overview on the historical development of the literature stream nowadays summarized beneath the term *endogenous growth theory* in section 2.1. The subsequent section 2.2 gives an overview of those factors driving economic growth that have been analysed and described in the existing literature. After that (in section 2.3) related research fields are sketched, which also form part of the base of the multifactor model. And finally (section 2.4) the concept of the multifactor model is described and the reasons for reducing the analysis to education investments are laid out.

2.1 Endogenous Growth History

Endogenous growth theory is the latest wave of economic growth theory which started in the late 1980. Generally, economic growth theory investigates the factors influencing economic growth. Its development occurred in three waves according to Solow (1994) over the last 50 years. Currently, the third wave - *endogenous growth theory* - is still running and improving. A highly simplified indication for this is the rise in the shares of publications containing the term "endogenous growth" on all publications, calculated based on query results from Google Scholar[1] as shown in figure 2.1.

The first wave, the so called *Classical Growth Theory*, was based on the idea of output being proportional to (physical) capital input and investments. This theory was established by the work of Domar (1947) and Harrod (1948), summarized in the so called *Harrod-Domar* model (equations 2.1). There, output is a function of capital only and the change in capital stock equals investments less deprecation. Investments were assumed to be equal to savings and the marginal product of capital to be constant.

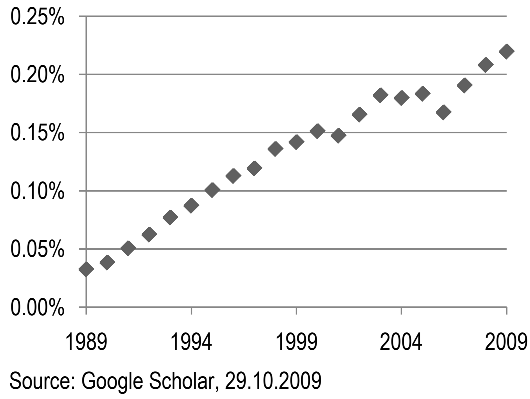


Figure 2.1
Shares of "endogenous growth" publications in all scientific publications

$$
\begin{aligned}
Y &= f(K) & Y &: \text{output} \\
\frac{dY}{dK} &= const & K &: \text{capital} \\
I &= S = sY & I &: \text{investments} \\
\Delta K &= I - \delta K & S &: \text{savings} \\
& & s &: \text{saving rate} \\
& & \delta &: \text{deprecation rate}
\end{aligned}
\tag{2.1}
$$

The *Harrod-Domar* model was an attempt to dynamise the Keynesian theory according to Obinger (2004). The growth rate of output was proportional to the investment rate as well as the marginal capital productivity, which was assumed to be constant. This led to investments being perceived as the central policy tool, controlled via tax incentives for the private sector or public spending. And, according to Solow (1994) this was the policy subscribed under the influence of this line of thinking. But looking at reality, something seemed (and still seems) to be wrong with this model. This led to a series of extensions and improvements, trying to endogenize exogenous model parameters.

The second wave became known as the *Neoclassical Growth Theory*, extending the classical growth theory by endogenizing the output-capital ratio. This line of thinking was established by Solow (1956, 1957), who introduced

[1] *http://scholar.google.de*

labour as a separate input to the production function. The crucial assumptions are diminishing returns to both labour as well as to capital and constant returns to scale for both factors combined. This model is referenced as *Solow-Swan* model due to additional contributions from Swan (1956). Solow assumed the difference between the model's results and the empirical data to reflect technological change. This difference became widely known as *Solow-Residual*.

This model can be described with the following group of equations (2.2). A Cobb-Douglas production function with capital and labour input, capital change and investments unchanged compared to the classical model (equations 2.1 on the facing page) and a function for labour force growth . This production function provides diminishing returns $\forall \alpha \in (0;1)$.

Output as well as capital input into the production function is used on a per worker base ($^{Y}/_{L}$ and $^{K}/_{L}$). In this model, if net capital (i.e. investments minus deprecation) is growing as fast as the population, output per worker is constant, the so called *steady state* of this model is reached. Then the total output is growing at the speed of population growth.

$$
\begin{aligned}
Y &= AK^{a}L^{1-\alpha} \\
\Leftrightarrow \frac{Y}{L} &= A\left(\frac{K}{L}\right)^{\alpha} \\
I &= S = sY \\
\Delta K &= I - \delta K \\
L_{t+1} &= g(L_t)
\end{aligned}
\qquad
\begin{aligned}
Y &: \text{output} \\
K &: \text{capital} \\
L &: \text{labour} \\
A &: \text{multifactor productivity} \\
I &: \text{investments} \\
S &: \text{savings} \\
s &: \text{saving rate} \\
\delta &: \text{deprecation rate} \\
g(.) &: \text{labour growth function}
\end{aligned}
\tag{2.2}
$$

A major prediction of the neoclassical growth model is the convergence of poor and wealthy countries due to the inverse dependence of the growth rate on the initial per capita output, i.e. poorer countries are expected to grow faster than rich ones. The obvious contradiction to reality is said (Obinger, 2004) to be a major driver for the development of an even more sophisticated theory.

This third, currently ongoing, wave of economic growth theory extension became known as *New Growth Theory* or *Endogenous Growth Theory*. An early summary of the concepts was compiled by Aghion and Howitt (1998). Its roots are seen mostly in the work of Romer (1986, 1990) and Lucas (1988). They started to put the focus on endogenous explanation of technological progress based on human capital accumulated in a knowledge capital stock.

These highly influential papers mark the beginning of the development of a broad set of models trying to add additional variables into the right hand side of the equation for explaining the growth of economic output. That development was triggered by "overwhelming evidence that technological change is not an exogenous variable that can be simply defined outside the model, but to an important degree endogenous, induced by needs and pressures" according to Grubb et al. (1995). These findings had been enabled by the strongly improved data availability due to rapid progresses in the development of information technologies in the preceding decades. Of high importance became the abundantly used *Summers-Heston*[2] data set, first published in 1988 and extended in 1991.

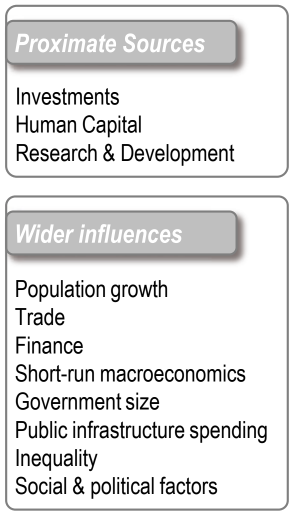


Figure 2.2
Drivers of growth

Temple (1999) classified these drivers into eleven categories, of which he considers three to be *proximate sources* and eight to be *wider influences* as shown in figure 2.2. Durlauf et al. (2005) compiled a comprehensive overview of studies carried out. I combined this information in order to obtain an overview of what analysis have been undertaken in which field, resulting in table 2.1 on the facing page.

2.2 The main drivers of economic growth

From an empirical point of view, the problem with endogenous growth theory is its *openendedness*, first explicitly stated by Brock and Durlauf (2001). Thereby, they refer to the fact that many different drivers of economic growth have been identified, both theoretically and empirically. Durlauf et al. (2005) identified 43 conceptually distinct growth regressors, each of which "is found to be statistically significant in at least one study" (p.75). All these 43 regressors fit into the categories given in table 2.1 on the next page.

On the one hand, all these different regressors do not exclude each other logically. On the other hand, the more regressors are included into a statistical growth model, the stronger the problems of endogeneity and multicollinearity become. When specifying the empirical model the choice on the

[2] Summers and Heston (1988) and Summers and Heston (1991). Set of national account economic time series for more than 130 countries. Denominated in a common set of prices in a common currency, enabling real quantity comparisons.

Table 2.1
Categories of independent variables used in endogenous growth models

Investments	***Social & political factors***
Investments in pyhsical capital	Inequality
Investment Ratio	Political Instability
Investment Type	Political Institutions
Human Capital	Political Rights
Education level	& Civil Liberties
Education Investments	Property Rights
Research & Development expenditures	Economic freedom
private R&D	Institutions
public R&D	Labor Force Particip. Rate
Population	Rule of Law
Population growth	Social Capital
Demographic Characteristics	Social Infrastructure
Ethnicity and Language	***Others***
Fertility	Information
Trade	Health
Trade Policy	Geography
Trade Statistics	Democracy
Foreign Direct Investment	Capitalism
Manufacturing Exports	Constraints on Executive
Finance	Coups
Capital account liberalization	Infrastructure
Capital Controls	Labor Productivity
Capital market imperfections	Luck
Stock markets	Religion
Short-run macroeconomics	War
Inflation	Weather
Budget deficit	Regional Effects
Real exchange rate instability	Industrial Structure
Government	Enterprise Size
Government size	Neighboring Countries Dev.
Government Change	Money Growth
Government expend. and taxation	Price Distortions
Corruption	Price Levels
Judicial Independence	Real Exchange Rate
Others	Scale Effects
Public infrastruct. spend.	Technology Gap
Growth rate of the G-7	Initial Income
Growth rate in prev. period	Initial GDP

Own compilation based on Durlauf et al. (2005); Temple (1999) including own additions.

amount of drivers becomes crucial, as discussed later on.

In this section I give an overview on the current knowledge concerning what the main drivers of economic growth are according to how strong the statistical and causal links are. This forms the basis for the concept of the multifactor model which is then reduced to the empirical model implemented within the work for this thesis.

2.2.1 Investments in physical capital

Physical capital was the first explanatory variable used in the early efforts to explain economic growth, as described in the section 2.1. All subsequent models incorporated physical capital and only added further explanatory variables but never replaced physical capital.

A robust correlation between investment rates and growth along with diminishing returns to scale of physical capital can be observed according to Temple (1999). This is in contrast to the traditional interpretation of the Solow-Swan model, after which long-run growth is likely to be independent of investment rates. But, according to Temple (1999), this is not at all surprising, because even in a finite time period this correlation can be expected from the theoretical model contrary to common interpretation. Additionally, strong externalities to investments have been identified empirically by De Long and Summers (1991) as a *social rate of return to equipment investment* well above the private rate of investment. They estimated a growth of 25 percentage points of the total factor productivity to be composed of 10 percentage points of extra privately appropriable value and 15 percentage points of external effects induced (De Long and Summers, 1991, p. 192).

Taking physical capital accumulation as proxy for technological progress implies the accumulation of knowledge along with the new capital. This leads to a major critique of model explicitly incorporating human capital modelling. Theoretically, it can be argued that there exist strong collinearity in the development of both types of capital. Empirically though, human capital accumulation, as described below, remains a significant driver of growth.

The growth accounting framework from EUKLEMS, forming the basis for the economic analysis within *SEGESD*, differentiates a whole set of capital types listed in table A.3 on page 161 in appendix A.3. The details of the implementation in *SEGESD* are described in section 4.2.4 on page 52.

2.2.2 Human capital & Effects of education levels

For the history of the inclusion of education in economic growth models, I would like to refer to the very abundant paper by Conrad (2007). It shows, as was described in the history of endogenous growth above within this work, that the inclusion started with the extension of growth models considering human capital during the third wave of economic growth theory in the 1980s.

Investments into education, health, training etc. most certainly have an effect on economic growth. But in contrast to clear findings at micro-level that schooling has a significant return in the form of higher wages, discerning positive effects on macroeconomic level is not easy at all according to Temple

(1999, p. 139). Two main reasons are identified for that. On the one hand, only education rather than training is taken as proxy for human capital development. This is done simply due to limitations in the available data. On the other hand, the long time lags of the effect in question were not taken into account. Especially this problem is tackled with the population cohort model implemented in *SEGESD* (see chapter 4).

Nevertheless, the explicit modelling of human capital in an production function was introduced by Mankiw et al. (1992). Krueger and Lindahl (2001) discuss in detail the problems estimating empirically the contribution of education on economic growth. Their analysis suggests that both the change and initial level of education are positively correlated with economic growth. And Bils and Klenow (2000) find that "estimated returns to schooling [expenditures] average 7 percent in high-income countries but 10 percent in Latin America and Asia and 13 percent in Africa."

A standard data set measuring the education level of the population in OECD countries used in many studies was compiled by Barro and Lee (1996). For several countries, no clearly positive return to education could be discerned based on that data set according to Bosworth and Collins (2003). They summarize that "nearly all of the contributors to the empirical literature recognize that measurement error might account for the lack of association between economic growth and gains in educational attainment" (p.139).

Because of these problems, Fuente and Domenech (2006) revise the Barro and Lee (1996) data set by exploiting additional data sources and by removing sharp breaks in the time series. They report that their revised data "perform much better than the Barro and Lee [...] series in a number of growth specifications". From that finding they conclude that data quality due to changes in the specifications of education level classifications significantly contribute to findings of weak correlations between education investments and economic growth.

Their estimation of the relation between average schooling years and average annual economic growth on a set of 21 OECD countries yields a range of 0.15 to 2% per year. Even though this range is huge, it is a lot better than the range of -1.35 to 7.8% per year reported by the initial study from Barro and Lee (1996).

More detailed quantitative results are not available (i.e. have not been found by me) currently. And these results are cross country estimates. Detailed estimates for Germany are therefore also not available. And Aghion (2009) performed a survey of this research field. His paper confirms my impression that no more detailed analyses are available.

The effect of education on inequality was broadly discussed by Stiglitz (1973). He stressed the importance of the education system for the perpetuation of inequality. Even though Stiglitz especially discussed these issues for countries of the developing world, this criticism can be translated to the German society in the beginning of the 21st century. Also here, the issue is broadly discussed, though on a different level of general education, but with similar tendencies. In the German education system the education success is also strongly connected to the degree achieved by the parents of the students, a result found by the PISA tests (Prenzel et al., 2008) internationally comparing pupils performance.

2.2.3 R&D expenditures

Research and development investments form one of the main drivers of technological change. They form the systematic basis for technological advancements. According to the Frascati Manual (OECD, 2002) R&D "comprise creative work undertaken on a systematic basis in order to increase the stock of knowledge [...] and the use of this stock of knowledge to devise new applications". Naturally, the link between expenditures and innovation is highly complex and most definitively non-linear. The process itself is seen as a mixture of learning by doing and dedicated improvement by systematic searching for it.

Early studies on the rates of return to R&D expenditures found 30 to 50 percent for the USA in the 50's and 60's of the last century according to Temple (1999). These values have been revised in succeeding studies, discussing many methodological drawbacks and measurement problems, but there seems to be strong evidence for even *higher* social rates of return according to two influential papers by Griliches (1979, 1992). Jones (1995) stresses that the linear scaling of the per capita growth rate with the R&D input proxy as predicted by early endogenous growth models can not be found in the empirical data. The main reason for that is identified in the growing complexity of the existing technologies which lead to the need for increased R&D efforts in order to maintain a given growth rate.

External effects (or spillovers) of research and development efforts are a widely discussed issue in endogenous growth literature. Griliches (1979) was an early article discussing theoretical issues on modelling knowledge spillovers. Griliches (1992, p. 29) finds that "R&D spillovers are both prevalent and important". He discusses the difficulties of the econometric estimations to come up with convincing evidence for this finding and he concludes that "social rates of return [of R&D] remain significantly above private rates". This public goods character of R&D investments forms the main argument for public R&D subsidies.

Many empirical analysis have been undertaken, presenting abundant evidence for positive effects of R&D expenditure on economic growth. A recent econometric study analysed the impact of investments in R&D on long term economic growth in OECD countries between 1970 and 2004. Falk (2007) finds that "both the ratio of business enterprises' R&D expenditures to GDP and the share of R&D investment in the high-tech sector have strong positive effects on GDP per capita and GDP per hour worked in the long term".

Looking at the USA only on an even longer time periode (1953-2000) also with econometric tools, Goel et al. (2008) also find positive effects of R&D on growth. Additionally, they distinguish three types of R&D expenditures: (1) federal, (2) non-federal and (3) defence spending. They find that the strongest positive effects come from defence expenditure, followed by federal spending and non-federal R&D expenditures coming last. The leading position of defence spending in this list can be explained with the huge quantity of that category and the large part the defence spending makes up in the USA's government budget.

International spillovers of research and development activities had been expected theoretically and have been investigated empirically in the nineties when the required data sets became available. Grossmann and Helpman (1994) explained them based on the international interdependence due to trade activities in a summary of new (in 1994) endogenous growth literature. Knowledge can be transferred in many ways, e.g. by direct licensing of patented knowledge, but also through illegal copying of knowledge codified in patents or through reverse engineering. A very important way of international knowledge transfer are foreign direct investments, analysed theoretically as well as empirically by Blomström et al. (1999)

Coe and Helpman (1995) developed an empirical growth model analysing international R&D spillovers, finding that estimated rates of return domestically as well as internationally are very high. Modelling the invention of new technologies and their diffusion across counties, Eaton and Kortum (1994) found for the USA that roughly half the productivity growth depends on foreign technology improvements.

In order to use these empirical findings, many differing approaches have been developed. Roughly, these can be separated in two groups. On the one hand, some frameworks explicitly model spillovers, e.g. based on technological distances between firms or industries. On the other hand, various approaches can be interpreted as implicitly containing spillovers, e.g. simple trend extrapolation because it can be argued that spillovers are already included in the historical data. That approach can naturally not account for changes in the technological structure of the products of a particular sector, which can be modelled assuming a changing technological distance between pairs of sectors.

2.2.4 Population growth

Population growth alone clearly is important to economic growth, since a larger population can produce a higher output on the base of a constant output per capita. The interesting question is whether there is a causal relation on *per head* basis. Statistical data as well as theoretical thinking provide a mixed picture. There is a slightly negative correlation between population growth and economic growth, but the direction of causality is difficult to determine. It is well possible that higher incomes lead to lower fertility, and not vice versa. At the same time, this negative link is at least partly driven by labour force participation according to Temple (1999) citing Brander and Dowrick (1994) as well as Pritchett (1996).

In a more recent revision of existing models and papers and in a statistical meta analysis Kelley and Schmidt (2001) compile confirming evidence for the early finding that a growing total population influences negatively per capita growth. But they also list studies finding positive effects, especially those looking at population density measures. They reckon that a higher population density reduces transaction costs of various kinds, therefore boosting economic output.

But not only *per capita* growth matters, also the question of the development of the total gross output of the economy is relevant, especially when looking at aging and shrinking economies like those of various European countries. Therefore the relation between *per head* output growth and the population development is relevant. In the case of a diminishing workforce, the question is whether the reduction of labour input can be compensated by the growth of total factor productivity. This is a field of strong controversy, and consensus on the development of the total output does not exist among economists. E.g. Fougère and Mérette (1999) analysed seven OECD countries, finding a broad range of possible developments for GDP per capita - from increasing to decreasing - due to the aging of the population.

2.2.5 Trade

The interaction between trade policies and macroeconomic performance is one of the traditional fields in economics. The classical thinking generally assumed a positive correlation between the openness of an economy and the macroeconomic growth rate.

For example, Dollar and Kraay (2004) have analysed the effect of the openness of economies on their economic growth rates and on their welfare distribution. They compare developing countries open to the globalisation process with those keeping their markets closed in a cross-country analysis.

Both groups according to the authors each make about half of the developing countries. Their analysis shows that the more open developing economies are, the faster they grow and, crucially, that *on average* the increase of the national wealth leads to proportional increase of the wealth of the poor. They conclude that "globalisation leads to faster growth and poverty reduction in poor countries".

But some authors have emphasised that certain countries may perform less well when specialising according to their comparative advantage than under autarky. It appears that openness is the more advantageous, the more specialized a country already is in manufacturing for export, whereas natural resource abundance in poor economies seems to work against long-run growth according to Sachs and Warner (1995).

Also, when analysing the effects of trade on the economy, distance is relevant. Krugman (1991) started to stress the importance of distance in trade and the regional specialisations resulting thereof. He argues that increasing returns of scale and transport costs increasing with distance are the main drivers for regional concentration and specialisation patterns observable around the world.

And for advanced industrialised countries trade is essential for their economic performance. Keeping or establishing a technological leadership position constitutes a strategic goal. For example, Ragwitz et al. (2009) stress the importance of the subsidies for the renewable energy market in Europe in order to establish a technological leadership position. They find that renewable energy technology is already a substantial part of the European economy, forming 0.6% of GDP and employment in Europe. For the future they are optimistic that this development is likely to be accelerated if policies are improved in order to reach the 20% renewable energy target for 2020 in Europe. Especially if the technological leadership position leads to high exports of the according products.

2.2.6 Finance

The role of financial factors has been marginalized by many economists arguing that financial development is simply a passive consequence of growth according to Temple (1999). But Levine and Zervos (1998) argue that active stock markets indeed do play a role in subsequent growth. They show empirically that stock market liquidity and banking development both positively predict growth, capital accumulation, and productivity improvements when entered together in regressions, even after controlling for economic and political factors. In a more recent working paper, Levine (2004) again stresses the importance of the financial system for economic growth, since the "financial systems may influence saving rates, investment decisions, technological innovation, and hence long-run growth rates”.

The widely discussed *world economic crisis* triggered by the collapse of the USA’s subprime mortgage market and it’s short as well as long term impacts on economic growth are a large academic field by itself and should not be discussed at this point. The idea here is rather the compilation of the set of explaining approaches for economic growth.

2.2.7 Short-run macroeconomics

Regressions with significant correlations between growth rates and short-run macroeconomic indicators like budget deficits, inflation and instability of real exchange rates are easy to produce on the one hand, but on the other, isolating the effect of any individual policy variable is virtually impossible. This is probably, according to Temple (1999), due to the fact that things go wrong simultaneously.

2.2.8 Government size

Government size, measured through ratio of social security transfer to GDP or high government consumption, is commonly claimed to be negatively correlated with economic growth in political discussions. In contrast to that, Temple (1999) finds no strong evidence for that in the literature. According to him, ”no correlation between small government and fast growth leaps out from the data”. But he admits that microeconomic evidence show responses of labour supply and investments to tax rate changes. And Jones and Hall (1998) find that high government consumption lowers the level of income.

A good recent example for that is the debt crisis of Greece. Excessive government spending boosted incomes for a couple of years. But now, as the cumulated government debt reaches probably 125% of GDP in 2010 according to a forecast from Economist (2009), the credit rating for Greek government bonds surged. This forced the government to cut spending, dropping the national income level, as more and more money is needed to pay interests. Since many government bonds are held be non-Greek institutions, this leads to a significant money flow out of Greece.

2.2.9 Public infrastructure spending

Clearer empirical results are available for the case of public spending on infrastructure. Easterly and Rebelo (1993) found that investments in transport and communication infrastructure have a significant effect on subsequent growth. Also, investments in the energy infrastructure and the education system infrastructure are of high relevance, as well as the implementation of a health system. And building up a stable communication infrastructure is also crucial for economic growth. Aschauer (1989) even found the "core infrastructure of streets, highways, airports, mass transit, sewers, water systems, etc." to have the most explanatory power for the development of productivity in the USA between 1950 and 1985.

Agénor and Moreno-Dodson (2006) give an overview of the various *channels* through which public infrastructure spending influencing growth is treated in the economic literature from a theoretical point of view. They list productivity effects, complementary (or external) effects and crowding out effects as *conventional*. Additionally, they identified indirect effects on the labour productivity, effects on the adjustment costs, effects on the durability of private capital. Also, they list accelerating effects through education and increased health.

2.2.10 Social and political factors

Social and political factors are expected to have strong influence on economic growth, but at the same time quantification is rather difficult. Various approaches have been undertake, but all with overwhelming measurement problems. Indices of civil rights, political rights, economic rights, ease of enforcing contracts, risk of expropriation have been found to correlate positively with growth, but the question which kind of rights are most important are left unanswered according to Temple (1999). Also, the influence of democracy on growth does not show in the data and for autocratic systems it seems important whether they are based on self-interest or on national economic goals. Alesina and Perotti (1994) suggest that the most significant influence lies in social and political stability rather than in social and political freedom. Also the impact of social arrangements on growth appears relevant, but again empirical studies showing clear relations are not yet available, mainly due to problems in measurement and data availability.

In a broad literature survey of the impact of inequality on growth and based on two equilibrium models Benabou (1996) finds in agreement with most of the relevant literature a negative effect of high inequality on subsequent growth. But Barro (2000) concludes based on broad country panel data that "evidence [...] shows little overall relation between income inequality and rates of growth and investment". Aghion et al. (1999), developing a theoretical model of the effects of inequality on economic growth, list the classical arguments favouring the perspective of equality supporting growth: (1) rich people make dissaving or unproductive investments, (2) the poor hold lower levels of human capital, (3) the demand pattern of the poor are more biased towards local goods and (4) the masses reject the political system in an unequal society. At the same time, Aghion et al. (1999) point out that the conventional textbook approach is that high inequality even fosters growth since it provides strong incentives for the poor. This might be true to a certain point, and inequality beyond that point probably turns counterproductive if people lack the perspective of improving their situation by means of hard work and large efforts. And, the distribution of wealth can also influence the relative growth figures. If wealth is strongly unevenly distributed, the economic growth in a small elite group can be sufficient to result in significant economic growth of the average of the total economy.

2.2.11 Further factors

Many more factors have been investigated, as summarized in table 2.1 on page 9. As characterized by Temple (1999), the quantitative effects of those factors are less clear and not suitable for a simulation model due to measurement problems or weak correlations. Therefore, these factors will not be treated in more detail. Only one aspect will be covered as an example.

The importance of access to information in a very broad sense was introduced theoretically in a model by Jones (2006), extending the model by Kremer (1993), which did not include explicit modelling of information availability. The rough model significantly improves the ability to explain the large income differences between developed and developing countries over the past 50 years.

2.2.12 Relevance for a sectoral model

The drivers of growth discussed above clearly do not all share the same importance. Temple (1999) distinguished two groups - *proximate sources* and *wider influences* as shown in figure 2.2 on page 8.

Most of the drivers listed in the category *wider influences* have only been found to be empirically significant, if at all, in cross-country analysis. Based on this differentiation, a selection of the variables for a sectoral endogenous growth model has been undertaken. It should only contain explaining variables with a strong empirical connection to the explained variable, i.e. to economic growth. With this restriction, the following groups of variables remain:

- Investments in pyhsical capital
- Human capital accumulation

— Research & Development expenditures
— Population growth

2.3 Related research: technological change

Trying to find an answer to the question of what drives economic growth is closely related to the question how technological change happens and what drives innovations. Löschel (2002) and Köhler et al. (2006) give an comprehensive overview on the historical development of the implementation of technological change in economic modelling. The outline given here mainly draws on that work.

Scientific explanation of the causes of technical change and how it happens started in the first half of the twentieths century. In the forties, Schumpeter (1942) distinguished three stages of technological change:

1. **Invention** of a new product or process.
2. **Innovation**, i.e. the transformation of an invention into a commercial product, accomplished through continual improvement and refinement of the new product or process.
3. **Diffusion**, i.e. the gradual adoption of the innovation by other firms or individuals from a small niche community to widespread use.

Technological change is seen as one of the main drivers of productivity change. Economically it is perceived as factor accumulation leading to higher output due to increased inputs. Still though, according to the literature review work by Temple (1999), the analysis of macroeconomic data gives unconvincing results. On a disaggregated level though, and especially on a technology specific level, the effect is clearly observable.

Analysing the sources of technical change, three major traditions have evolved according to Ruttan (1997).

First, the **neoclassical induced innovation approach**, based on the hypothesis on induced innovation of Hicks (1932, p. 124f): 'a change in the relative prices of factors of production is itself a spur to innovation and to inventions of a particular kind - directed at economizing the use of a factor which has become relatively expensive'. An early implementation of this approach was the econometric *demand-pull model* by Griliches (1957) analysing 'the factors responsible for the wide cross-sectional differences in [..] the rates of use of hybrid seed corn in the United States'. Examples for the investigation of *induced innovation* can be found in the field of environmental regulation. Clearly, higher costs imposed by regulation trigger innovation efforts in order to avoid them. Jaffe and Palmer (1997) analyse the effect of environmental compliance costs on inventive output for the USA on industry level for the years 1976 to 1991. They find a significant positive effect of compliance costs on R&D expenditures and little to slightly positive evidence of individual industries inventive output measured in patent applications. Brunnermeier and Cohen (2003) find clearer results for the US manufacturing industries applying panel data models on data from 1983 to 1992. According to them "environmental innovation (as measured by the number of successful environmental patent applications granted to the industry) responded to increases in pollution abatement expenditures" and with that responded clearly to environmental regulation.

Second, the **evolutionary approach** based on local searching for innovations and imitation of other firms, with firms not optimising but rather engaged in routines, inspired by Schumpeter's insights into processes economic development according to Nelson and Winter (1982).

And third, the **path dependence approach**, stressing the fact that increasing returns to scale of technologies imply a *lock-in* onto the chosen technological path, i.e. making it more difficult or even prohibiting to leave that path (David, 1985; Arthur, 1989, 1994).

The quantification of these three concepts of technological change has been attempted in several ways. In the following the major approaches are summarized.

An early attempt to quantify the concept of technical change within energy economic models was the introduction of an *autonomous energy efficiency improvement* (AEEI), i.e. an exogenous assumption on the yearly efficiency improvement rate. This concept was heavily critized, among others by Chapman and Khanna (2000), the main point of criticism being the too rapid efficiency improvement. Nevertheless, the concept was widely used, and can still be found in current modelling exercises according to Webster et al. (2001).

Later on, concepts were developed aiming at endogenizing technological change, i.e. to make the technological change depended on variables from within the model. This lead to the broad field of *experience curve literature* which tries to explain technological progress as depending on cumulated output of a certain product, assuming that acquired experience can be measured by proxy of the total quantity of a product produced with a given technology. It is based on the theories on *learning curves*, which was developed by Ebbinghaus (1885) according to Wozniak (1999). This concept in turn was first applied to the field of the economics of mass production by Wright (1936) analysing the costs for the production of airplanes.

Mathematically, the experience curves can be described by a power law function of the form

$$C_n = C_1 \cdot n^{-a} \tag{2.3}$$

with C_1 being the costs for the first unit of production, C_n being the nth unit of production, n being the cumulative volume of production and the parameter a indicating the elasticity of cost with regard to output.

According to Köhler et al. (2006) there has been considerable developments in macroeconomic and energy economics in the "recent years" before that article, leading to widespread use of experience curves as a tool to model endogenous technical change in energy economy modelling.

And connected to the experience curve theory is the theory on diffusion of new technologies in the market. Rogers (1995) describes the core assumption of the diffusion of innovations in the market. "The diffusion of new, economically superior technologies is never instantaneous, but typically follows an S-shaped (sigmoid) curve that measures the rate of diffusion of innovations over time."

Including experience curves in economic models introduced the possibility to analyse the effects of policy interventions. Based on the combination of market diffusion and experience curve theory, the recommendation for support of new technologies at early development stages is justified. Supporting technologies in an early diffusion stage, when they are still expensive and little implemented lead to an increase of the cumulated output and thereby to cost reductions, due to experience curve effects. E.g. the effects on the price and on the market diffusion of subsidies for photovoltaic cells for electricity generation can be analysed this way.

The main critique of this approach focuses on the difficulties of estimating the experience curve parameters for the extrapolation of the observed price development during the early phase of the market penetration of a new technology into the future. Small parameter changes lead to large differences in the cost estimates due to the non-linear functional form. If used for long term forecasts, the uncertainties can reach intolerably high levels. Despite that critique, experience curves remain a widely applied and useful tool for the integration of the observable production cost decline due to gathered experience. Crucial, as always in modelling, is the disclosure of the underlying assumptions.

2.4 From a multi-factor concept to a single-factor model

The model described in detail in chapter 4 of this thesis focuses on the effect of education investment on the economic growth of various sectors. Before this though, the implementation of a model taking into account various explaining variables was conceptualised based on the theory compiled in sections 2.2 and 2.3. In the following, first the original concept is sketched and the reasons for reducing the scope of the analysis are laid out. Afterwards, the reasons for choosing education investments as explaining variable are described.

2.4.1 Multifactor model

After having developed an understanding of the concepts of *endogenous growth theory* (sec. 2.2) as well as of some related research fields (sec. 2.3), the question *how to implement these in a system dynamics model* had to be answered. A concept was developed which essentially combines ideas from the two literature streams *endogenous growth theory* as well as *experience curve theory*.

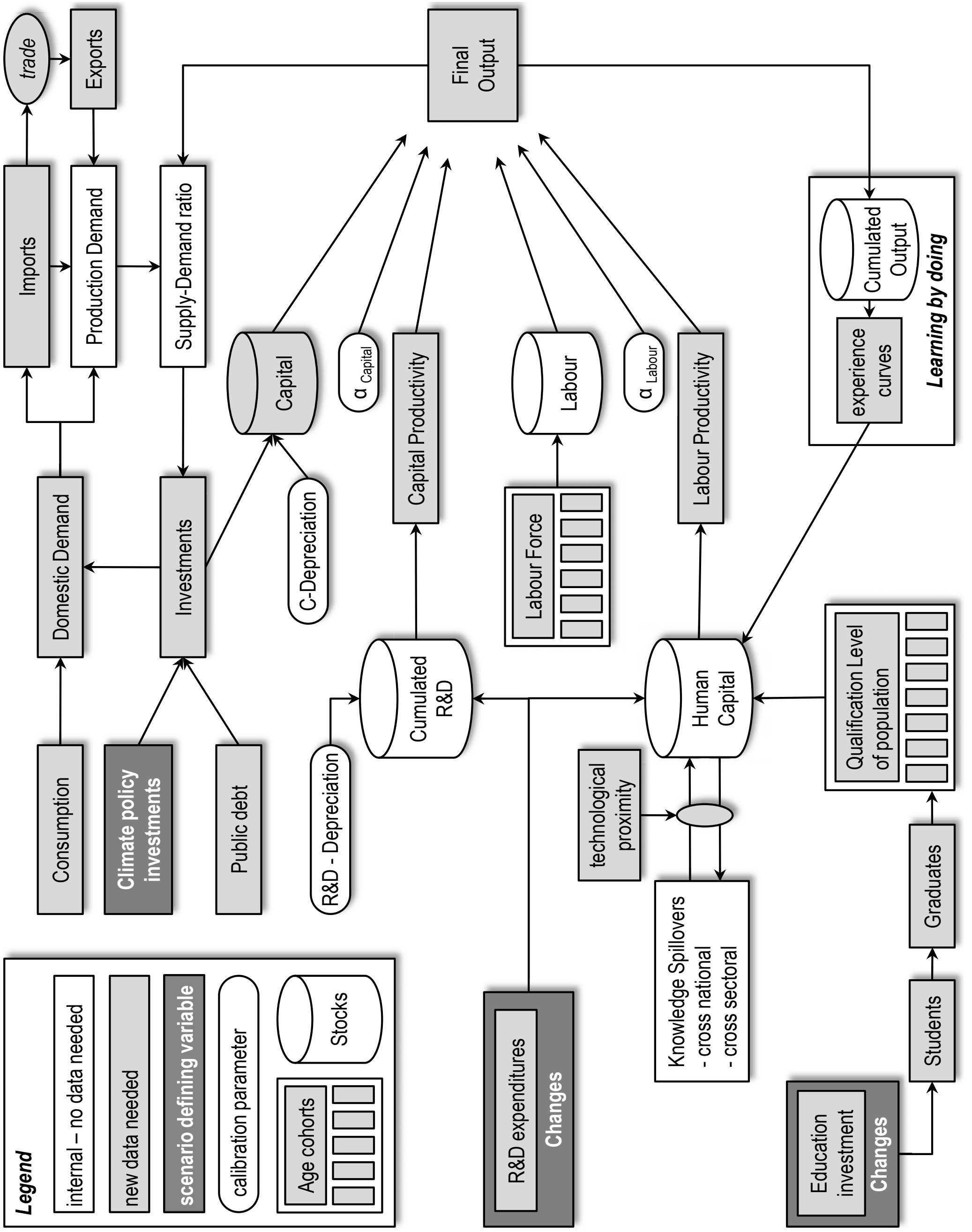
To achieve that, the first step was to decide what effects should be included into the analysis and what the functional form should be. An extended Cobb-Douglas production function was chosen, with the parameters of that function driven by a set of variables. These variables and the ways they influence each other are abstractly visualized in figure 2.3 on the facing page. This initial concept - referenced as *multifactor model* hereafter - included the variables

— Education investments
— R&D expenditures
— Accumulation of technological knowledge
— Experience accumulation
— Knowledge spillovers
— Climate policy investments
— General investments
— Trade (Imports / Exports)

influencing the parameters

— Capital Stock
— Capital Productivity
— Labour Force

Figure 2.3
Multifactor model - Overview graph



own graph

— Labour Productivity

of the Cobb-Douglas production function with $\alpha_{Capital}$ and α_{Labour} as calibration parameters. Particularly, the concept was based on the idea that the cumulated R&D expenditures drive the capital productivity and an abstract human capital stock drives the labour productivity. The functional form was planned to be

$$Output = LabProd \cdot Labour^{\alpha_{Labour}} \cdot CapProd \cdot Capital^{\alpha_{Capital}} \tag{2.4}$$

This concept was then reduced to a *single factor model* as described in the following section.

2.4.2 One vs. multiple factors

Based on the concept described in the previous section, a discussion was initialised within the doctoral seminars of the IWW, resulting in the decision to reduce the analysis to the effects of one factor only.

The main arguments for reducing the analysis to one variable were problems due to endogeneity and due to multicollinearity of the chosen set of independent variables.

Endogeneity refers to the presence of an endogenous explanatory variable according to Wooldridge (2006, p. 862), fittingly described as a "a loop of causality between the independent and dependent variables of a model" in Wikipedia[3]. In the multifactor model specification (→ fig. 2.3 on the previous page), human capital and physical capital were explicitly specified as endogenous variables, and others are implicitly endogenous, e.g. R&D expenditures or private consumption. Both cases lead to problems in the analysis of empirical data as well as in the calibration of the resulting SD model. It would contain additional parameters and the feedback loops would lead to non-linear relations. This would strongly increase the degrees of freedom of the model, largely increasing the amount of data sets needed to estimate the parameters correctly. In the case at hand the available timelines of no more than 15 to 20 yearly observations are simply not long enough. And for the case of the endogenous loop not being explicitly modelled but existing in the real world, the parameter estimates are biased.

Multicollinearity refers to correlation among the explanatory variables in a multiple regression model (discussed in detail in Maddala 2001, chp. 7). In the multifactor model, multicollinearity is on the one hand side explicitly

[3] http://en.wikipedia.org/wiki/Endogeneity, 1.4.2010

included in the model design - both *labour productivity* as well as *capital productivity* depend on R&D expenditures - and on the other can be found implicitly e.g. in the case of correlations between investments and R&D expenditures, both depending on expectations on the development of markets in the future by the acting enterprises.

Furthermore, the separation between human capital on the one hand and technological knowledge in the form of cumulated R&D expenditures on the other results in multicollinearity, since they both depend on a common variable (R&D expend.) as described before. Finally, both effect the same variable *Final Output*. Additionally, the spillover effects of human capital are also difficult to quantify, introducing an additional non-observable parameter. This design makes the variable *human capital* difficult to calibrate.

In order to estimate the parameters for a model of this design reliably and stable, long time series would be necessary. The available time series of the relevant variables contain at best 15 to 20 years, mostly even less. This is by far too short.

Therefore, for this analysis, mono-causality was assumed. As described in the following section, the isolated effect of education investments on economic growth was analysed. This assumption can lead to both overestimation as well as underestimation of the effect. Overestimation can result from substitution effects, discussed e.g. by Gramlich (1994) reviewing papers on econometric analysis of growth contributions from infrastructure investments. And underestimation can result from synergies between various variables. In the *multifactor* model, this could for example be the case for cross sector spillover effects, leading to a higher growth *in reality* than calculated by a model which does not take these effects into account.

2.4.3 Education investments driving growth

After having decided to reduce the analysis to one factor, the choice of which factor to analyse had to be made. *Education investments* were taken for two reasons. On the one hand, they were not yet included in *ASTRA*. On the other hand, due to the ever accelerating spreading of computer technologies from the 1990s on, larger data sets of highly detailed data became available in recent years, opening new possibilities of analysis.

Current status in ASTRA

Some elements of the endogenous growth theory as described in the preceding section 2.2 within this chapter are already implemented in *ASTRA*, though most of them not on a sectoral level but as national aggregate (with the exception of sectoral investments).

Gross domestic production is calculated as weighted average of final demand on the one hand and potential output on the other. The potential output side is where the endogenous growth concepts are implemented. It is calculated based on an extended Cobb-Douglas production function with the explaining variables *Labour Stock*, *Capital Stock*, *Stock of natural resources* and *Total Factor Productivity* as well as the corresponding output elasticities for each one of the three stocks.

Investments on sectoral level, freight transport times and labour productivity figures are used to calculate the *Total Factor Productivity*. The investment figures on sectoral level are also used to form the *Capital Stock*. Population and Employment numbers form the basis for the calculation of the *Labour Stock* on national level. The output elasticities are obtained as result of the model calibration as part of the System Dynamics methodology.

Education investments are not yet included in this endogenous calculation of potential output and therefore offer a good possibility to develop a highly relevant and necessary extension to the existing *ASTRA* model.

Availability of *EUKLEMS* framework

When searching for existing data sets for a sectoral economic analysis of European countries, the *EUKLEMS*[4] database quickly emerges as most comprehensive collection of harmonized information, freely available in the Internet for download.

It provides a large set of data for all countries within the European Union for 72 disaggregation levels of economic sectors according to the NACE[5] Rev. 1 classification. The construction of the *EUKLEMS* database is financed by the European Commission's Research Directorate General as part of the 6th as well as 7th framework program. It is carried out by the *Groningen Growth and Development Centre*. The complete project is described in Timmer et al. (2007a,b). The disaggregation level of the data varies largely between the various indicators and also depends on the country following the familiar pattern of old EU member states providing more data than new ones. Still, the available data allows for an application of the methodology developed within this thesis on several of the large economies of the EU and is therefore a good basis for an extension of *ASTRA*. The database version used for the development of the model concept as well as for its implementation

[4]EUKLEMS: EU Measures on Capital(K) Labour Energy Material and Services

[5]NACE: Nomenclature statistique des activités économiques dans la Communauté européenne

was *2008-03*, available in the second half of 2009, when the implementation work for this thesis was carried out. The project is still ongoing, so for the future longer timelines and more detailed coverage of the data can be expected.

EUKLEMS contains indicators on *gross output*, *intermediate inputs separated by energy, service as well as material*, *labour input*, *capital stocks* as well as *labour and capital compensation*. Furthermore, it is not only a broad database of statistical economic data, but also the implementation of a standard growth accounting methodology, described in detail in section 4.2 on page 44. It's aim is the decomposition of output growth into the growth of its components. These are the growth of *capital input*, of *labour input* as well as of *intermediate inputs*.

Building on the *EUKLEMS* framework, a model was implemented which connects the qualification of the population via the labour market with the economic output of the economy, described in detail in chapter 4.

Within the *EUKLEMS* framework, the labour input is one input variable for the gross output on sectoral level, laid out in detail in section 4.2. The labour input in turn, measured in hours worked, forms the connection point for the estimation of the effects of an increased availability of highly qualified employees on the labour market, described in detail in section 4.3. The correlation between the labour supply, i.e. the amount of persons per qualification level in the population on the one side and the labour demand, i.e. the labour input on sectoral level on the other side form the connection between the calculation of the economic output within the *EUKLEMS* framework and a population model representing the German population. In this population model, the qualification structure of the population is determined by the education system. Better conditions lead to more graduates at each qualification level. The implementation of the education system and the estimation of its parameters from historical data is described in detail in section 4.4. The conditions in the education system in turn are strongly determined by its funding, as shown in section 4.5. More persons of medium and high qualification can be obtained through improved conditions in the education system by increasing the funding.

In this way, the effects of additional education investments on growth rates of economic output were modelled on a sectoral level, quantifying the positive effects of schooling on the gross output described in section 2.2.2 on page 10 from a macroeconomic perspective.

Chapter 3

Methodology

This chapter gives a short overview of the methodological approach applied for the development of *SEGESD*, which is described in detail in chapter 4. The approach was determined by the research question introduced in chapter 1: *In what way could the concepts of the broad field of 'endogenous growth theory' be included into a system dynamics simulation model on a sectoral level for all European Countries?* The choice for *system dynamics* as modelling methodology was preset in previous research projects, when the development of *ASTRA* started. This is discussed in the dissertation of Schade (2005b). Since the goal of this thesis is a conceptual extension of *ASTRA*, *SEGESD* had to be implemented in system dynamics as well. The results presented within this thesis form the theoretical basis for an extension of *ASTRA* in following projects. With a *proof-of-principal* implementation (chap. 4) for Germany the capabilities of the developed concept are shown. The quantitative results thereof are complied in chapter 5.

Closely connected with the development of a *system dynamics* model is the application of *econometrics* for the estimation of those model parameters that can be underpinned with empirical data. In the development of *SEGESD*, particular emphasis was put on the goal to obtain a model that is completely based on empirical data. Therefore, a crucial element of the methodology is the determining character of the availability of data. Links that could not be underpinned by statistical data were not included in the simulation model. Therefore, *SEGESD* was implemented using a *data driven approach*. The *mental creativity* part of the system dynamics methodology, i.e. the deliberate implementation of links for which no data is observable (explained in detail below in sec. 3.1) was not applied for *SEGESD*.

System dynamics and econometrics complement each other on various levels of the analysis. In the case of the analysis of the effect of investments in education on the economic growth, this is (a) the direct link between investments and growth, or (b) the links between parts of the chain of effects (compare fig. 5.8 on page 115), e.g. the connection between the quantities of available qualified workforce and the employment of these persons in individual industry sectors. The *shorter* links (b) are either analysed econometrically in order to estimate parameters needed for the development of the SD model. Or the parameters are derived in a *backwards calculation process* as in the case of the educated population model (sec. 4.4 on page 65). The *longer* link (a) is then analysed in a system dynamics model combining the short links in one closed framework. Also, the longer link can be analysed econometrically in order to obtain statistical information on whether the assumed link exists and to what extend. In this thesis the focus is on the development of an SD model, therefore the shorter links are part of the analysis, and the direct (long) link of education investments on growth is the result of the simulations computed with *SEGESD*.

To complete the picture of methodological options, *computable general equilibrium (CGE)* models have to be mentioned. These can be seen as the mainstream in economic modelling. A discussion of differences between both methodologies is omitted here, since this has been done many times before in other theses, as e.g. by Sensfuss (2007) or by Schade (2005a).

The following chapter contains a short description of system dynamics in sec. 3.1 as well as of econometrics in sec. 3.2. Afterwards, in sec. 3.3 an overview of the application of both methodologies for the development of *SEGESD* is given.

3.1 System Dynamics

System dynamics is a methodology designed to improve the understanding of complex systems over time. First, the elements of a system dynamics model are laid out (sec. 3.1.1). Then, a short overview of the historical development is given (sec. 3.1.2). After that, the procedure of developing a system dynamics model is described (sec. 3.1.3). And finally, common critique of SD is shortly summarized (sec. 3.1.4).

3.1.1 Elements

It's core elements are stocks and flows, with the flows determining the levels of the stocks. For example, the world population (=stock) in the year 2000 is increased by new born babies and decreased by all deceases (=flows), resulting in the stock of the population in 2001.

Essential to this methodology is the use of time delays and feedback loops, with feedback loops enabled through time delays. This means that a level variable can directly or indirectly influence itself. For example the number of new born children as well as that of deceases depends on the size of the population, thereby the population determines its own development over time. Assuming constant birth as well as mortality rates with *birth rate* > *mortality rate* would lead to exponential growth.

The preceding example assumes birth and mortality rates to be exogenous. Now it is extended with a deer population, providing food for the human population and itself depending on the number (and thereby the demand for food) of humans. The growth of the human population could lead to a decreasing deer population. This in turn might reduce the human birth rate due to a lack of food. And this again could reduce the human population, leading to the recovering of the deer stock. Eventually, this system will come to an equilibrium.

This short example demonstrates the potential complexity of a system. In it, the quantitative outcome would already be difficult to predict without a simulation run. And as more real life effects would be included, like e.g. the effect of diseases, it would be the only way to achieve a quantitative estimation of the effects by developing a large simulation model.

Following the introduction to system dynamics given by Bossel (2004), a system can be defined as a set of elements and a set of relations between these elements. A system is called dynamic if it changes its state in a period defined as relevant by the observer. Furthermore, a model is a simplifying reproduction of reality, which makes it the standard to work with for economists when trying to obtain quantitative reactions to assumed changes in the economy, since experiments in the real system are not possible and ethically not acceptable.

The behaviour of a system is determined by its structure as well as of external influences. External influences, by definition, are not affected by the system. These influences are called exogenous. Internal behaviour, resulting from the structure of the system, is called endogenous. In the previous example, the amount of yearly newborn children would be endogenous, while the birth rate (=children per woman) would be exogenous at first. But after taking the deer population into account (or e.g. the arable land), the birth rate would be turned into an endogenous variable, determined by the human population and the supporting deer population respectively the available land.

3.1.2 History

The system dynamics methodology was initially developed by Jay W. Forrester. It was first developed in Forrester (1961) and later refined in Forrester (1969). Nowadays, it is widely applied in a large variety of fields according to the System Dynamics Society (http://www.systemdynamics.org/, 20. Aug. 2009). These include corporate planning and policy design, public management and policy, biological and medical modelling, energy and the environment, theory development in the natural and social sciences, dynamic decision making as well as complex nonlinear dynamics.

This methodology became well known to a broader audience with the publishing of *Limits to growth* by Meadows et al. in 1972. Unfortunately, the criticism on results and conclusion of this book was mixed with criticism on the system dynamics methodology. But questionable results of this book have to be rather attributed to the assumptions and the structure of the model rather than system dynamics itself.

Important for the spreading of the application of the system dynamics methodology became *Business dynamics - System Thinking and Modelling for a complex world* (Sterman, 2000), as it gives a very comprehensive overview of the theory of methodology along with practical examples. It forms an indispensable base of knowledge for any system dynamics modelling endeavour, and without this book, *SEGESD* would not have been possible. Before that, Randers (1979) provided a standard set of articles on how to apply the methodology, which formed for various years a standard reference.

3.1.3 Procedure

Building a System Dynamics model includes various steps. Robinson (1980) describes the process of building a system dynamics model for management consultation. Thereof, I deduce the steps needed for the purpose of this thesis, removing steps like interaction with stakeholders or clients. Relevant for the development of *SEGESD* were:

1. Identifying preconceptions
2. Conceptualisation
3. Construction
4. Testing
5. Documentation

In the following, each step is shortly described in general and the link to the development of *SEGESD* is given.

As Robinson (1980) puts it, "**Preconceptions** are always there. [...] To the extent that [the modeller] does not see them, preconceptions will lurk behind his work, shaping it in fashions unrelated to his intended purpose." In order to make preconceptions explicit, Robinson recommends to be self-critical, to examine ones motives and a priori assumptions, to look at biases inherent in the chosen techniques and to continually ask what one is trying to do and why. This introspection and self-correction is ranked as essential for avoiding the modelling study to steer into irrelevance. This part appears to be the most difficult to document, but it was continuously undertaken during the development of *SEGESD*.

The **conceptualisation** of the model is the essential phase in the complete modelling process. On the one hand, errors in this phase are difficult to correct later on, on the other the model concept defines all relevant structures of the model and therefore determine the results as well as the potential errors.

When developing the concept for the model, the essential choice between a close connection to real statistical data or a freer form of modelling has to be taken. Forrester (1980, 1994) argues for the explicit modelling of effects for which no explicit statistical data is available - so called unobserved variables - but which are expected to exist based on theoretical thinking, press reports or anecdotal evidence. This approach is summarized under the term *mental creativity*. It forms one of the major points for criticism of SD. Since this process does not rely on strong empirical evidence it appears as rather arbitrary. But the concept can be well defended when perceiving it simply as an extension of modelling capacities rather than describing reality with numbers where no numbers exist. It is well suited for developing hypothesis on the structure of a system. But much care has to be applied when working like this, and model results must not be confused with real empirical data. In *SEGESD*, this way of modelling was not applied, but the focus was rather put on observable real statistical data.

The **construction** or **implementation** of the model forms the larges part in terms of time intensity. This is mainly due to data processing work and repetitive tasks concerning the development of the model code. The details of this work are not included in this thesis. Only the result is documented in form of the complete model source code in the appendix D. Also, the complete exogenous data can not be included in the thesis document, since this would extend the already large appendix unacceptably. Of course, the full references to the origin of the data is given (see appendix B).

Testing forms the next essential step of the modelling process. By testing the model, weaknesses can be unveiled, to the point of the manifestation of the inappropriateness of a model. Actually, the possibility to be tested is the main advantage of a mathematical model over a verbal one. The important methods according to Forrester (1961) are sensitivity and policy tests as well model comparisons. But how these tests should be conducted is not formalised, it is rather a matter of judgement, which in turn is gained by experience.

According to Robinson (1980, p. 263), poor judgement in model testing can be found in many cases as well as a tendency of modellers to rather *tune* than *test* their model. This problem was completely avoided during the development of *SEGESD* by waiving the calibration of model parameters and instead only rely on econometric test results for those parameters.

Additionally, models should be tested for sensitivity to different amplitudes and frequency of noise, since plenty of noise is included in observed real world data according to Robinson (1980, p. 263). Also, sets of extreme parameter values, where non-linearities become particularly important, have to be investigated. And, most important, models have to be tested in a formal process rather than informally and intuitively, as it is often the case. This is true especially for complex mathematical models, which are designed to gain insights beyond intuition and therefore are, by definition, impossible to be tested based on it. The sensitivity and scenario analyses (chap. 5) carried out with *SEGESD* are realisations of these testing principles.

The main reason for not formally testing an SD model are identified by Robinson (1980, p. 264) in the resistance of a modeller to manipulate his model to a point which could disprove its validness. Validity testing should not be an attempt to show that a model is valid, but rather a serious effort to locate structures which are not valid in order to improve them. "Testing should involve careful observation of model variables under a variety of experimental conditions. The modeller should identify the structural reasons for variable behaviour under different experimental conditions. Then he should question whether the model's structural causes are plausible in the real system.[...] The modeller should be explicit about how he expects the model to perform in each test" (Robinson, 1980, p. 264). And deviations signal that either the model or the modellers understanding of its behaviour is unrealistic. For *SEGESD*, this is described in the analyses of the quantitative behaviour in chapter 5.

Ultimately, **documentation** of the efforts and results is of high importance, but unfortunately often neglected. It is essential in order for other scientist be able to reproduce, to understand and to evaluate the contribution of the implemented model. Therefore, this thesis forms a highly comprehensive documentation for *SEGESD*. It contains details on all the steps essential to the development of a system dynamics model listed within this section. Unfortunately, certain parts of the underlying empirical data basis, particularly the labour force survey (see sec. B.3), are not publicly available and are subject to re-publishing restrictions. Due to that, this data could not be included in the thesis. But detailed references are given in order to make clear what data was used, so the results remain reproducible.

3.1.4 Critique

One major point of critique of the system dynamics methodology is its explicit modelling of unobservable variables, mentioned above. This is discussed broadly by Sommer (1981, p. 167ff). Two main problems - closely connected - with the estimation of values for the unobservable variables arise. First, the non-observable variable can not be validated against empirical data by definition. If the number of such unobserved variables is low, this can be acceptable, especially if a dependent variable of the unobservable variable can be validated against empirical data. But if this number increases, that leads to the second problem. Since the variable itself can not be validated, a depended variable has to be validated against empirical data. But the more unobserved variables influence one single observable variable, the more arbitrary the values of the dependent variable become, and the easier the empirical values of the observable variable can be matched by the model counterpart of that variable. This leads to highly arbitrary results and reduces the empirical significance and validity of the model.

At this point it should be mentioned again, as in the previous chapter, that validity can mean many different things. A system dynamics model including many different unknown parameters can still be a valid model. The remaining question is to what extend the results are useful for policy recommendations. The fewer parameters which can not be estimated directly from empirical data are included in a model, the stronger the empirical validity of the model becomes. But also models solely including empirically estimated parameters, as it is the case for *SEGESD*, contain plenty of uncertainty. Models, after all, are an abstraction of reality, and the basic problem remains that one can never be certain that an assumed explaining mechanism implemented in a model is the correct abstraction of reality, even if the results perfectly match empirical data.

Additionally, SD can be criticized - just as econometrics - for relying on historical data and therefore assuming continuity of the structure of the system, summarized in the so called *Lucas Critique*. This is discussed in more detail in section 3.2.

One often cited advantage of SD addressing this problem in contrast to econometrics is the possibility to break with the existing structures of the system by introducing new elements. But then, the fundamental problem arises that no empirical data exists for the calibration of this model.

Nevertheless, these can be worthwhile modelling efforts, if all assumptions are made explicit and if the results are interpreted having the hypothetic structure of the model in mind.

Therefore, the complete modelling process for the development of *SEGESD* is described in detail within this thesis. Thereby, the significance as well as the limitations of the results are well understandable from the reading of this work.

3.2 Econometrics

Literally, the word *econometrics* means *measurement in economics*. But this is too broad a definition, and according to Maddala (2001, p. 3) "we mean by *econometrics* the application of statistical and mathematical methods to the analysis of economic data, with the purpose of giving content to economic theories and verifying them or refuting them." In short, one could say econometrics is the application of statistical methods in order to answer economic questions. Or as the econometric society's homepage defines it: *Combining economic theory with statistics and math to close the gap between theory and reality* according to Eckey et al. (2004).

Econometrics has evolved as a separate discipline from mathematical statistics as a branch focusing on problems inherent in *nonexperimental* economic data. Econometrics deals with nonexperimental or *observational* data since - in contrast to natural science experiments carried out in laboratories - social experiments most of the time can not be devised because it would be prohibitively expensive, morally repugnant or simply impossible (Wooldridge, 2006). One of the often cited pioneering work in the field is the statistical testing of business cycle theories by Tinbergen (1939).

The procedure of an econometric analysis according to Maddala (2001) can be split into three steps:

1. Specification of econometric model(s) from economic theory

2. Estimation and testing of this model(s) with observed data

3. Use model(s) for prediction and policy purposes

Depending on the theory that should be tested as well as on the structure of the observed data it can make sense to specify and test various models and to compare the results.

While in the 1940s the correct specification received a lot of scientific attention, during the 1950s and 1960s mainly estimation and testing procedures were developed. In the 1970s, the focus shifted back on the specification part of the analyis, especially stressing the need for feedback of insights from estimation results into the specification process.

The essential question during an econometric analysis is *what constitutes a successful test?* According to Maddala (2001, p. 9) "it is customary to report that the signs of the estimated coefficients are correct, [...] termed *the approach of confirming economic theories*". There remains the problem that "in many areas of economics, different econometric studies reach conflicting conclusions and, given the available data, there are frequently no effective methods for deciding which conclusion is correct. In consequence, contradictory hypotheses continue to co-exist sometimes for decades"(Blaug 1980, p. 261 in Maddala 2001).

Among the large set of statistical tools applied in econometrics - simple regressions, multiple regressions, panel data analyses, time series analyses, simultaneous equation models, discrete choice models, logit & probit models, non-linear methods, semi- & non-parametric methods to name only a few - only the simple regression is relevant to the work presented within this thesis. The reason for that, as discussed in chapter 4, is the short length of the analysed time series. More complex models could not have been estimated. Simple Regressions analyse the relation between two variables x and y studying how y varies with changes in x in cross-sectional data sets. Therefore, a simple linear regression model of the form $y = \beta_0 + \beta_1 x + u$ is tested with u forming the so called error term taking all the deviation of the observed data from the linear relation. The parameters β_0 and β_1 are then calculated using ordinary least squares estimates.

A major critique of econometrical analysis is the fact that it is highly problematic to predict the effects of policy change from the observation of historical data, especially on the highly aggregated level. This is commonly denominated as the *Lucas Critique*, named after Robert Lucas (1976). His recommendations to solve this problem was the development of more disaggregated models in order to be able to analyse links on a level where the effects are not directly changed by the proposed policy change in order to be able to observe the effects of the proposed policy change after aggregating the disaggregated results.

This approach was realized during the development of *SEGESD* in form of the econometric estimation of *deep parameters* (as called by Lucas) and their application in a SD model, aggregating these effects in a larger model. It results in a detailed disaggregated model implemented as a chain of rather simple, specific formulas in stead of few highly complex formulas. The complexity of the system then emerges as the combined effect of these equations.

With this approach, the ability of the model to predict future reactions of the economy to increased economic spending is improved over the direct prediction based on the econometric estimation of the direct effect of education spending and economic growth.

A further problem with econometrics can be it's high data requirements, both in quality and quantity. When using the methodology, it is therefore most important to be aware of the requirements of the selected statistical method, and to be particular aware of its limits, especially when it comes to the interpretation of the results when the available data set does not fulfil the requirements. A common problem in this context is the use of a statistical procedure with a data set of too few observations. Then no significant results can be obtained.

3.3 Application for *SEGESD*

Both methodologies - *system dynamics* as well as *econometrics* - complement each other very well, as mentioned before. Here follows a condensed overview of *how* and *why* the two methodologies were applied for the development of *SEGESD*. It is implemented as *SD* model, and crucial parameter sets were estimated using econometrical tools.

System Dynamics is an appropriate methodology for modelling endogenous economic growth driven by education investment mainly due to

— it's capability to model behaviour over time and
— the possibility to include feedback loops.

The capability to model the behaviour over time is essential for reproducing the dynamics of the education system and its effects on the labour market, due to lag times of various years up to decades. This is a central aspect making system dynamics a highly appropriate tool for this modelling endeavour. And the possibility to include feedback loops are essential for modelling population dynamics.

Econometrics was applied in the development of *SEGESD* in the estimation of the model parameters at two crucial points. First, in the analysis of the relation between the availability of qualified labour to the market and the employment of these persons on sectoral level (→ sec. 4.3 on page 57). Second, in the estimation of the connection between the amount of money flowing into the education system and the shares of persons succeeding in increasing their personal formal education level (→ sec. 4.5 on page 85). This was necessary, since the system dynamics calibration process would not have been able to produce valid results due to too many degrees of freedom.

SEGESD is based on the system dynamics methodology applied for the development of *ASTRA*. It could technically and conceptually be integrated into the existing *ASTRA* model. In order to do this, the sectoral disaggregation of *SEGESD* has to be adapted to the one of *ASTRA*, which would lead to a loss of information. Also, *SEGESD* covers only Germany, while *ASTRA* covers the EU27 plus Norway and Switzerland. In order to connect *SEGESD* with *ASTRA* technically, either *ASTRA* would have to be reduced to only Germany or *SEGESD* would have to be extended by one dimension to cover these countries.

Also, it is important to stress that *SEGESD* does not implement a complete system dynamics context of the economy as this is done within *ASTRA*. It rather focuses on one single chain of effects, forming a small part of the larger interdependencies implemented in *ASTRA*, elaborating this chain in much more detail than in *ASTRA*.

3.4 Small models or large models?

Small models are developed in order to obtain fundamental insights within a highly abstract environment. Within controlled laboratory conditions theorems can be tested.

Large models are developed in order to reflect reality as well as possible. With this approach, the behaviour of dynamic systems can be modelled as numeric simulation experiments.

As the model size increases, so does the amount of parameters that have to be estimated. With that, the degrees of freedom of the model also rapidly increases. Therefore, not the complete model is calibrated in one step, but rather the parameters for individual equations are estimated step by step. After that, the feedback loops are calibrated. In this way, step by step larger parts of the model are calibrated, until eventually the complete model is calibrated.

Also, instead of using system dynamics calibration procedure, an econometrically tested relation can be integrated into the model. Thereby, the parameters of the assumed functional relation are obtained using statistical parameter estimation instead of the heuristic algorithms which from part of the system dynamics calibration procedure. This approach implies the assumption that all effects between the dependent and the independent variables of the econometrically tested equation remain constant throughout the simulation experiments carried out with the obtained model.

SEGESD can be classified as large model. It incorporates various functional relations depending on each other. Each individual relation consists of parameters either estimated within the scope of this thesis or obtained from external sources. As described in the following chapter 4, two relations were econometrically tested. For the model simulations, the parameters of these functional relations were assumed to remain constant.

Chapter 4

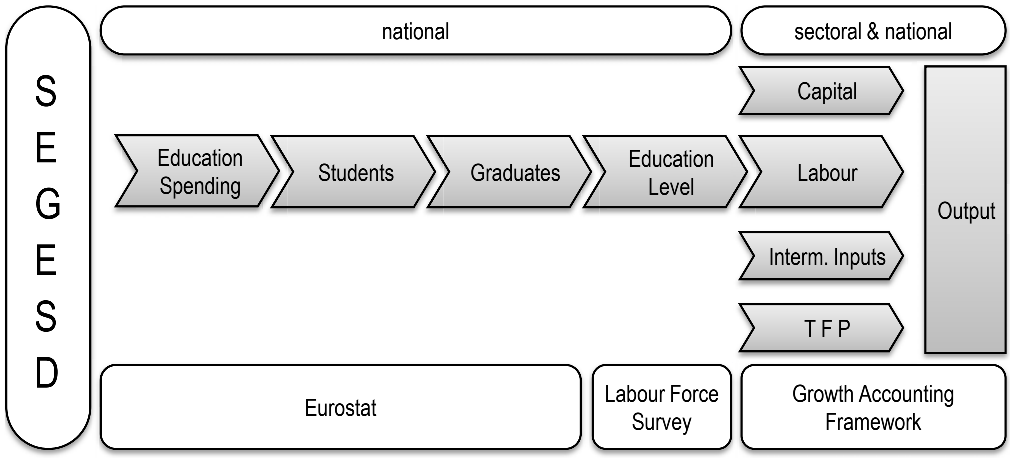
Endogenous Growth Model *SEGESD*

This chapter contains the detailed description of the implementation of a system dynamics model of endogenous growth driven by education spending. For the sake of easier referencing, the model was named SEGESD, **S**ectoral **E**ndogenous **G**rowth driven by **E**ducation in **S**ystem **D**ynamics. It starts in the year 1970 and runs till 2100. The early start year is needed to let graduation rates endogenously determine the qualification level in the population as described in section 4.4 on page 65. And the long trail is need due to the large temporal lags in the educations system on the one hand and the long time the whole system needs to fall back to the baseline, which is needed for a cost-benefit analysis. This is explained in detail in section 5.2 on page 104. The assumptions for the baseline scenario until 2100 are described in section 5.1 on page 99.

Figure 4.1 on the next page gives a high level overview of the implemented relations. In short, the model works as follows. Using a *Growth Accounting Framework* the growth of gross output of 30 sectors is calculated as the sum of the growth of labour input, capital input, intermediate inputs and of total factor productivity (→ sec. 4.2 on page 44). *SEGESD* uses this framework to analyse the effect of an hypothetical change of the labour input triggered through additional education investments.

The labour input is defined monetary as the sum of all wages paid, calculated as the product of the hours worked and the according wage per hour, differentiated by age, education and sex of the workforce. *SEGESD* models a change of the hours worked on sectoral level, assuming the wages per hour to remain unchanged in the scenarios compared to the baseline. Because of this fixed relation between the monetary labour input and the hours worked, both variables are referred to as labour input. In order to distinguish be-

Figure 4.1
Model overview graph



own graph

tween the two, the units are always provided. Especially in the subsequent chapter 5 the changes in labour input are given as hours worked.

The core mechanism implemented within *SEGESD* models an increase of the education levels achieved by all individuals of the population triggered by an increase of the education spending. The increase of medium and highly qualified persons lead to a shift towards more qualified labour input. And since the wages per hour are the higher, the higher the qualification of the according individual, this implies a shift towards an higher average wage and with that to more productive labour.

The qualitative composition and quantity of hours worked is calculated based on the education level of the population. Based on statistical analysis of the labour market, increased availability of highly educated persons results in a raise of the employment of these persons in certain sectors, modelled as an increase of the hours worked, which directly leads to an increase of the monetary labour input (→ sec. 4.3 on page 57). The population in turn is simulated as an age cohort model differentiating the persons by their achieved level of education and sex (→ sec. 4.4 on page 65). And the probabilities of persons to raise their formal education is influenced by the flow of money into the education system (→ sec. 4.5 on page 85). With this chain of effects, the influence of changing the spending for education on the volume of gross output on a sectoral level can be analysed.

SEGESD endogenously calculates the change of output based on this chain of effects within the *EUKLEMS* growth accounting framework, i.e. it endogenously calculates a change of the labour input based on a change in the education spending. That labour input change is used within the *EUKLEMS* framework to calculate a change of the sectoral gross output. All other elements contributing to gross output (i.e. capital, intermediate inputs as well as total factor productivity) within the growth accounting framework are assumed to remain constant. Therefore, within *SEGESD* one cause for the change of gross output is analysed isolatedly - changes in education spending. And that change is assumed to influence only the quantity and qualitative composition of labour input. All other influences are kept constant.

Figure 4.2 on page 50 gives an overview of the variable dependencies within *EUKLEMS*. In *SEGESD*, the variable *labour input* - measured as hours worked - of this framework is modified depending on changes in the education level of the population. All other variables remain unchanged. So the labour input, exogenous in *EUKLEMS*, becomes an endogenous variable in *SEGESD*.

This chapter is organized as the previous paragraphs, i.e. going backwards through the effects modelled in *SEGESD* sketched in figure 4.1 on the preceding page in the sections 4.2 to 4.5. Before these main parts, a short general section (4.1) on the aggregation level of *SEGESD* is included.

4.1 Aggregation level of analysis

Different parts of the model work on varying aggregation levels, determined by the aggregation level of the available data. This section gives a short overview of these and explains how the transition between differing aggregation levels is handled.

The **education level** is distinguished within the population cohort model (→ sec. 4.4 on page 65) as well as in the growth accounting framework (→ sec. 4.2 on the next page) using three education classes - low, medium and high. These classes are aggregations of ISCED97 (International Standard Classification of Education) codes as shown in table 4.1 alongside. This aggregation is necessary due to breaks in data on the disaggregated ISCED97 levels in the underlying *Labour Force Survey* data (→ app. B.3 on page 169). On the aggregated level the data appears in consistent timelines.

ISCED97	
code	class
0	low
1	low
2	low
3	med
3a	med
3b	med
3c	med
4a	med
4b	med
4c	med
5a	high
5b	high
6	high

Table 4.1
ISCED map.

The **age** is represented on yearly basis within the population cohort model (→ sec. 4.4 on page 65). The data from the labour force survey which was used to calibrate the population cohort model is available disaggregated into six age classes - *below 14*, *15 to 24*, *25 to 32*, *33 to 49*, *50 to 64* and *above 64*. Within the growth accounting framework (→ sec. 4.2), three age aggregation classes are used - *15 to 29*, *30 to 49* and *50 to 65*. The population cohort model was designed using *yearly* age cohorts (1.) in order to bridge the different aggregations in the labour force data on the one hand and the growth accounting framework data from *EUKLEMS* on the other and (2.) in order to model the temporal dynamics and delays of the education system.

The **economy** is disaggregated into 30 sectors (→ tab. A.2 on page 160) based on NACE Rev. 1 (Nomenclature statistique des activités économiques dans la Communauté européenne) industry classification for the analysis within the growth accounting framework (→ sec. 4.2).

4.2 *EUKLEMS* Growth Accounting Framework

The aim of the growth accounting framework is to explore the origins of gross output growth. Therefore, it decomposes this growth into the contributions from the growth of capital input, labour input, intermediate inputs and of the residual total factor productivity. As shown in figure 4.2 on page 50, this decomposition is then used to calculate the growth of *total factor productivity* based on *gross output*, *investments*, *depreciation rates*, *capital compensation*, *hours worked*, *labour compensation* and *intermediate inputs*.

For my work, I use those results, and explore the effect of a hypothetical change in the qualitative and quantitative composition of the input factor *labour* on the gross output and the gross output growth. Therefore, *total factor productivity*, *investments*, *depreciation rates*, *capital compensation* and *intermediate inputs* are assumed to remain unchanged compared to the time series reported by *EUKLEMS* throughout my analyses. Changes in *labour input* in monetary terms results from changed amounts of *hours worked* within the differing labour types triggered by changes in the structure of the education levels in the population leading to changes in the *labour compensation*. This leads to changes of *gross output* on sectoral level.

The methodology for growth accounting used within SEGESD is the international standard in growth accounting. Based on this methodology, a large international consortium collaborated within the *EUKLEMS* project in order to compile data on European economic growth. This data is the base for the calculation of the changes in gross output due to changed education spending within *SEGESD*. The *EUKLEMS* database was chosen because it currently[1] provides the best disaggregation of growth data on sectoral level as well as the decomposition of labour input by sex, age and education for European countries, especially for Germany.

The core idea of the *Growth Accounting Framework* is the decomposition of output growth into the growth of the input factors, based on the *Production Possibility Frontiers* methodology in which sectoral gross output is a function of capital, labour and intermediate inputs as well as the technological level reflected in *total factor productivity.* As visualized in figure 4.1 on page 42, the gross output is calculated based on intermediate inputs, capital input, labour input and total factor productivity.

A detailed discussion of the advantages and shortcomings of the *production possibilities frontiers* compared to *aggregate production functions* as well as *direct aggregation across sectors* in order to construct economy wide estimates of output growth and the sources of it was compiled in Jorgenson et al. (2007, sec.2). They describe in detail in what ways the *aggregate production function* is more restrictive and the *direct aggregation of sectors* less restrictive than the *production possibility frontiers* approach.

Essentially, the aggregate production function approach implies that heterogeneous types of capital and labour are aggregated equally across sectors and each type of capital and labour must command the same price in each sector. On the other hand, the direct aggregation across sectors relaxes all restrictions on value added functions and inputs across sectors and treats the aggregate economy as a wheighted average of the individual sectors. In terms of restrictedness the production possibility frontiers approach is situated between these two. Essential is the fact that value added prices are not required to be identical across sectors.

This framework was originally developed by Jorgenson et al. (1987) and applied to the USA. It was further elaborated in Jorgenson et al. (2005) and later applied to a set of European countries within the *EUKLEMS* project as described in Timmer et al. (2007a). According to Jorgenson et al. (2005, p.55), this methodology has been accepted as the international standard used by the OECD (Schreyer, 2001) for productivity measurement.

For a detailed history of growth accounting approaches see Jorgenson et al. (2005, chp. 2.3). In short, the constant quality index of capital input was first introduced in official statistics by the USA Bureau of Labour Statistics (BLS) in 1986 and the constant quality index of labour input replaced *hours worked* as a measure in 1994.

[1] during the conceptualisation phase of the model in the 2nd half of 2009.

The following description (within section 4.2) of the *Growth Accounting Framework* implemented in SEGESD is derived from the sources[2] referenced in the previous paragraphs. To improve the readability of the description, explicit referencing in each case is omitted. The complete picture is not laid out in any single publication, the following description only emerges as a combination of the individual sources.

All variables are subscripted with *time*, but this has been omitted wherever possible, i.e. wherever all values within one formula are taken from the same point in time. Only in those cases where lags where used, time is subscripted using t.

4.2.1 Production Possibility Frontier

The *production possibility frontier* describes efficient combinations of outputs and inputs for the economy as a whole. Aggregate output Y consists of outputs of investment goods and consumption goods. These outputs are produced from aggregate input, consisting of capital and labour services as well as intermediate inputs. Productivity is a *Hicks-neutral* augmentation of aggregate input.

The *gross output production function* for each sector is a function of labour input, capital input, intermediate inputs and of the efficiency:

$$Y_{ind} = f_{ind}(L_{ind}, K_{ind}, X_{ind}, T_{ind}) \tag{4.1}$$

with:		
	Y	Gross Output
	L	Labour input
	K	Capital input
	X	Intermediate inputs
	T	Efficiency
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)

The sector specific *value added function* is:

$$V_{ind} = g_{ind}(L_{ind}, K_{ind}, T_{ind}) \tag{4.2}$$

with:		
	V	Value added
	L	Labour input
	K	Capital input
	T	Efficiency
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)

[2] Jorgenson et al. (1987, 2005, 2007); Timmer et al. (2007a)

And the *relation between value-added and gross output* is:

$$Y_{ind} = f_{ind}(X_{ind}, g_{ind}(L_{ind}, K_{ind}, T_{ind})) \tag{4.3}$$

with:	Y	Gross Output
	L	Labour input
	K	Capital input
	X	Intermediate inputs
	T	Efficiency
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)

explicitly breaking the symmetry between intermediate inputs and the remaining inputs. The efficiency is not influenced by the intermediate inputs.

Assuming *competitive product and factor markets*, producer equilibrium implies that the value of output is equal to the value of all inputs. Gross output is the sum of labour compensation, capital compensation and intermediate inputs:

$$\begin{aligned} & YM_{ind} &&= LC_{ind} &&+ KC_{ind} &&+ XM_{ind} \\ \Longleftrightarrow\ & P^Y_{ind} \cdot Y_{ind} &&= P^L_{ind} \cdot L_{ind} &&+ P^K_{ind} \cdot K_{ind} &&+ P^X_{ind} \cdot X_{ind} \end{aligned} \tag{4.4}$$

with:	YM	Gross Output (monetary) at nominal prices
	LC	Labour Compensation (nominal)
	KC	Capital Compensation (nominal)
	XM	Intermediate Inputs (monetary) at nominal prices
	P^Y	Price of Output
	Y	Gross Output Volume
	P^L	Price of Labour Input
	L	Labour Input [hours worked]
	P^K	Price of Capital Input
	K	Capital Input, i.e. capital stock
	P^X	Price of Intermediate Inputs
	X	Intermediate Inputs Volume (Quantity)
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)

For the implementation of this framework for *SEGESD*, the calculation of gross output was chosen instead of value added. The results remain the same, since the difference is given by the intermediate inputs, which will not be modified in the scenarios analysed within the scope of this thesis. For the calculation of relative differences between gross output volumes in varying scenarios of education spending, this has no effect. But in order to implement a more general model, intermediate inputs were taken into account, to include the possibility to analyse the effects of changes in the intermediate input structure on a sectoral level. This is not within the scope of this work, but necessary for the integration of *SEGESD* into *ASTRA*.

4.2.2 Aggregation method

For aggregations of inputs of differing values within the growth accounting framework implemented in the EUKLEMS project a *Törnqvist quantity index* (developed by Törnqvist 1936, cited in Hillinger 2008) was used.

This choice along with a discussion of advantages and disadvantages is discussed in detail in Jorgenson et al. (2005, p. 96). In short, the *Törnqvist* index is a discrete time approximation to a Divisia index, it falls into the category of *superlative* indices defined by Diewert (1976), uses moving weights unlike Paasche or Laspeyres and offers a close approximation to the Fisher-ideal index used in the US National Income and Product Accounts. This was relevant in the original development of the methodology for the USA.

A *Divisia* index (Divisia, 1925) is a continuous weighted sum of the growth rates of the various components, with the weights given by the component's shares in the total value. The *Tornqvist* index, i.e. the discrete time version of the *Divisia* index, is defined as

$$
\begin{aligned}
& \ln I_t - \ln I_{t-1} && = \sum_{j=1}^{n} \overline{vs}_{j,t} \; (\ln x_{j,t} - \ln x_{j,t-1}) \\
\iff \quad & \ln \frac{I_t}{I_{t-1}} && = \sum_{j=1}^{n} \overline{vs}_{j,t} \; \ln \frac{x_{j,t}}{x_{j,t-1}} \\
\iff \quad & \Delta \ln I_t && = \sum_{j=1}^{n} \overline{vs}_{j,t} \; \Delta \ln x_{j,t}
\end{aligned}
\tag{4.5}
$$

with:	I	Tornqvist Index
	x	quantity of a component
	$\overline{vs}_j$	two period averaged value share of component j in total
	j	Index for component
	t	Index for time

according to which the growth rate of the aggregate index I is the weighted average of the growth rates of the components x. The weights used in the index calculation are two period averages of the value shares vs:

$$
\overline{vs}_{j,t} = {}^1\!/_2 (vs_{j,t} + vs_{j,t-1}) \tag{4.6}
$$

with:	vs_j	value share of component j in total
	j	Index for component
	t	Index for time

This method is used for the calculation of total factor productivity growth, capital service growth and labour service growth. Total factor productivity growth is calculated as the residual between gross output growth and the aggregation of the growth of intermediate inputs, labour service and capital service (→ sec. 4.2.3). Capital service growth in turn is the value weighted aggregation of growth of stocks of several capital types (→ sec. 4.2.4 on page 52). And labour service growth is the weighted aggregation of the growth of hours worked by various labour types, i.e. by persons of different age, sex and education level (→ sec. 4.2.4 on page 52). All these equations are *Tornqvist* indices. Therefore, they are all defined as a logarithmic function. An overview of these relations is given in figure 4.2 on the following page.

4.2.3 Total Factor Productivity & Output

In order to separate the development of the observed gross output into the *real* part due to changes in the quantity of output and the *inflation* part due to the changes in prices, gross output at nominal prices YM is defined as the product of the two factors price P^Y and volume Y

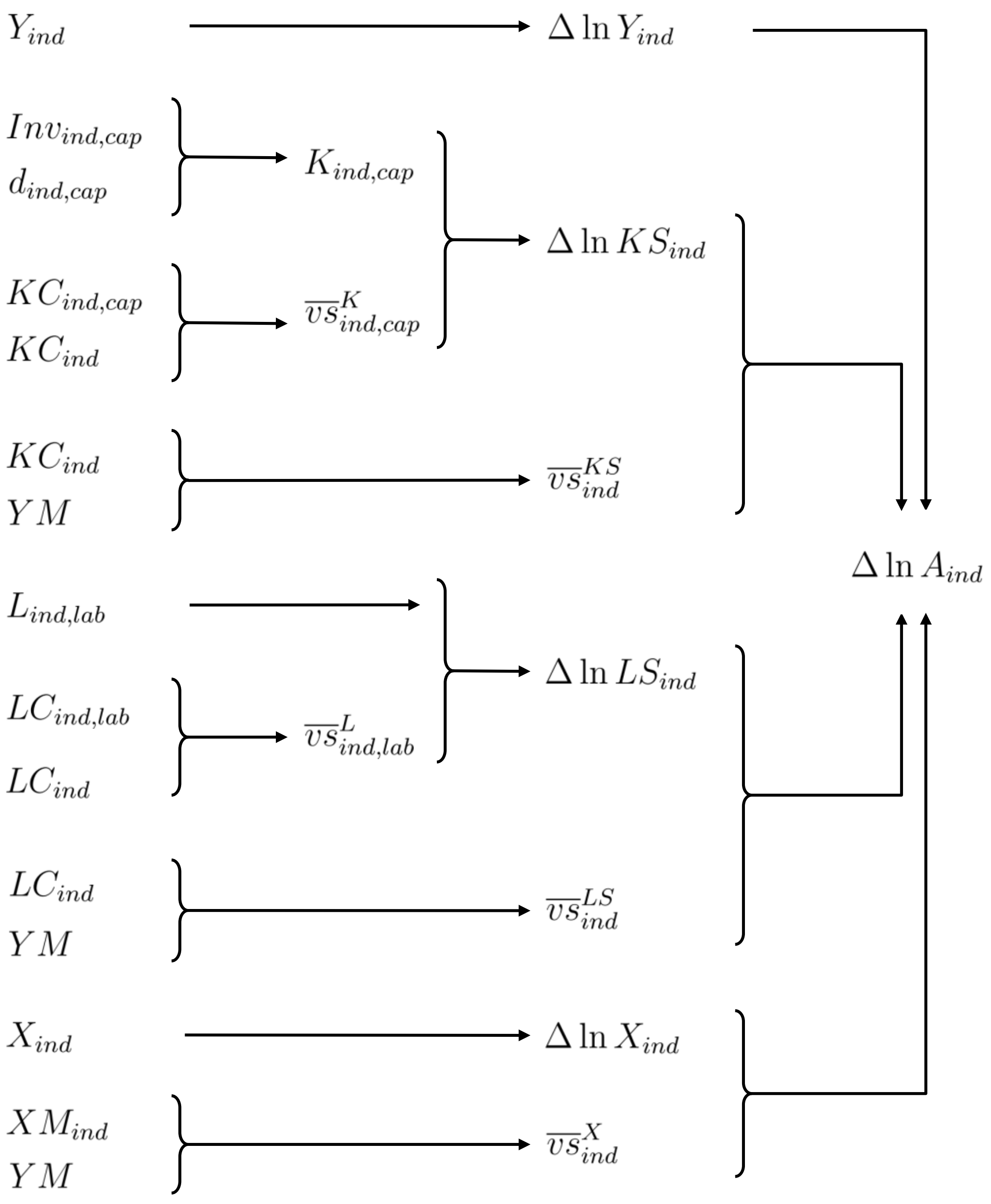
$$YM_{ind} = P^Y_{ind} \cdot Y_{ind} \tag{4.7}$$

with:
- YM Gross Output (monetary) at nominal prices
- P^Y Price of Output
- Y Gross Output Volume
- ind Index for sectors (or industries) (List →Table A.2 on page 160)

Growth accounting as implemented within the *EUKLEMS* project starts with the definition of the calculation of the growth of the volume of output as value share weighted aggregation of the growth of *capital*, *labour*, *intermediate inputs* and of *total factor productivity* as a *Törnqvist quantity index* (→ sec. 4.2.2 on the facing page). Capital, labour and intermediate input growth, each an aggregate defined in equations 4.16 on page 55 (KS & LS) and in sec. 4.2.5 (X), is weighted by the two period value shares $\overline{vs}$ ($\overline{vs}^{KS}$ & $\overline{vs}^{LS}$ → eq. 4.17 on page 55 and $\overline{vs}^{X}$ → eq. 4.19 on page 56) of these inputs in the total output.

$$\begin{aligned} \Delta \ln Y_{ind} = \; & \overline{vs}^{KS}_{ind} \cdot \Delta \ln KS_{ind} \\ + \; & \overline{vs}^{LS}_{ind} \cdot \Delta \ln LS_{ind} \\ + \; & \overline{vs}^{X}_{ind} \cdot \Delta \ln X_{ind} \\ + \; & \Delta \ln A_{ind} \end{aligned} \tag{4.8}$$

Figure 4.2
Variable dependencies - Total Factor Productivity



own graph

with:	Y	Gross Output Volume
	$\overline{vs}^{KS}$	Two periode averaged value share of capital service in gross output
	KS	Capital Service
	$\overline{vs}^{LS}$	Two periode averaged value share of labour service in gross output
	LS	Labour Service
	$\overline{vs}^{X}$	Two periode averaged value share of intermediate inputs in gross output
	X	Intermediate Inputs Volume (Quantity)
	A	Total Factor Productivity
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)

with $\Delta \ln Y_{ind,t} = \ln Y_{ind,t} - \ln Y_{ind,t-1} = \ln \frac{Y_{ind,t}}{Y_{ind,t-1}}$ and similar for all the other cases.

At this point it appears important to mention that this growth decomposition formula is *not* a Cobb-Douglas production function. It rather is a *value-weighted* sum of the growth of various capital stock types, labour input types, intermediate input types and the growth of the total factor productivity.

Total factor productivity A is defined as the residual, explaining the amount of growth not explained by the growth of capital service KS or labour service LS (→ sec. 4.2.4 on the next page) or the growth of intermediate inputs X (→ sec. 4.2.5). So equation 4.8 can be rearranged to

$$\begin{aligned}\Delta \ln A_{ind} = & \quad \Delta \ln Y_{ind} \\ & - \overline{vs}^{KS}_{ind} \cdot \Delta \ln KS_{ind} \\ & - \overline{vs}^{LS}_{ind} \cdot \Delta \ln LS_{ind} \\ & - \overline{vs}^{X}_{ind} \cdot \Delta \ln X_{ind}\end{aligned} \tag{4.9}$$

with:	Y	Gross Output Volume
	$\overline{vs}^{KS}$	Two periode averaged value share of capital service in gross output
	KS	Capital Service
	$\overline{vs}^{LS}$	Two periode averaged value share of labour service in gross output
	LS	Labour Service
	$\overline{vs}^{X}$	Two periode averaged value share of intermediate inputs in gross output
	X	Intermediate Inputs Volume (Quantity)
	A	Total Factor Productivity
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)

visualized in figure 4.2 on the preceding page. Based on the yearly growth rates of total factor productivity an index for A can be calculated as

$$\begin{aligned}\Delta \ln A_{ind,t} &= \ln \frac{A_{ind,t}}{A_{ind,t-1}} \\ \Longleftrightarrow \quad e^{\Delta \ln A_{ind,t}} &= \frac{A_{ind,t}}{A_{ind,t-1}} \\ \Longleftrightarrow \quad A_{ind,t} &= A_{ind,t-1} \cdot e^{\Delta \ln A_{ind,t}}\end{aligned} \tag{4.10}$$

with:	A	Total Factor Productivity
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)
	t	Index for time

In analogy to this equation, indices for all other variables appearing as $\Delta \ln ...$ can be calculated, especially for sectoral gross output volume Y_{ind}. This index of Y_{ind} is later used for analysing growth effects of investments into education as described in chapter 5 on page 99.

Within *SEGESD*, in a first step TFP was calculated according to the methodology described in this section with equation 4.9. In a second step, the resulting sector specific TFP was then used to calculate the volume of gross output according to equation 4.8 for various scenarios of education spending. The change in gross output volume is thereby driven by changes of labour input in the form of hours worked by persons differentiated by age, sex and education level.

The calculation of TFP within *SEGESD* became necessary since the reported values within EUKLEMS were reproducible using the described methodology with the reported values of the independent variables only in most of the sectors, but not for all of them. This is interesting by itself but was not further investigated. No comments on that was found in the documentation of the EUKLEMS project. For most of the sectors, the deviation was well below 1% and can therefore be well attributed to rounding imprecision due to the data file format.

Then in turn the endogenously calculated sectoral gross output volume Y based on the EUKLMES data as well as on the endogenous calculation of TFP became the baseline for the scenario analysis. The deviation between the calculated values and the reported values were also all well below 1%.

4.2.4 Capital & Labour Services

Capital and labour services are defined and calculated similarly and therefore laid out in parallel.

The terms *input* and *service* in the context of capital and labour are alternately and inconsistently used in the publications cited here. Most of the time though, *service* appears as term for the value share weighted translog aggregation index (equation 4.16) while input refers to the monetary stock of capital or the quantity of hours worked. This terminology is used consistently here.

Capital Service growth is a value share weighted aggregation of the growth of stocks of various capital types with a *Törnqvist index* (→ sec. 4.5 on page 48). Eight different capital types are differentiated, grouped into IT assets, machinery and buildings. For a full list of the capital types see table A.3 on page 161. The subscript used for indicating that a certain variable is disaggregated by capital types is *cap*.

The capital stock is defined as the aggregation of yearly investments Inv, deprecated with capital type and sector specific depreciation rates d calculated based on the *perpetual inventory* method. For the start year, the initial capital stock is needed, any subsequent year's capital stock is then calculated only base on Investments and depreciation rates.

Those depreciation rates are *technical*, rather than *accounting* depreciation rates. According to the *EUKLEMS* documentation, they represent the loss of utility of the machines due to physical and technological aging rather than the loss of value used in bookkeeping. Therefore, the resulting capital stock represents the production possibility rather than a financial capital stock listed in balance sheets. It is calculated as

$$K_{ind,cap,t} = \left(1 - d_{ind,cap}\right) \cdot K_{ind,cap,t-1} + Inv_{ind,cap,t} \tag{4.11}$$

with:
- K Capital Input, i.e. capital stock
- Inv Investments
- d Depreciation rate
- ind Index for sectors (or industries) (List →Table A.2 on page 160)
- cap Index for capital type (List →Table A.3 on page 161)
- t Index for time

Similarly, growth of labour service is a value share weighted aggregation of the growth of hours worked by various groups of the workforce, called labour types, differentiated by age, sex and education level. The EUKLEMS data provides labour input, i.e. hours worked, differentiated by three age classes - 15 to 29, 30 to 49 and 50 to 65 - as well as by three education levels - low, medium and high. Along with the differentiation by sex this makes 18 labour types (→ Table A.1 on page 159). The subscript used for indicating that a certain variable is disaggregated by labour types is *lab*.

Each capital and labour type is assumed to be identical across sectors and to receive the same price in all sectors:

$$P^K_{cap} = P^K_{ind,cap} \qquad \text{and} \qquad P^L_{lab} = P^L_{ind,lab} \tag{4.12}$$

with:
- P^K Price of Capital Input
- P^L Price of Labour Input
- ind Index for sectors (or industries) (List →Table A.2 on page 160)
- cap Index for capital type (List →Table A.3 on page 161)
- lab Index for labour type (List →Table A.1 on page 159)

The value shares used for the calculation of the *Törnqvist* indices are based on the compensation paid to each input, i.e. their value shares in the sectoral capital or labour compensation. The sector specific capital and labour *compensation* (KC & LC) is defined as the aggregation of all money spent for capital or for labour services. It is also the product of the *price* for a service multiplied with the *service* :

$$\begin{aligned} KC_{ind} &= \sum_{cap} P^K_{ind,cap} \cdot K_{ind,cap} &&= P^{KS}_{ind} \cdot KS_{ind} \\ LC_{ind} &= \sum_{lab} P^L_{ind,lab} \cdot L_{ind,lab} &&= P^{LS}_{ind} \cdot LS_{ind} \end{aligned} \tag{4.13}$$

with:	KC	Capital Compensation (nominal)
	P^K	Price of Capital Input
	K	Capital Input, i.e. capital stock
	P^{KS}	Price of Capital Service
	KS	Capital Service
	LC	Labour Compensation (nominal)
	P^L	Price of Labour Input
	L	Labour Input [hours worked]
	P^{LS}	Price of Labour Service
	LS	Labour Service
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)
	cap	Index for capital type (List →Table A.3 on page 161)
	lab	Index for labour type (List →Table A.1 on page 159)

Capital compensation is calculated as residual in equation 4.4 on page 47, i.e. as

$$KC_{ind} = YM_{ind} - LC_{ind} - XM_{ind} \tag{4.14}$$

with:	KC	Capital Compensation (nominal)
	YM	Gross Output (monetary) at nominal prices
	LC	Labour Compensation (nominal)
	XM	Intermediate Inputs (monetary) at nominal prices
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)

and labour compensation is simply the sum of all wages paid, differentiated by labour types.

Based on these definitions, the sector specific value shares are defined as

$$\begin{aligned} vs^K_{ind,cap} &= \frac{KC_{ind,cap}}{KC_{ind}} &&= \frac{P^K_{cap} \cdot K_{ind,cap}}{\sum_{cap} P^K_{cap} \cdot K_{ind,cap}} \\ vs^L_{ind,lab} &= \frac{LC_{ind,lab}}{LC_{ind}} &&= \frac{P^L_{lab} \cdot L_{ind,lab}}{\sum_{lab} P^L_{lab} \cdot L_{ind,lab}} \end{aligned} \tag{4.15}$$

with:
vs^K_{cap}	Value Share of capital type compensation in aggregate
KC	Capital Compensation (nominal)
P^K	Price of Capital Input
K	Capital Input, i.e. capital stock
vs^L_{lab}	Value Share of labour type compensation in aggregate
LC	Labour Compensation (nominal)
P^L	Price of Labour Input
L	Labour Input [hours worked]
ind	Index for sectors (or industries) (List →Table A.2 on page 160)
cap	Index for capital type (List →Table A.3 on page 161)
lab	Index for labour type (List →Table A.1 on page 159)

and these value shares are used in the capital and labour service growth calculation as two period averages $\overline{vs}^K_{ind,cap}$ and $\overline{vs}^L_{ind,lab}$ defined in analogy to eq. 4.6 on page 48. The growth of the hours worked and the capital stocks are aggregtated using a *Törnqvist index* (→ eq. 4.5 on page 48) resulting in the growth of capital service KS and labour service LS calculated as

$$\begin{aligned}\Delta \ln KS_{ind,t} &= \ln \frac{KS_{ind,t}}{KS_{ind,t-1}} = \sum_{cap} \overline{vs}^K_{ind,cap,t} \cdot \ln \frac{K_{ind,cap,t}}{K_{ind,cap,t-1}} \\ \Delta \ln LS_{ind,t} &= \ln \frac{LS_{ind,t}}{LS_{ind,t-1}} = \sum_{lab} \overline{vs}^L_{ind,lab,t} \cdot \ln \frac{L_{ind,lab,t}}{L_{ind,lab,t-1}}\end{aligned} \tag{4.16}$$

with:
KS	Capital Service
K	Capital Input, i.e. capital stock
$\overline{vs}^K_{cap}$	Two periode averaged value share of capital type compensation in aggregate
LS	Labour Service
L	Labour Input [hours worked]
$\overline{vs}^L_{lab}$	Two periode averaged value share of labour type compensation in aggregate
ind	Index for sectors (or industries) (List →Table A.2 on page 160)
cap	Index for capital type (List →Table A.3 on page 161)
lab	Index for labour type (List →Table A.1 on page 159)
t	Index for time

For the aggregation of the growth of capital and labour service along with the growth of intermediate inputs and TFP in eq. 4.9 on page 51, the sector specific value shares of labour services and capital services in the gross output are defined as the labour or capital compensation divided by the gross output:

$$\begin{aligned}vs^{KS}_{ind} &= \frac{KC_{ind}}{YM} = \frac{P^{KS}_{ind} \cdot KS_{ind}}{P^Y_{ind} \cdot Y_{ind}} \\ vs^{LS}_{ind} &= \frac{LC_{ind}}{YM} = \frac{P^{LS}_{ind} \cdot LS_{ind}}{P^Y_{ind} \cdot Y_{ind}}\end{aligned} \tag{4.17}$$

with:
vs^{KS}	Value Share of Capital Service in Gross Output
KC	Capital Compensation (nominal)
P^{KS}	Price of Capital Service
KS	Capital Service
vs^{LS}	Value Share of Labour Service in Gross Output
LC	Labour Compensation (nominal)
P^{LS}	Price of Labour Service
LS	Labour Service
YM	Gross Output (monetary) at nominal prices
P^{Y}	Price of Output
Y	Gross Output Volume
ind	Index for sectors (or industries) (List →Table A.2 on page 160)

with the according two period averages $\overline{vs}_{ind}^{KS}$ and $\overline{vs}_{ind}^{LS}$ in analogy to equation 4.6 on page 48.

4.2.5 Intermediate Inputs

Intermediate inputs at nominal prices are decomposed into the product of volume and price per volume:

$$XM_{ind} = P_{ind}^{X} \cdot X_{ind} \tag{4.18}$$

with:
XM	Intermediate Inputs (monetary) at nominal prices
P^{X}	Price of Intermediate Inputs
X	Intermediate Inputs Volume (Quantity)
ind	Index for sectors (or industries) (List →Table A.2 on page 160)

Value shares of intermediate inputs in gross output per sector are

$$vs_{ind}^{X} = \frac{XM_{ind}}{YM} = \frac{P_{ind}^{X} \cdot X_{ind}}{P_{ind}^{Y} \cdot Y_{ind}} \tag{4.19}$$

with:
XM	Intermediate Inputs (monetary) at nominal prices
YM	Gross Output (monetary) at nominal prices
P^{X}	Price of Intermediate Inputs
X	Intermediate Inputs Volume (Quantity)
P^{Y}	Price of Output
Y	Gross Output Volume
ind	Index for sectors (or industries) (List →Table A.2 on page 160)

and the according two period averaged value shares $\overline{vs}_{ind}^{X}$ defined analogously to eq. 4.6 on page 48.

Intermediate input volume growth is defined as a value share weighted aggregation of the growth of various input products using a *Törnqvist index*

(→ sec. 4.5 on page 48). The subscript to indicate a variable's disaggregation into products is *prod*. The intermediate volume growth is calculated as

$$\Delta \ln X_{ind,t} = \ln \frac{X_{ind,t}}{X_{ind,t-1}} = \sum_{prod} \overline{vs}^X_{ind,prod,t} \cdot \ln \frac{X_{ind,prod,t}}{X_{ind,prod,t-1}} \tag{4.20}$$

with:	X	Intermediate Inputs Volume (Quantity)
	$\overline{vs}^X_{prod}$	Two period averaged value share of intermediate input of one product in all
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)
	$prod$	Index for products
	t	Index for time

with $\overline{vs}^X_{ind,prod}$ denoting the two period averages (→ eq. 4.6 on page 48) of the value shares of one product in all products used as intermediate inputs by a certain sector. These are calculated as

$$vs^X_{ind,prod} = \frac{p^X_{ind,prod} \cdot X_{ind,prod}}{\sum_{prod} p^X_{ind,prod} \cdot X_{ind,prod}} \tag{4.21}$$

with:	X	Intermediate Inputs Volume (Quantity)
	p^X	User price of intermediate inputs
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)
	$prod$	Index for products

using the price paid in a certain sector for a certain product $p^X_{ind,prod}$ and the quantity used of this product in the according sector.

In the EUKLEMS database, only aggregated intermediate input indices for three input groups are given - energy, materials and services. The underlying more disaggregated data is not reported. Therefore, the implementation in *SEGESD* separates intermediate inputs also into these three groups.

4.3 Education Level driving Labour Input

The qualitative composition and the quantity of the labour input for the calculation of the labour service (→ eq. 4.16 on page 55) used in equation 4.8 on page 49 is the key link between the spending for education on the one side and the gross output on the other.

Within this section, first the statistical relation between the education level distribution in the population and the labour input per economic sector is analysed (→ sec. 4.3.2 on page 59). Then, this relation is used to calculate the change in labour input per sector in the case of an hypothetical change in the structural composition of education level within the population in *SEGESD* (→ sec. 4.3.3 on page 62). Before these two quantitative sections, the causality of the relation and it's direction is discussed (→ sec. 4.3.1).

The labour input distinguished by sector and labour type is contained in the variable $L_{ind,lab}$ introduced in the previous section 4.2.4 on page 52.

The composition of the population by age, sex and education level according to the *labour types* classification (→ tab. A.3 on page 161) is derived from the *Labour Force Survey* (→ sec. B.3 on page 169), represented in the variable Pop_{lab}. Three age classes - *15 to 29*, *30 to 49* and *50 to 65* - the sex as well as three education classes - *low*, *medium* and *high* - are distinguished. The original labour force survey data distinguishes more age classes, with differing limits than those used for the *labour types* subscript. LFS data is dissaggregated into age classes 15 to 24, 25 to 32, 33 to 49, 50 to 64 and above 65. In order to bridge this gap, the statistical analysis has been carried out on age aggregates of the baseline of the educated population cohort model (→ sec. 4.4 on page 65) fitting the EUKLEMS data. The population cohort model represents the population on a yearly age basis, calibrated on the LFS data and fitting that data very well as described in the according section (4.4). Therefore, this step is considered valid.

4.3.1 Causality

Whenever statistical relations are analysed, the question for causality emerges. But there is a fundamental problem with statistical causality measures - they are *only* statistical. So whatever the result, it remains a statistical conclusion, i.e. at best evidence for causality can be obtained, but causality can not be proved. Especially, even though the name might suggest, in the case of e.g. *Granger causality*, a successful hypothesis test does not automatically mean causality in the non-statistical sense. And an unsuccessful test does not mean non-causality either. The idea of statistical causality measures is to analyse whether a change in variable A precedes or coincides with a change in variable B. In the case of Granger causality, this is done by comparing the parameter results of two regressions. In the first case, variable A is explained with lags of itself, in the second case, variable A is explained with lags of itself and with lags of B. If the probability, that the parameters in the multiple linear regression for the lagged values of B is within a given confidence interval, then B is said to *granger-cause* A.

The obvious problem here is that this analysis only works with long time series. In the analysis at hand, the time series contain only 13 years. Therefore, statistically, causality cannot be determined. Granger causality tests have been carried out within the work for this thesis, and the results are not meaningful in any way. Parameter estimates result in completely random distributions.

But assuming causality is still valid, based on the results described in section 4.3.2. The question at hand is whether the education level within the population influences the qualitative composition of labour within individual sectors of the economy. The natural answer for me is *of course*. The important open question is *in what way?* Also, the direction of the causality appears clear. Education level of the available workforce determines the qualitative composition of the labour input in each sector, not the other way around.

Due to the described problems, and similar problems in many other cases, the question for statistical causality should not be allowed to be used to question the general usefulness of correlation analysis. Statistical causality is not a necessary condition for meaningful correlation analysis.

So for *SEGESD* the essence of this discussion is that *it is build on the assumption that the qualification level of the population and it's age structure determines the qualitative composition of the labour input in each one of 30 economic sectors*.

4.3.2 Correlation

For the analysis of the relation between the education level of the whole population on the one hand and the quality as well as quantity of labour input per sector on the other the *Pearson's product moment correlation coefficient* was used. That means the strength of the linear relation between sectoral labour input, i.e. hours worked per year by labour type and the amount of persons of that labour type in the whole population was calculated:

$$L_{ind,lab} = f(Pop_{lab}) \tag{4.22}$$

with: L Labour Input [hours worked]
Pop Population [#]
ind Index for sectors (or industries) (List →Table A.2 on page 160)
lab Index for labour type (List →Table A.1 on page 159)

As concrete function, a simple regression was chosen, assuming a stochastic linear relation between labour input per sector and labour type on the one hand and the education level of the population on the other along with the disturbance u:

$$L_{ind,lab} = \alpha^{PL}_{ind,lab} + \beta^{PL}_{ind,lab} \cdot Pop_{lab} + u \tag{4.23}$$

with:	L	Labour Input [hours worked]
	Pop	Population [#]
	α^{PL}	Regression coefficient for Population →Labour Input
	β^{PL}	Regression coefficient for Population →Labour Input
	u	Regression error term
	ind	Index for sectors (or industries) (List →Table A.2 on page 160)
	lab	Index for labour type (List →Table A.1 on page 159)

This correlation could be analysed for 18 labour types (lab) in 30 sectors (ind). So the regression coefficients α^{PL} and β^{PL} along with the correlation coefficients $corr^{PL}$ could be calculated for 540 linear models. In the case of Germany, data for both variables was available for 13 years, from 1993 to 2005.

The absolute value of correlation coefficients do not have very much explanation power, especially for shorter time series as in the case of 13 observations. But comparing correlation coefficients of differing analysis can give an indication of whether the assumed relation exists or not. For the relation under investigation here, the distribution of correlation coefficients gives a clear indication that the assumed relation does exist.

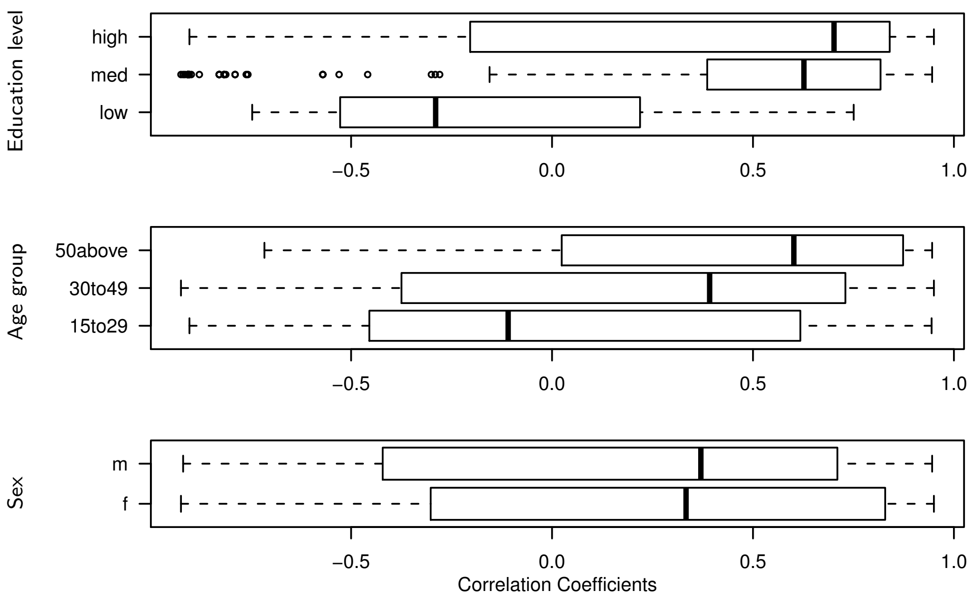
The distributions are visualized as boxplots in figure 4.3 on the next page. The left and right border of the boxes represent the 0.25 and 0.75 quantile and the bar within the box the 0.5 quantile, i.e. the median, of the observations. The whiskers to the left and right indicate the furthest observation no further than 1.5 times the width of the box away from its border. The individual points beyond that are considered outliers. The same distributions are visualized as histograms in figure 4.4 on page 62. There, each bar indicates the frequencies of correlation coefficients within the interval limits of that bar.

The distribution of correlation coefficients per education level - *low*, *medium*, *high* - is shown in the first group of three boxplots in figure 4.3 on the next page as well as in the histograms of the left column in figure 4.4 on page 62. Within each education level the distribution of 180 correlation coefficients (3 age groups * 2 sexes * 30 sectors) is visualized.

Similarily, the distribution of correlation coefficients per age group - *15 to 29*, *30 to 49*, *50 to 65* - is shown in the second group of boxplots in figure 4.3 and the right column of figure 4.4. Within each age group the distribution of 180 correlation coefficients (3 education levels * 2 sexes * 30 sectors) is drawn. Finally, the third boxplot in figure 4.3 shows the distributions per sex. Therefore, 270 correlation coefficients - 3 age groups * 3 education levels * 30 industries - were visualized. Since the results are quite similar for both sexes, no histogramms are included.

Additionally, the full set of all 540 correlation coefficients is plotted in appendix C.1 on page 173. There, for each sector one plot visualizes, distin-

Figure 4.3
Education Level - Labour Input Correlation Coefficients Distribution - Boxplots



visualisation of own calculations

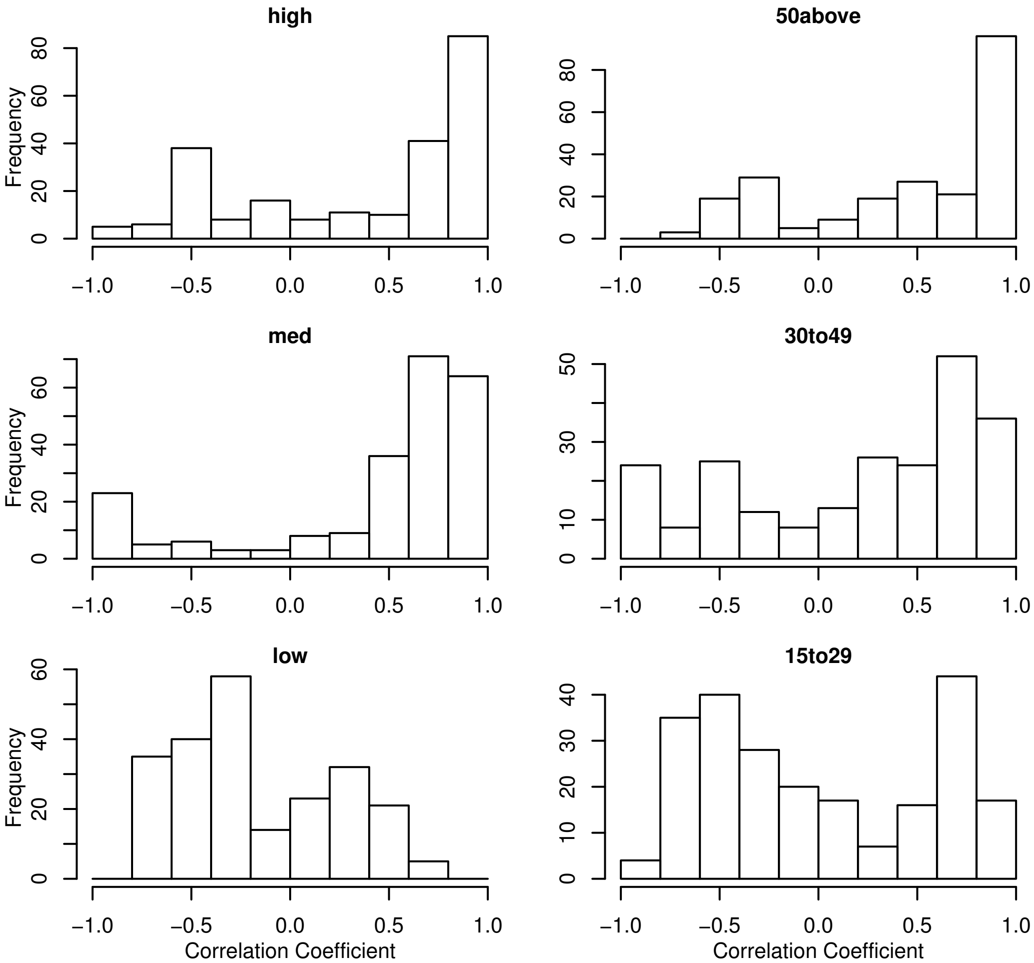
guished by labour type, the results of the correlation analysis which forms the base for the condensed presentation of the results here in histograms and boxplots.

The distributions of those correlation coefficients within the education and age classes clearly show the importance of both experience and formal education of the workforce as input factor for the production in Germany.

The higher the formal education, the stronger the linear correlation. This is taken as an indication of the scarcity of high qualified labour input and the overabundance of low qualified labour. Low qualified labour input quantity even correlates negatively with the labour force in most cases, which can be interpreted as an indication that the employment of low qualified persons is driven by other effects than the availability.

Also, the older the analysed group, the higher the correlation coefficient, which is interpreted as stronger demand for more experienced workers.

Figure 4.4
Education Level - Labour Input Correlation Coefficients Distribution - Histograms



visualisation of own calculations

4.3.3 Implementation in model

Within *SEGESD*, the calculation of the sectoral labour input from the education level of the population is based on equation 4.23 on page 59, with the disturbance u removed

$$L_{ind,lab} = \alpha^{PL}_{ind,lab} + \beta^{PL}_{ind,lab} \cdot Pop_{lab} \tag{4.24}$$

with: L Labour Input [hours worked]
Pop Population [#]
α^{PL} Regression coefficient for Population →Labour Input
β^{PL} Regression coefficient for Population →Labour Input
ind Index for sectors (or industries) (List →Table A.2 on page 160)
lab Index for labour type (List →Table A.1 on page 159)

and the parameters α^{PL} and β^{PL} taking the values calculated in the regression presented in the previous section 4.3.2.

But this equation does not take into account the correlation coefficients, which give an indication of the strength of the link between the predictor variable Pop_{lab} and the response variable $L_{ind,lab}$. Therefore, the labour type and sector specific correlation coefficients were included into equation 4.24 as additional factor multiplied with β^{PL} resulting in

$$L_{ind,lab} = \alpha^{PL}_{ind,lab} + \overline{corr}^{PL}_{ind,lab} \cdot \beta^{PL}_{ind,lab} \cdot Pop_{lab} \tag{4.25}$$

with: L Labour Input [hours worked]
Pop Population [#]
α^{PL} Regression coefficient for Population →Labour Input
β^{PL} Regression coefficient for Population →Labour Input
$\overline{corr}^{PL}$ Correlation coefficient for Population →Labour Input
ind Index for sectors (or industries) (List →Table A.2 on page 160)
lab Index for labour type (List →Table A.1 on page 159)

using only the positive correlation coefficients

$$\overline{corr}^{PL}_{ind,lab} = \begin{cases} corr^{PL}_{ind,lab} & \forall\ corr^{PL}_{ind,lab} > 0 \\ 0 & \forall\ corr^{PL}_{ind,lab} \leq 0 \end{cases} \tag{4.26}$$

with: $corr^{PL}$ Correlation coefficient for Population →Labour Input
ind Index for sectors (or industries) (List →Table A.2 on page 160)
lab Index for labour type (List →Table A.1 on page 159)

This is one of the central assumptions in *SEGESD*, reflecting the interpretation of negative correlation coefficients as cases in which the according labour type is not a scarce input factor in the according sector as discussed in the previous section 4.3.2. Also, the correlation coefficient serves in this construction as proxy for the insecurity inherent in the estimation of the linear correlation model based on its interpretation as a measure for the strength of the linear link between explaining and explained variable. Due to its codomain in the range [0; 1] to which it is restricted due to equation 4.26 it can be directly used as factor in equation 4.25.

So, the changed set of labour input values $\widetilde{L}$ in a scenario of a changed education level in the population $\widetilde{Pop}$ can be calculated according to

$$\begin{aligned} \widetilde{L}_{ind,lab} - L_{ind,lab} = & \left(\alpha^{PL}_{ind,lab} + \overline{corr}^{PL}_{ind,lab} \cdot \beta^{PL}_{ind,lab} \cdot \widetilde{Pop}_{lab}\right) \\ - & \left(\alpha^{PL}_{ind,lab} + \overline{corr}^{PL}_{ind,lab} \cdot \beta^{PL}_{ind,lab} \cdot Pop_{lab}\right) \end{aligned} \tag{4.27}$$

with:
- L Labour Input [hours worked]
- Pop Population [#]
- α^{PL} Regression coefficient for Population →Labour Input
- β^{PL} Regression coefficient for Population →Labour Input
- $\overline{corr}^{PL}$ Correlation coefficient for Population →Labour Input
- ind Index for sectors (or industries) (List →Table A.2 on page 160)
- lab Index for labour type (List →Table A.1 on page 159)
- $\sim$ Tilde indicating scenario values. No tilde for baseline values.

which can be rearranged to

$$\begin{aligned} & \widetilde{L}_{ind,lab} - L_{ind,lab} = \overline{corr}^{PL}_{ind,lab} \cdot \beta^{PL}_{ind,lab} \cdot \left(\widetilde{Pop}_{lab} - Pop_{lab}\right) \\ \Longleftrightarrow\ & \widetilde{L}_{ind,lab} = L_{ind,lab} + \overline{corr}^{PL}_{ind,lab} \cdot \beta^{PL}_{ind,lab} \cdot \left(\widetilde{Pop}_{lab} - Pop_{lab}\right) \end{aligned} \tag{4.28}$$

with: same variables as previous equation.

The changed labour compensation $\widetilde{LC}$ is calculated assuming a proportional change to the change in labour input:

$$\begin{aligned} \frac{\widetilde{LC}_{ind,lab}}{LC_{ind,lab}} &= \frac{\widetilde{L}_{ind,lab}}{L_{ind,lab}} \\ \Longleftrightarrow\ \widetilde{LC}_{ind,lab} &= \frac{\widetilde{L}_{ind,lab}}{L_{ind,lab}} \cdot LC_{ind,lab} \end{aligned} \tag{4.29}$$

with:
- L Labour Input [hours worked]
- LC Labour Compensation (nominal)
- ind Index for sectors (or industries) (List →Table A.2 on page 160)
- lab Index for labour type (List →Table A.1 on page 159)
- $\sim$ Tilde indicating scenario values. No tilde for baseline values.

With the sector and labour type specific changed labour input $\widetilde{L}_{ind,lab}$ as well as the accordingly changed labour compensation $\widetilde{LC}_{ind,lab}$ changed values of labour service growth can be calculated based on equations 4.16 and 4.17 on page 55. With equation 4.8 on page 49, this results in changed growth rates of gross output, which in turn leads to changed gross output over the timeframe of the analysis.

4.4 Educated Population Cohort Model

The next step, going backwards from sectoral gross output to education spending in figure 4.1 on page 42, is the modelling of the process through which graduates of differing education programs form the human capital stock of a country.

Therefore, a yearly population cohort model of educated persons was developed. It represents the population within the analysed country distinguished by three education levels on *ISCED* basis, 86 yearly age cohorts as well as by sexes. The population is denoted by the variable *Pop* subscripted with $age \in [0\ ..\ 85]$, $sex \in \{\text{f, m}\}$ and $isced \in \{\text{low, medium, high}\}$. An exemplary visualisation of these results is given in 4.11 on page 83.

This model essentially is a combination of two models, visualized schematically in figure 4.5 on the next page. The *first part* is formed by a population model without differentiation for the education level. It's element are

— the initial population structure (by age and sex) in 1970
— aging
— births
— deaths
— immigration

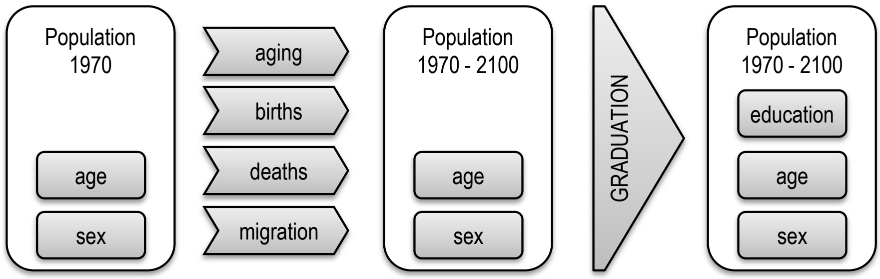
The *second part* it the modelling of the education levels in the population, combined with the population model adding two more elements:

— the initial education level of the population in 1970
— graduation probabilities by age, sex and year

With these elements, a yearly structure of the population differentiating for age, sex and education level was modelled starting in 1970, running till 2100. Each of these elements and their interaction is described in detail in the following sections. The start year 1970 was determined by the availability of detailed population data, namely by the *DESTATIS* yearly age cohort data set. In general, the earlier the simulation can start, the better this is for the degree of endogeneity of the results, to the point in time when the graduation process is completely endogenous for the time interval under analysis. As in the case of *SEGESD*, more than 20 years of forerun before the year 1991, i.e. when *EUKLEMS* economic data starts for all sectors (→ appendix B.2 on page 169) and when the time interval of the economic analysis starts is more than sufficient to fulfil this condition (compare sec. 4.4.3 on page 70).

The description of the complete *educated population cohort model* is split into several parts. First, the data basis of the model is shortly described

Figure 4.5
Educated Population Cohort Model Schema



own graph

in section 4.4.1. Then (sec. 4.4.2) the population model is described without differentiating for the education level, which is afterwards added in the subsequent section 4.4.3. Finally, the derivation of the parameters of the graduation process is described in section 4.4.4. This approach enables a more comprehensible exposition of the implemented model compared to a one-step-description.

4.4.1 Data basis

The data basis for the educated population cohort model is the *Labour Force Survey (LFS)*[3] provided by *DESTATIS*, the German statistical office, on the one hand, and a set of variables on the structure and the development of the population as well as on the education system provided by *Eurostat*, the European statistical office, on the other.

In many cases, the needed data is formally offered by both institutions, but the data sets vary in coverage of the dimensions and in the interval of available years. Nevertheless, the decision on which data set to use was mostly simple due to obvious differences in coverage between the two alternatives. *Eurostat* data coverage on Germany is often better[4] - i.e. more disaggregated and more available years - than that by *DESTATIS*.

Details on the sources of the LFS data set used for the calibration of *SEGESD* are given in appendix B.3 on page 169. For details on the sources of the population variables see appendix B.4 on page 170. And details of the

[3]see appendix B.3 on page 169 for more details
[4]comparing the online available data

sources of the education variables are given in appendix B.5 on page 171.

4.4.2 Population model

Exogenous population data

The exogenous population figures needed for the calibration and verification of the endogenous results were calculated based on two data sets, on the one hand figures on the population differentiated by yearly age cohorts from *DESTATIS* for Western Germany and on the other figures differentiated by 5-year age cohorts and by sex from *Eurostat* for East and West Germany summed up. Multiplying the distributions of sex and yearly age within each 5-year age group derived from the *DESTATIS* data set with the absolute numbers of the 5-year age cohorts in the *EUROSTAT* data set resulted in the absolute numbers of persons per yearly age cohort and per sex for all Germany (east and west together) used for the population model. These figures form the initial values of the variable *Pop* in the year 1970, needed for the start of the endogenous simulation.

Aging on yearly basis

The aging process is modelled in the population cohort model as a conveyor. It can be imagined as a process which transfers in each year the mass in one age cohort to the subsequent age cohort, thereby moving the persons through time, making them one year older step by step. Therefore, two variables $AgingOutflow$ and $AgingInflow$ were defined, which are equal as long as graduation is not taken into account, what will be added later in equations 4.36 and 4.37 on page 72. The $Outflow$ represents the mass of persons removed from one age cohort $\widetilde{age}$ in timestep $\widetilde{t}$ to be added in the form of $Inflow$ to the one year older age cohort $\widetilde{age}+1$ one year later in timestep $\widetilde{t}+1$.

$$AgingInflow_{age,sex,t} = AgingOutflow_{age,sex,t} = Pop_{age,sex,t-1} \tag{4.30}$$

with:	*Pop*	Population [#]
	AgingInflow	Persons added to a population group[#]
	AgingOutlow	Persons removed from a population group [#]
	age	Index for yearly age, $\in$ [0 .. 85]
	sex	Index for sex, $\in$ {f, m}
	t	Index for time

With the *age-lagged* ($age-1$) use of $AgingInflow$ within equation 4.34 on page 69 and the one year lagged assignment of *Pop* to both In- and Outflow in the equation above the conveying process is implemented.

Births

The amount of newborn children is calculated endogenously based on the number of women being at least 13 years old and not older than 49. For this interval age specific fertility rates are provided by *Eurostat* (→ app. B.4 on page 170), which are used here.

$$Births_t = \sum_{age=13}^{49} Pop_{age,sex,t-1} \cdot FertilityRate_{age,t} \quad \forall\ sex = f \tag{4.31}$$

with:	*Births*	Newborn children [#]
	Pop	Population [#]
	FertilityRate	Babies per woman by age of mother [.]
	age	Index for yearly age, ∈ [0 .. 85]
	sex	Index for sex, ∈ {f, m}
	t	Index for time

Since the fertility rates are not provided sex specific, the distribution of sexes of newborn children was calculated based on data about children *below 5* in the *Eurostat* population data. The ratio of females to males thereby obtained is 0.48726 to 0.51274, used for the calculation of sex specific numbers of newborns as

$$Births_{sex,t} = \begin{cases} 0,48726 \cdot Births_t & \forall\ sex = f \\ 0,51274 \cdot Births_t & \forall\ sex = m \end{cases} \tag{4.32}$$

with:	*Births*	Newborn children [#]
	sex	Index for sex, ∈ {f, m}
	t	Index for time

Deaths

Death numbers are calculated based on age and sex specific dying probabilities provided by *Eurostat* (→ app. B.4 on page 170).

$$Deaths_{age,sex,t} = Pop_{age,sex,t-1} \cdot DeathProbability_{age,sex,t-1} \tag{4.33}$$

with:	*Deaths*	Death cases by age and sex [#]
	Pop	Population [#]
	DeathProbability	Share of persons dying within one year [.]
	age	Index for yearly age, ∈ [0 .. 85]
	sex	Index for sex, ∈ {f, m}
	t	Index for time

Migration

Migration was calculated as difference between endogenous model results *without migration* and the exogenous population data described before. Those figures were then compared to migration figures from *DESTATIS* and *Eurostat* (→ app. B.4 on page 170), finding only minor deviations. This approach was chosen because no age and sex specific migration figures are published by these sources. So the deviation figures were aggregated and compared to the aggregated migration figures, finding, as said, no major differences. With this findings, I assumed the endogenous population age cohort model to be correct and also the age and sex specific migration numbers to reflect reality. Migration figures are represented in the variable $Immigration$, indicating that positive figures stand for immigration, and negative figures for emigration.

Population

With these variables defined, the population in each year t of the simulation *without differentiating for education level* can be calculated as integral over the interval [1970 .. t] according to

$$
\begin{aligned}
&Pop_{age,sex,t} \\
&= \begin{cases}
\int_{1970}^{t} \; AgingInflow_{age-1,sex,\tau} & \forall\ age \in [1..85] \\
\quad -AgingOutflow_{age,sex,\tau} & \\
\quad -Deaths_{age-1,sex,\tau} & \\
\quad +Immigrants_{age-1,sex,\tau} & \\
\quad +Pop_{age,sex,1970} \qquad \mathrm{d}\tau & \\
\int_{1970}^{t} \; Births_{sex,\tau} & \forall\ age = 0 \\
\quad -AgingOutflow_{age,sex,\tau} & \\
\quad +Pop_{age,sex,1970} \qquad \mathrm{d}\tau &
\end{cases}
\end{aligned}
\tag{4.34}
$$

with:

Pop	Population [#]
$Births$	Newborn children [#]
$Immigration$	Migration numbers by age and sex. Positive ≙ Immigration. [#]
$Deaths$	Death cases by age and sex [#]
$AgingInflow$	Persons added to a population group[#]
$AgingOutlow$	Persons removed from a population group [#]
age	Index for yearly age, ∈ [0 .. 85]
sex	Index for sex, ∈ {f, m}
t	Index for time

The *Pop* figures in period t are calculated based on the values of the right hand side variables of the previous period $t-1$ due to the time lags in the definitions of those variables (see above). The mass of persons within the age cohort previous to the one being calculated ($AgingInflow_{age-1}$) is added, while the persons in the same age cohort are subtracted ($AgingOutflow_{age}$). Deaths which occurred within the previous age cohort are subtracted from the inflow, and Immigrants are added. This structure results in the conveying of age cohorts through time.

The age cohort 0 forms the special case with the inflow being births, and neither deaths nor immigration is considered. Those effects are accounted for during the aging from age 0 to age 1, since both dying and immigration are accounted for with a delay of one year.

4.4.3 Educated population model

As laid out in the beginning of this section (4.4), the previously described population model forms the basis of the *educated population cohort model*. Additionally to the development of the population, the distribution of three education levels - *low*, *medium* and *high* - within this population is modelled. This is described in the following paragraphs.

Based on the *LFS* data for the years 1993 to 2007 (→ app. B.3 on page 169) two parameter sets have been derived:

1. eduacation level distribution in 1970
2. graduation probabilities per age and sex after 1970

With those parameters, the distribution of education levels for the whole population distinguished by yearly age cohorts could be calculated on a yearly basis.

First, the model structure is described, since this is necessary to understand how the parameters are calculated from the *LFS* data set. The actual derivation of the parameters is described afterwards in section 4.4.4 on page 73.

The population cohort model as described before in section 4.4.2 on page 67 is now extended with the dimension *education level*, denoted by $isced \in \{low, medium, high\}$. To all variable definitions introduced before, the subscript *isced* is added.

The graduation process is modelled with *graduation probabilities*, i.e. the shares of persons of a certain age and education level that raise one education level - from *low* to *medium* or from *medium* to *high* - within the running year.

So, persons not only get older, as modelled in equation 4.30 on page 67, but also parts of them change their education level by achieving a higher degree. Using these probabilities, figures of graduates are defined as

$$Graduates_{age,sex,isced,t}$$
$$= \begin{cases} 0 & \forall\ isced = low \\ Pop_{age,sex,isced=low,t} \cdot GradProbLowMed_{age,sex,t} & \forall\ isced = med \\ Pop_{age,sex,isced=med,t} \cdot GradProbMedHigh_{age,sex,t} & \forall\ isced = high \end{cases} \tag{4.35}$$

with:	*Graduates*	Persons shifting to a higher education level. [#]
	Pop	Population [#]
	GradProbLowMed	Share of persons raising from low to medium education level. [.]
	GradProbMedHigh	Share of persons raising from medium to high education level. [.]
	age	Index for yearly age, ∊ [0 .. 85]
	sex	Index for sex, ∊ {f, m}
	isced	Index for education level group, ∊ {low, medium, high}
	t	Index for time

implying that no graduation from *low* to *high* is possible, as in reality. With the graduates defined, equation 4.30 on page 67 is extended to

$$Grad\&AgingInflow_{age,sex,isced,t}$$
$$= \begin{cases} Pop_{age,sex,isced,t-1} & - Graduates_{age,sex,isced=med,t-1} & \forall\ isced = low \\ Pop_{age,sex,isced,t-1} & + Graduates_{age,sex,isced,t-1} & \forall\ isced = med \\ & - Graduates_{age,sex,isced=high,t-1} & \\ Pop_{age,sex,isced,t-1} & + Graduates_{age,sex,isced,t-1} & \forall\ isced = high \end{cases} \tag{4.36}$$

with:	*Grad&AgingInflow*	Persons getting older and better eduacted. [#]
	Graduates	Persons shifting to a higher education level. [#]
	Pop	Population [#]
	age	Index for yearly age, ∊ [0 .. 85]
	sex	Index for sex, ∊ {f, m}
	isced	Index for education level group, ∊ {low, medium, high}
	t	Index for time

In this equation, the first case *isced* = *low* removes the mass of persons that obtain a *medium* level degree from the *low* level age cohorts. In the second case *isced* = *med* those freshly graduated persons are added to the age cohorts of *medium* education level, while those that achieve a *high* level degree are removed from the *medium* cohorts and added to the *high* level age cohorts within the third case $isced = high$. As in eq.4.30 above the time lag $(t-1)$ is needed for the conveying process.

The *outflow*, i.e. the amount of persons removed from each age cohort each time step is simply the total mass of persons in each cohort of the previous year as in equation 4.30 on page 67 but extended with the *isced* subscript

$$Grad\&AgingOutflow_{age,sex,isced,t} = Pop_{age,sex,isced,t-1} \tag{4.37}$$

with:		
	$Grad\&AgingOutflow$	Persons getting older and better eduacted. [#]
	Pop	Population [#]
	age	Index for yearly age, $\in$ [0 .. 85]
	sex	Index for sex, $\in$ {f, m}
	$isced$	Index for education level group, $\in$ {low, medium, high}
	t	Index for time

Outflow and Inflow - aggregated over all ISCED classes - are equal, as explained before (in sec. 4.4.2)

$$\begin{aligned}&\sum_{isced} Grad\&AgingInflow_{age,sex,isced,t}\\ &= \sum_{isced} Grad\&AgingOutflow_{age,sex,isced,t} \quad \forall age, sex, t\end{aligned} \tag{4.38}$$

with:		
	$Grad\&AgingInflow$	Persons getting older and better eduacted. [#]
	$Grad\&AgingOutflow$	Persons getting older and better eduacted. [#]
	age	Index for yearly age, $\in$ [0 .. 85]
	sex	Index for sex, $\in$ {f, m}
	$isced$	Index for education level group, $\in$ {low, medium, high}
	t	Index for time

And the *age-lag* in equation 4.40 on the next page results in the aging of the persons. In this way *graduation* and *aging* is implemented in parallel.

The calculation of newborn children remain the same. No differentiation of the fertility rates of the women by the education level was done, simply because these figures are not available by *Eurostat* or *Destatis*. So the effective formula in *SEGESD* is

$$Births_t = \sum_{age=13}^{49} \sum_{isced} Pop_{age,sex,isced,t} \cdot FertilityRate_{age,t} \;\forall\; sex = f \tag{4.39}$$

with:		
	Births	Newborn children [#]
	Pop	Population [#]
	FertilityRate	Babies per woman by age of mother [.]
	age	Index for yearly age, ∈ [0 .. 85]
	sex	Index for sex, ∈ {f, m}
	isced	Index for education level group, ∈ {low, medium, high}
	t	Index for time

with the split of the newborns into females and males as described before (→ eq. 4.32 on page 68).

With these additional respectively extended variables the population *including the differentiation by education level* for each year of the simulation can be calculated. This is effectively done in *SEGESD* with an extension of equation 4.34, defined as

$$
\begin{aligned}
&Pop_{age,sex,isced,t}\\
&= \begin{cases}
\int_{1970}^{t} \quad Grad\&AgingInflow_{age-1,sex,isced,\tau} & \forall\ age \in [1..85]\\
\quad -Grad\&AgingOutflow_{age,sex,isced,\tau} & \\
\quad -Deaths_{age-1,sex,isced,\tau} & \\
\quad +Immigrants_{age-1,sex,isced,\tau} & \\
\quad +Pop_{age,sex,isced,1970} \qquad d\tau & \\
\int_{1970}^{t} \quad Births_{sex,isced,\tau} & \forall\ age = 0\\
\quad -Grad\&AgingOutflow_{age,sex,isced,\tau} & \\
\quad +Pop_{age,sex,isced,1970} \qquad d\tau &
\end{cases}
\end{aligned}
\tag{4.40}
$$

with:		
	Pop	Population [#]
	Births	Newborn children [#]
	Immigration	Migration numbers by age and sex. Positive ≙ Immigration. [#]
	Deaths	Death cases by age and sex [#]
	Grad&AgingInflow	Persons getting older and better eduacted. [#]
	Grad&AgingOutflow	Persons getting older and better eduacted. [#]
	age	Index for yearly age, ∈ [0 .. 85]
	sex	Index for sex, ∈ {f, m}
	isced	Index for education level group, ∈ {low, medium, high}
	t	Index for time

4.4.4 Graduation paramter derivation

In this section, the derivation of the parameters for the graduation process is described. These parameters are used in the *educated population cohort model*, of which the structure is described above (sec. 4.4.2 and 4.4.3).

For the population model - defined by the initial population structure in 1970, fertility- and morbidity rates since then and migration figures - all parameters necessary are available from official statistical sources or can directly be derived from the available data as described above.

In contrast to that, the parameters of the graduation process, i.e. the distribution of education levels within the age cohorts of the initial population structure in 1970 and the graduation probabilities (as introduced in eq. 4.35 on page 71) of various age and sex cohorts in the years after are not that easily available.

Those parameters had to be estimated based on the *Labour Force Survey (LFS)* data set (→ app. B.3 on page 169) available for the years 1993 to 2007, distinguishing three education levels - *low, medium, high* - as used throughout *SEGESD* and by sex, but only differentiating 6 age classes: *below 14*, *15 to 24*, *25 to 32*, *33 to 49*, *50 to 64*, *above 64*.

The necessary calculation steps and assumptions are laid out here.

General idea

Both the initial education structure of the population in the year 1970 as well as $GraduationProbabilities$ were calculated backwards from the LFS data. Direct statistical estimation of the necessary parameters would not be possible, since there are too many degrees of freedom for the available data. The high amount of degrees of freedom result from the combinations of various education programs with differing graduation age. Because of that, basically at every age some share of persons of that age can possibly achieve a higher education level. In order to obtain the parameters for the model, reality was reduced to a significantly easier abstraction.

The core question is always *what share of persons in age cohort* $\widetilde{age}$ *needed to achieve a higher degree in year* $\widetilde{t}$ *in order to form the education level distribution observed between 1993 and 2007*?

Based on the education programs reflecting the ISCED classification in Germany as well as the empirical data first a simple model of graduation steps was developed and afterwards the parameters for this model were estimated. The German education programs, classified according to ISCED, are listed in detail in table B.3 on page 168 and the general ISCED classes are compiled in B.1 on page 166. Because of the availability of data differentiating for three education levels - *low, medium, high* - in the LFS data, two transition processes can be observed, i.e. graduating from low to medium level as well as from medium to high level.

Low to medium level transition reflects the acquisition of a formal education of ISCED level 3 (upper secondary) or 4 (post secondary non tertiary). In Germany, mainly this includes successful finishing of a job training (Lehrausbildung) or of the highest school level enabling entry to University (Fach-/Hochschulreife) among other programs. This happens mostly between the age of 18 and 20.

Medium to high level transition includes acquiring either level 5 (first stage of tertiary education) or level 6 (second stage of tertiary, i.e. an advanced reserach qualification) on the ISCED scale. For Germany, this means the completion of an advanced practical job qualification (Meister / Techniker / Berufsakademie) or of a theoretical program (Fachhochschule / Universität) as well as of a dissertation thesis (Promotion). This practically happens mostly between the age of 21 and 35.

Graduation age assumption

Identifying the age at which the transition actually happens requires some assumptions, since the LFS data is not disaggregated on yearly age basis, but only in 6 age classes as described before.

Raising from low to medium is assumed to happen within the one age cohort. In order to find a quantitative answer from the LFS data set on what age this is, the share of low qualified persons in the age cohort *15 to 24* was compared to those of low qualification in the age cohort *25 to 32* nine years later, since these two observations should contain roughly the same persons, of course with the imprecision of the first age group containing ten yearly age cohorts and the second containing only eight.

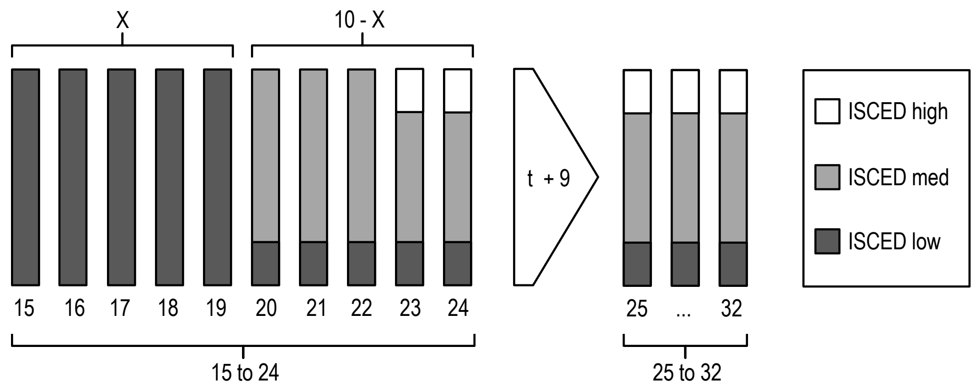
Assuming an equal relation of low level to medium plus high level persons for each age cohort within both age aggregations *after* the transition from low to medium, the assumed resulting age cohorts look like sketched in figure 4.6 on the next page.

With low_{15-24} and low_{25-32} denominating the shares of low educated people in the two according age aggregation groups as well as n_C giving the ammount of yearly age cohorts, the transition age cohort's number x within the age aggregation group (compare figure 4.6) can be calculated based on

$$low_{15-24,t} = \frac{x \cdot 1 + (n_C - x) \cdot low_{25-32,t+9}}{n_C} \tag{4.41}$$

with:	low_{15-24}	share of low educated persons of age 15 to 24. [.]
	low_{25-32}	share of low educated persons of age 25 to 32. [.]
	n_C	Amount of yearly age cohorts within age group. [#]
	x	Number of transition age cohort within age group. [#]
	t	Index for time

Figure 4.6
Estimation of age of graduation to medium level



own graph

With $n_C = 10$ this can be rearranged to

$$x = 10 \cdot \frac{low_{15-24,t} - low_{25-32,t+9}}{1 - low_{25-32,t+9}} \tag{4.42}$$

with: variables as in previous equation.

The average of this estimation for all available observations within the LFS data results in an empirically observable graduation age of 18.4, which is exactly within the theoretically expected range. Therefore, for the model a graduation age of 18 was assumed, meaning that the graduation happens during the aging process from 18 to 19, as can be seen also in figure 4.11 on page 83. Even though practically there are small numbers of persons graduating at medium level at a significantly higher age, their numbers are too low to be visible in the LFS statistics. Therefore, this was not included. Within *SEGESD* graduation from low to medium level is assumed to happen only at the age of 18.

Graduation from medium to high level is assumed to be possible at two ages. This is necessary since the high level class includes quite heterogeneous education programs (see before) with highly differing ages at which the programs can be completed. Also, while there is no significant change visible in the shares of low qualified persons at the transition from age aggregation group *25 to 32* towards *33 to 49*, change at this aging step is well observable for highly qualified persons, giving a clear indication that degrees of high level are obtained at higher age.

Applying the approach described before (equations 4.41 and 4.42 and figure 4.6 on the preceding page) to the transition from med to high within the age aggregation group *25 to 32* leads to the finding of differing graduation ages for males on the one hand and females on the other. According to my calculations, young women graduate on average at 22, while young men graduate one year later at 23. This is not surprising though, taking into account the compulsory military service for men.

And finally, when applying the same approach to the step from age group *25 to 32* to the group *33 to 49*, an additional graduation step towards the end of this time period emerges around age 31.

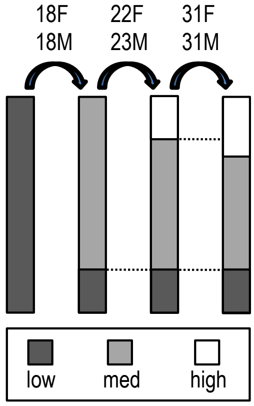


Figure 4.7
Graduation Points

Taken together, this leads to the assumption of three possibilities to graduate per sex, or six so called *graduation points* - *18F, 18M, 22F, 23M, 31F, 31M* - as basis for the parameter estimation described in the following section. These six points are visualized in figure 4.7.

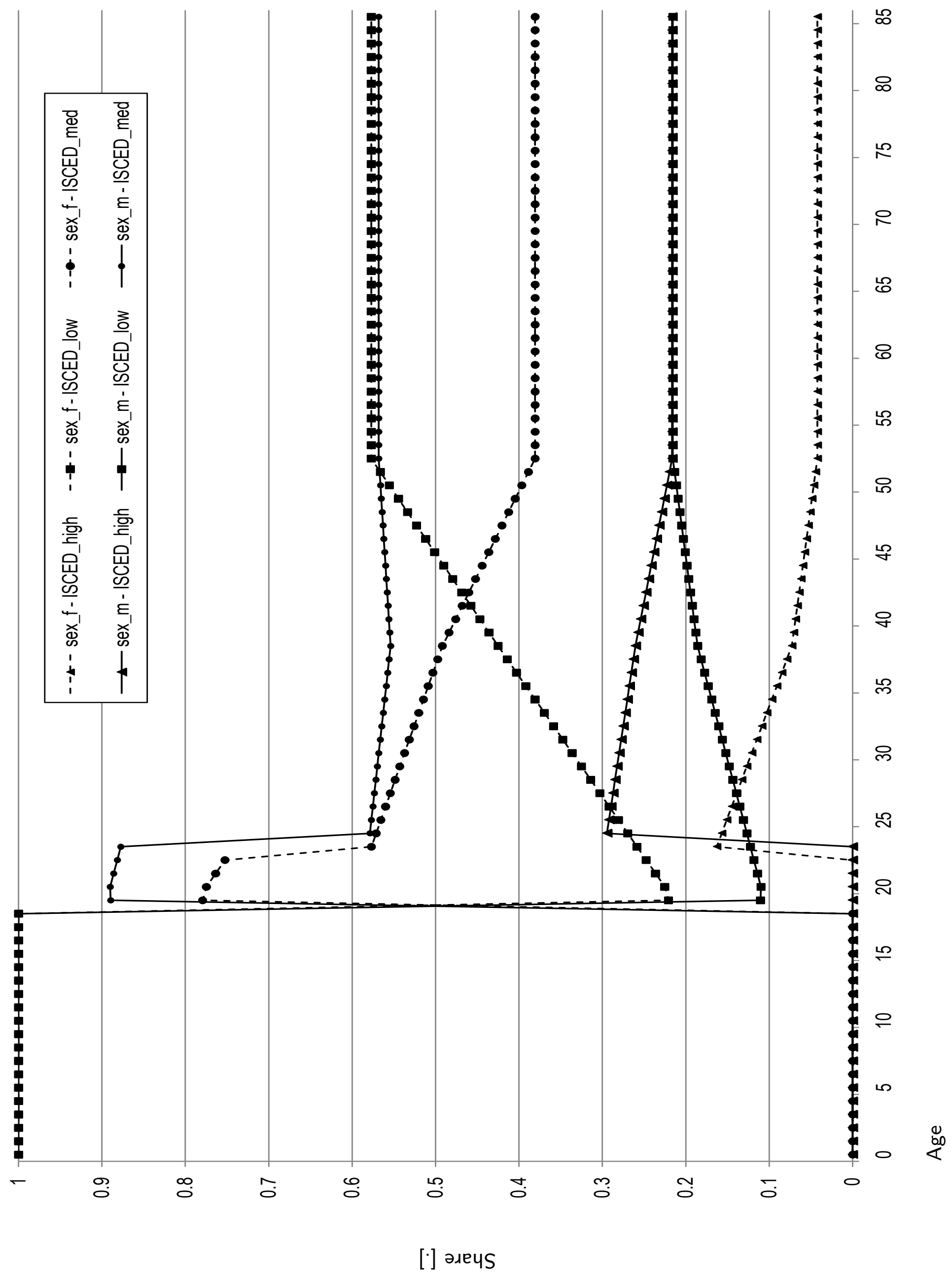
Initial education levels in 1970

The education levels of the initial population in the year 1970 was calculated backwards from the LFS data set, which reports levels of education for the years 1993 till 2007. This was done in two steps.

First, the values for each age group were assigned to the middle age and were used for the distribution of the according age cohort back in 1970. For example, of the age aggregation cohort *33 to 49* the middle is 41. So the value from 2007 was taken for the age cohort 4 (= 41 - (2007-1970)) in 1970. The values for the remaining age cohorts between these punctual results were then linearly interpolated. This was done for all age aggregation cohorts of age 33 and above, using all data sets, resulting in one *initial distribution* for each data set between 1993 to 2007, i.e. in 15 distributions. These 15 were then reduced to one distribution by calculating the arithmetic average.

Second, this distribution was then adjusted by setting all age cohorts of below 19 to only low education level, and to only medium and low level before 23 for females and 24 for males as well as to a reduced amount of high qualified persons before 32, reflecting the assumed graduation ages described before. The distributions obtained thereby form the starting values for the educated population cohorts in *SEGESD*. They are plotted in figure 4.8 on

Figure 4.8
Distribution of education levels in 1970



result of analysis. Shares [.] over yearly age cohort.

the preceding page.

The graduation probabilities, derived in the following section, then effectively lead to the education distribution for the years 1993 to 2007 in the educated population cohort model as reported by the LFS data.

Graduation probability derivation

So, based on the assumption of only four graduation ages laid out above and visualized in figure 4.7, the shares of persons per age cohort graduating and thereby increasing their education level from low to medium or from medium to high can be derived from the LFS data set.

Depending on the graduation step as well as the year for which graduation probabilities were calculated, this had to be done using a separate approach.

The year for which the graduation probabilities is calculated matters for the choice of the approach because the graduation distributions appear as stable for the age aggregation cohorts *33 to 49* and older. This can be assumed because the distributions within the aggregated cohort *33 to 49* of the year 1993 differ less than 2 percent from the distributions of the cohort *50 to 64* of the year 2007. The differences can well be attributed to the slight difference of persons covered by the two observations (the persons of the younger aggregated cohort in 1993 are of age 47 to 63 in 2007). Similarly, the distribution within the aggregated age cohort *50 to 64* of the year 1993 differs very little from the distribution within the *above 65* group in the year 2007. The difference is a little bit more pronounced, but this can well be explained by the fact that the persons of the younger cohort from '93 are by 2007 of age 64 to 78, which is certainly not the same as *above 65*.

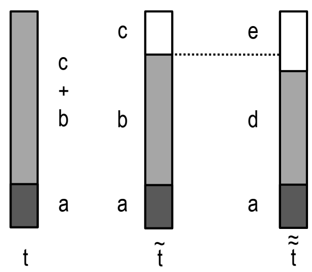


Figure 4.9
Graduation
Med → High

Graduation from low to medium at the age of 18 was estimated in three parts. For the years 1970 till 1984, the results from step one of the calculation of the initial distribution in 1970 described above could be used. For 1984, the last value of that distribution for this graduation step is available since then the 41 year old persons of 2007 are of age 18. For 1985 to 1997, the shares of low qualified persons in the age aggregation cohorts *25 to 32* of the years 1995 to 2007 were used due to the age class middle being 28.5, explaining the delay of 10 years. For the years 1998 to 2006 the graduation probabilities were calculated as continuation of the 1997 value proportional to the inverse development of the share of low qualified persons in the age aggregation cohort *15 to 24* with a lag of one year, due to the age class

Table 4.2
Graduation probabilities [.] as table

	1970	*1971*	*1972*	*1973*	*1974*	*1975*	*1976*	*1977*	*1978*	*1979*	*1980*	*1981*	*1982*	*1983*	*1984*	*1985*	*1986*	*1987*	*1988*
18F (to med)	0.784	0.788	0.793	0.797	0.802	0.806	0.811	0.815	0.820	0.824	0.829	0.833	0.838	0.842	0.847	0.846	0.826	0.836	0.831
18M (to med)	0.889	0.888	0.888	0.887	0.886	0.886	0.885	0.884	0.884	0.883	0.882	0.882	0.881	0.880	0.880	0.886	0.863	0.873	0.864
22F (to high)	0.148	0.153	0.157	0.159	0.161	0.163	0.165	0.167	0.169	0.171	0.173	0.175	0.177	0.178	0.180	0.182	0.214	0.206	0.215
23M (to high)	0.224	0.225	0.226	0.228	0.227	0.226	0.226	0.225	0.224	0.224	0.223	0.222	0.222	0.221	0.220	0.220	0.219	0.231	0.222
31F (to high)												0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076
31M (to high)											0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114

	1989	*1990*	*1991*	*1992*	*1993*	*1994*	*1995*	*1996*	*1997*	*1998*	*1999*	*2000*	*2001*	*2002*	*2003*	*2004*	*2005*	*2006*
18F (to med)	0.825	0.827	0.831	0.832	0.838	0.835	0.819	0.839	0.844	0.849	0.854	0.859	0.875	0.862	0.872	0.840	0.855	0.871
18M (to med)	0.854	0.859	0.862	0.860	0.869	0.861	0.847	0.858	0.858	0.857	0.857	0.856	0.859	0.846	0.852	0.833	0.862	0.875
22F (to high)	0.214	0.215	0.223	0.232	0.248	0.240	0.232	0.245	0.264	0.263	0.263	0.281	0.272					
23M (to high)	0.238	0.243	0.249	0.250	0.252	0.255	0.254	0.236	0.244	0.242	0.251	0.244	0.252	0.248				
31F (to high)	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.076	0.090	0.090	0.090	0.096	0.093	0.094				
31M (to high)	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.114	0.112	0.111	0.115	0.112	0.115	0.114				

middle of 19.5. This is necessary since in that young age aggregation cohort, the shares of *low* qualified persons does not show graduation shares since all persons below 18 are of level *low* by definition as described above.

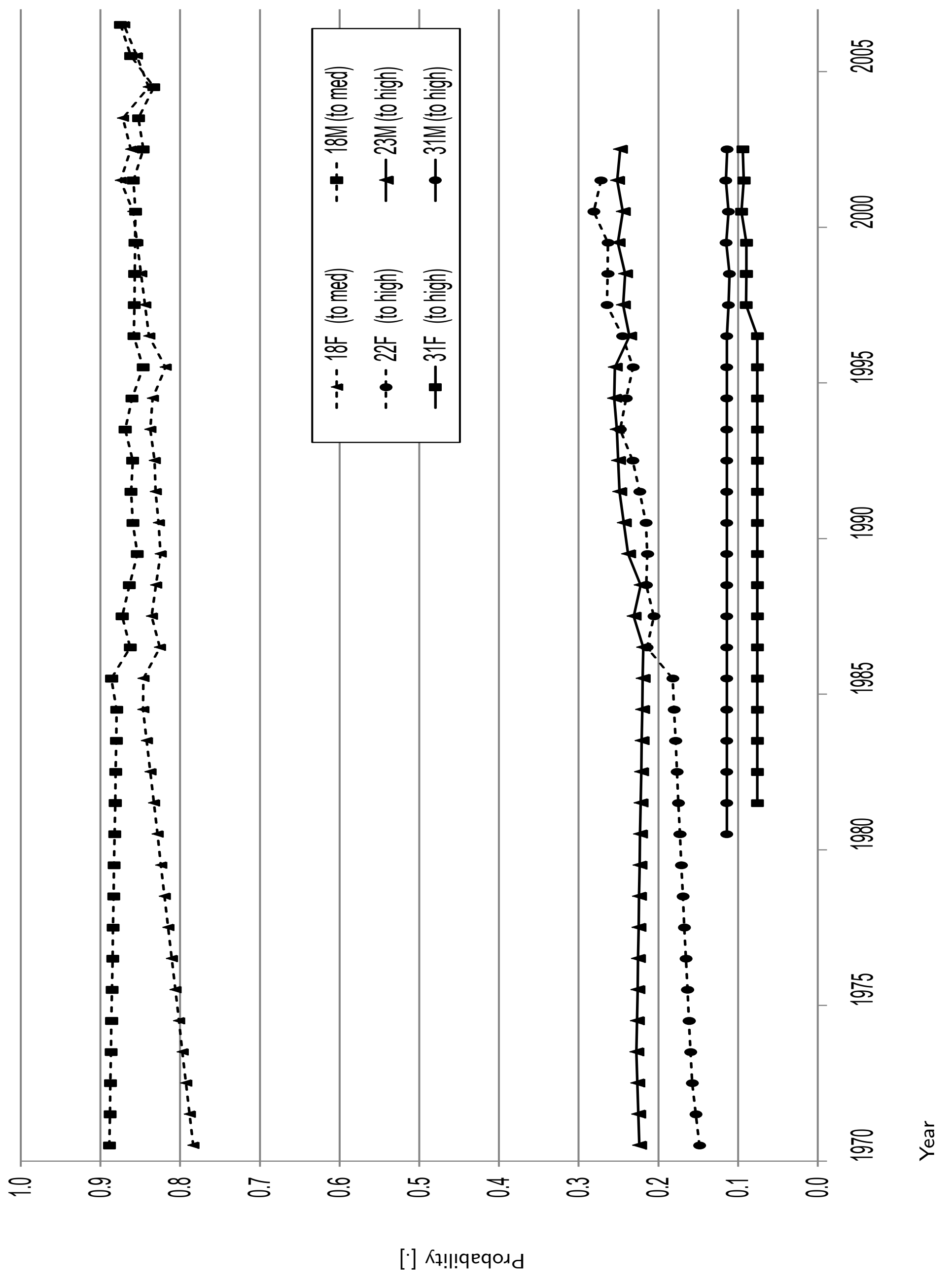
The shares of persons graduating at high education level was calculated as fraction of the shares of highly educated persons divided by the sum of the shares of medium and highly educated persons. Two graduation steps have to be distinguished according to the assumed graduation ages as described above. The first step, at age 22 (women) or 23 (men), was calculated as $^{c}/_{(b+c)}$ with the variables defined according to the left part of figure 4.9 on the preceding page. And the second step, at age 31, was calculated as $^{(e-c)}/_{b}$ as shown in the right part of that figure.

As described below, this second step could only be calculated from 1996 on. For the time before that year, the relation of the graduation probability at age 31 in 1996 to the one at age 22 (or 23 respectively) from 9 (or 8) years earlier was used to calculate the relation between the first and second step of medium to high graduation probability.

Graduating from medium to high at 22 of young women was estimated in two parts. Similar to the previous case (low to med at age 18), for the years 1970 to 1988 the results of the calculation of the distribution in 1970 could be used, with 1988 being the year in which the persons turn 22. For that first period, the resulting shares of persons graduating was split to this step at age 22 and the second step at age 31. For the years 1989 till 2001, the graduation probability could be calculated from the age aggregation cohort *25 to 32*. Since the age middle is 28.5, a lag of six years was used, so the probabilities of this period are calculated on the data of the years 1995 to 2007.

Graduating from medium to high at 23 of young men was estimated just

Figure 4.10
Graduation probabilities [.] as graph



result of analysis

as the parameters for women at age 22, only the break between the two time periods is 1989/1990 instead of 1988/1989. Also, due to the reduced lag of 5 years, the parameters could be estimated till 2002.

Finally, graduation probabilities for the step from medium to high at the age 31 were compiled as follows. For the years before 1996, this step can not be observed in the data, as described subsequently. Therefore, the relation between this probability and the probability of the previous step at age 22 (or 23) were used as for calculation of those probabilities described before. From 1996 till 2002 on, the probabilities were calculated as follows. The difference in the shares of persons on high education level of the age aggregation cohort *25 to 32* (indicated as $\tilde{t}$ in figure 4.9) to the shares of the persons in the older cohort *33 to 49* ($=\tilde{\tilde{t}}$) was used to calculate the probability to graduate at age 31 ($^{(e-c)}/_{b}$, as described above). Since the younger aggregation cohort contains 8 yearly age cohorts and the older aggregation cohort contains 17 yearly age cohorts, the calculation of the relative changes was done based on averaged values of the available values of the older aggregation cohort, with the earliest value of the older aggregation cohort reported eight years after the value of the younger aggregation cohort. Due to the age middle of 28.5 in the cohort *25 to 32* a lag of 3 years was applied. Therefore, e.g. the graduation probability for 1998 was calculated based on the LFS data of the year 1995 for the *25 to 32* cohort and the average of the values for 2003 to 2007 of the *33 to 49* cohort. Like this, graduation probabilities till the year 2002 could be estimated.

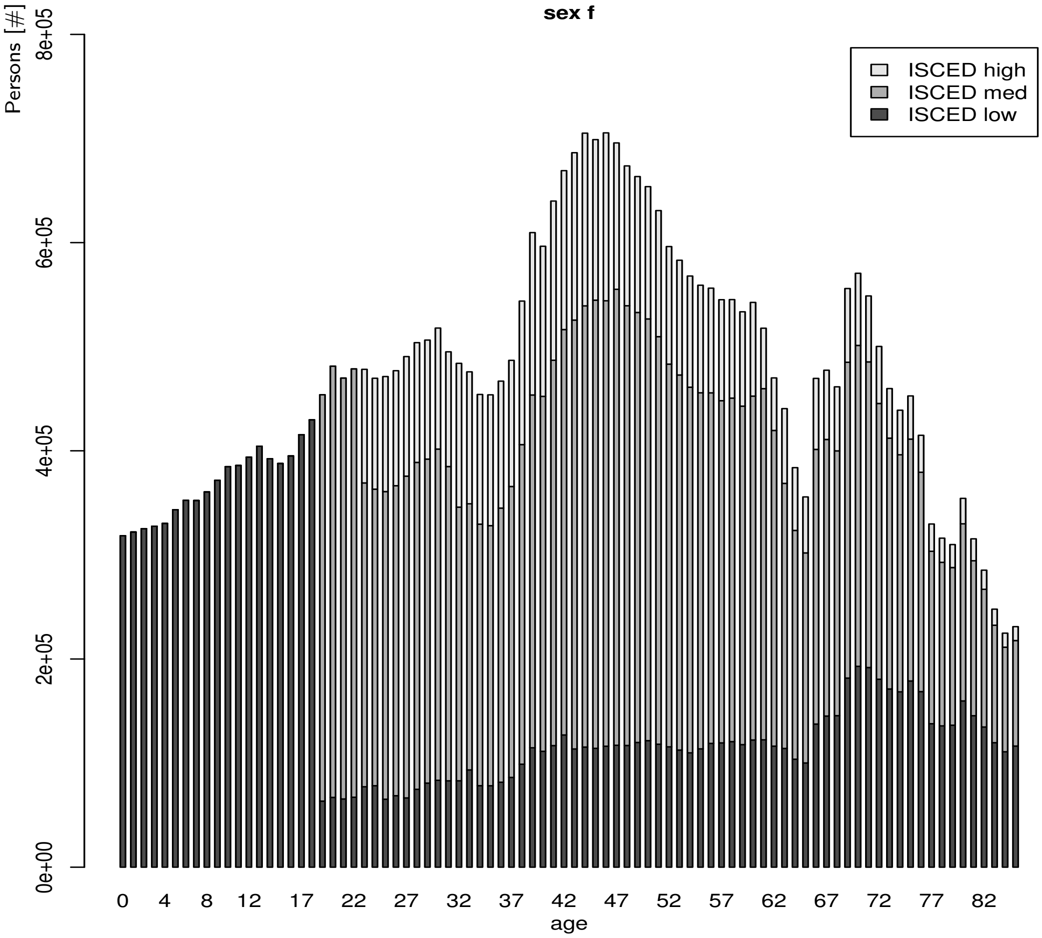
The resulting parameter set shows a trend break after the year 1997 for the graduation probabilities at age 18 from low to medium level. This is when the current ISCED97 classification was introduced. For the years 1998 and 1999, the results of the described procedure show a clear decline. From 2000 on, the values show a stable behaviour similar to the period before 1997. Therefore, this break was corrected by continuing in 2000 on the level of 1997, applying the course of the reported data. The values for 1998 and 1999 were linearly interpolated.

The resulting parameter set, used in *SEGESD*, is given both as table 4.2 on page 80 and as graph 4.10 on the preceding page.

Implications for *SEGESD*

The model starts running in 1970 due to the availability of the necessary population data. The economic analysis starts in 1990, when the complete *EUKLEMS* data starts. For everybody older than 31 in 1970, changes in the education system between 1970 and 1990 have no effect due to the assumed graduation steps according to figure 4.7 on page 77. But for all cohorts of age

Figure 4.11
Educated Population Cohorts: Baseline 2010 Females



SEGESD results. [Persons]

31 and younger in 1970 and naturally for those born afterwards, the education distributions are calculated endogenously in the model based on graduation probabilities as described before. These graduation probabilities are assumed to depend on the spending for education, as describe in the following section. Through this connection the core mechanism under analysis in *SEGESD*, the effect of education spending on economic growth, is implemented.

Table 4.3
Educated Population Cohort Model: Deviation of Baseline from exog. LFS [.]

	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007		
age15_24 sex_f ISCED_low	1.07	1.19	1.05	0.89	0.87	0.99	1.24	1.24	0.85	0.87	0.88	0.91	0.90	0.92	0.93	Average	0.990
age15_24 sex_f ISCED_med	0.95	0.87	0.95	1.16	1.22	1.04	0.86	0.86	1.25	1.20	1.20	1.15	1.17	1.12	1.11	Standard Deviation	0.181
age15_24 sex_f ISCED_high	0.87	0.93	0.95	0.94	0.74	0.63	0.51	0.52	0.88	0.92	0.88	0.81	0.96	1.03	0.93	Variance	0.033
age15_24 sex_m ISCED_low	1.00	1.08	0.96	0.83	0.82	0.91	1.10	1.12	0.82	0.83	0.84	0.87	0.86	0.90	0.87	Avg. dev. from mean	0.146
age15_24 sex_m ISCED_med	1.00	0.94	1.04	1.25	1.33	1.13	0.93	0.91	1.30	1.27	1.27	1.23	1.23	1.17	1.23		
age15_24 sex_m ISCED_high	1.00	1.03	1.00	1.14	0.60	0.62	0.66	0.80	1.09	1.09	1.08	1.02	1.36	0.97	1.13		
age25_32 sex_f ISCED_low	1.10	1.23	1.12	1.00	1.08	1.06	1.03	1.06	1.07	1.08	1.11	1.06	0.97	1.14	1.39	Average	1.027
age25_32 sex_f ISCED_med	0.96	0.94	0.97	0.99	0.98	0.99	1.00	1.01	0.99	0.97	0.97	1.00	1.01	0.97	0.95	Standard Deviation	0.083
age25_32 sex_f ISCED_high	1.04	1.05	1.00	1.02	1.01	0.99	0.98	0.93	0.98	1.04	1.00	0.95	1.00	0.99	0.90	Variance	0.007
age25_32 sex_m ISCED_low	1.16	1.26	1.17	1.01	1.12	1.07	1.01	1.07	1.09	1.09	1.16	1.09	1.02	1.17	1.24	Avg. dev. from mean	0.062
age25_32 sex_m ISCED_med	0.93	0.92	0.96	1.00	0.99	1.00	1.01	1.00	1.00	0.97	0.97	0.98	1.01	0.97	0.97		
age25_32 sex_m ISCED_high	1.15	1.14	1.03	0.98	0.96	0.97	0.97	0.95	0.96	1.02	0.98	1.00	0.97	0.98	0.94		
age33_49 sex_f ISCED_low	1.05	1.14	1.06	0.91	0.98	0.96	0.94	0.99	1.06	1.06	1.16	1.12	1.08	1.09	1.16	Average	1.006
age33_49 sex_f ISCED_med	1.00	0.97	0.99	1.04	1.02	1.03	1.03	1.02	0.98	0.97	0.97	0.98	0.98	0.96	0.95	Standard Deviation	0.060
age33_49 sex_f ISCED_high	0.95	0.96	0.96	0.98	0.95	0.96	0.97	0.96	1.00	1.05	0.97	0.96	1.01	1.05	1.02	Variance	0.004
age33_49 sex_m ISCED_low	1.05	1.12	1.07	0.87	0.97	0.91	0.86	0.92	1.03	1.05	1.13	1.08	1.02	1.04	1.11	Avg. dev. from mean	0.048
age33_49 sex_m ISCED_med	1.03	1.01	1.03	1.05	1.04	1.04	1.04	1.04	1.00	0.96	0.98	0.99	0.99	0.96	0.95		
age33_49 sex_m ISCED_high	0.92	0.95	0.93	0.96	0.94	0.97	1.00	0.97	1.00	1.06	0.99	0.99	1.01	1.06	1.05		
age50_64 sex_f ISCED_low	0.89	1.01	0.97	0.86	0.90	0.90	0.89	0.94	0.97	0.99	1.05	1.01	0.96	0.98	1.04	Average	0.996
age50_64 sex_f ISCED_med	1.06	0.99	1.02	1.11	1.07	1.07	1.06	1.04	1.01	0.98	0.98	1.01	1.02	1.00	0.99	Standard Deviation	0.065
age50_64 sex_f ISCED_high	1.22	1.04	1.04	1.06	1.02	1.04	1.06	1.01	1.04	1.09	0.99	0.95	1.01	1.01	0.97	Variance	0.004
age50_64 sex_m ISCED_low	0.89	1.03	0.99	0.82	0.88	0.86	0.83	0.88	0.94	0.98	1.07	1.00	0.93	0.96	1.09	Avg. dev. from mean	0.048
age50_64 sex_m ISCED_med	1.02	1.00	1.01	1.06	1.05	1.06	1.08	1.06	1.04	0.98	1.01	1.03	1.04	1.01	1.00		
age50_64 sex_m ISCED_high	1.04	0.99	1.00	1.00	0.98	0.97	0.96	0.95	0.96	1.05	0.95	0.94	0.95	0.99	0.97		
age65above sex_f ISCED_low	0.94	1.00	0.95	0.86	0.89	0.86	0.84	0.84	0.86	0.86	0.89	0.85	0.82	0.83	0.83	Average	1.026
age65above sex_f ISCED_med	1.07	0.99	1.05	1.25	1.18	1.21	1.24	1.23	1.18	1.15	1.12	1.17	1.21	1.17	1.15	Standard Deviation	0.112
age65above sex_f ISCED_high	1.18	1.06	1.12	1.06	1.02	1.08	1.16	1.10	1.14	1.19	1.10	1.12	1.14	1.19	1.24	Variance	0.013
age65above sex_m ISCED_low	0.96	1.09	1.00	0.81	0.90	0.87	0.84	0.89	0.98	1.00	1.03	0.97	0.95	0.96	1.01	Avg. dev. from mean	0.089
age65above sex_m ISCED_med	0.99	0.97	0.98	1.07	1.04	1.05	1.06	1.03	0.99	0.96	0.97	0.99	1.00	0.98	0.96		
age65above sex_m ISCED_high	1.06	1.01	1.04	1.05	0.99	1.01	1.03	1.02	1.04	1.11	1.04	1.03	1.03	1.08	1.08		
															for all values:	Average	1.009
																Standard Deviation	0.110
																Variance	0.012
Results of *SEGESD rev. 874*																Avg. dev. from mean	0.078

4.4.5 Resulting Baseline & Deviation from LFS

Applying the methodology laid out in sections 4.4.2 and 4.4.3 with the population data described in section 4.4.1 and with the graduation parameters estimated as described in the previous section 4.4.4 results in a data set of yearly age cohorts of the German population distinguishing three education levels - *low, medium, high* - for both sexes, from 1970 till 2100.

An example of the composition of the female population in the year 2010 is given in figure 4.11 on page 83. The full visualization in 5 year steps can be found in the appendix C.2 on page 188.

The quality of the model results is evaluated in terms of deviation from the statistical data reported in the Labour Force Survey. Therefore, the endogenous calculations within *SEGESD* are aggregated to the age aggregation cohorts as used in the LFS data set. The relative deviation in terms of endogenous figures divided by exogenous data is compiled in table 4.3 on the facing page. There, also some descriptive statistical figures (mean value, standard deviation, variance as well as the average deviation from the mean value) are given per age aggregation cohort as well as calculated over all deviation figures.

The table shows that the approach described before leads to useful results for the baseline of the educated population cohort model. Of course, deviations can not be avoided completely. The main reason for this is that the time series in the LFS data set contain breaks in the definition of the ISCED classification as well as changes in the methodology of gathering the survey data. Therefore, the exogenous LFS data can not be completely matched by a model continuously calculating the structure of the population.

4.5 Spending driving graduation probabilities

Finally the first step in the analysis of how investments in education can effect economic growth is described. The essence of this first step is answering the question *how does the spending in the education system influence the graduation probabilities?* Thereby, the influence of the amount of money spent on the education level of the population is modelled within *SEGESD*. In figure 4.1 on page 42, this part is visualized as the steps *Education Spending* $\rightarrow$ *Students* $\rightarrow$ *Graduates* $\rightarrow$ *Education Level*.

In *SEGESD*, this relation is implemented as a linear relation between education spending and graduation probabilities, differenced for each graduation point (*GradPoint*) as defined in figure 4.7 on page 77. The formula is

$$\begin{aligned} & GraduationProbability_{GradPoint} \\ = \; & GradProbIntercept_{GradPoint} \\ & + GradProbInclination_{GradPoint} \cdot EducationSpending_{GradPoint} \end{aligned} \tag{4.43}$$

with:	*GraduationProbability*	Share of persons raising to next education level. [.]
	GradProbIntercept	Interception [Mio €] of linear relation *Education Spending →Graduation Probability*
	GradProbInclination	Inclination [1/Mio €] of linear relation *Education Spending →Graduation Probability*
	EducationSpending	Spending for education. [Mio €]
	GradPoint	Index for graduation point, ∈{18F, 18M, 22F, 23M, 31F, 31M}

These graduation probabilities are equivalent to the $GradProbLowMed$ and $GradProbMedHigh$ parameters in formula 4.35 on page 71 according to the assignment

$$\begin{aligned} GradProbLowMed_{age18,f} &= GraduationProbability_{18F} \\ GradProbLowMed_{age18,m} &= GraduationProbability_{18M} \\ GradProbMedHigh_{age22,f} &= GraduationProbability_{22F} \\ GradProbMedHigh_{age23,m} &= GraduationProbability_{23M} \\ GradProbMedHigh_{age31,f} &= GraduationProbability_{31F} \\ GradProbMedHigh_{age31,m} &= GraduationProbability_{31M} \end{aligned} \tag{4.44}$$

with:	*GraduationProbability*	Share of persons raising to next education level. [.]
	GradProbLowMed	Share of persons raising from low to medium education level. [.]
	GradProbMedHigh	Share of persons raising from med to high education level. [.]
	GradPoint	Index for graduation point, ∈{18F, 18M, 22F, 23M, 31F, 31M}

The relevant education spending for each graduation point is the spending associated with the ISCED level at which the students graduate, i.e. for the graduation probability from *low* to *medium* this is the spending on level *medium* and for graduation from level *medium* to *high* this is the spending associated with ISCED level *high*.

This linear relation is applied in the calculation of scenario specific modified education level distributions within the population relative to the baseline using the educated population cohort model described in section 4.4 on page 65. For the calculation of modified graduation probabilities for the various scenarios only the inclination in the linear model is relevant, i.e. the relative change of the graduation probability in response to a relative change of the education spending. For this calculation, the interception is not relevant, as it disappears in the calculation of the difference of two graduation probabilities calculated with formula 4.43. It is

$$\begin{aligned} & \Delta GraduationProbability_{GradPoint} \\ = \ & GradProbInclination_{GradPoint} \cdot \Delta EducationSpending_{GradPoint} \end{aligned} \tag{4.45}$$

with:	*GraduationProbability*	Share of persons raising to next education level. [.]
	GradProbInclination	Inclination [1/Mio €] of linear relation *Education Spending →Graduation Probability*
	EducationSpending	Spending for education. [Mio €]
	GradPoint	Index for graduation point, ∊{18F, 18M, 22F, 23M, 31F, 31M}

The estimation of the parameter *GradProbInclination* in this formula is described in the following. Because of the shortness of available timelines, this part of the analysis is subject to high uncertainty. Therefore, several relations are analysed, each leading to a range for this parameter. These ranges are then used as basis for the analysis of varying scenarios of the magnitude of the reaction of the education system to increased spending in the education system.

Two analytical approaches are combined. First, the direct relation between spending in the education system and the graduation probabilities are analysed (4.5.1). Second, a more disaggregated analysis is carried out (4.5.2). Unfortunately, due to strong limitations in the availability of the necessary data, this can only be done for the high education level and only for a limited range of age cohorts. Nevertheless, it supports the findings of the first analysis.

4.5.1 Education Spending → Graduation Probability

First, the development of the graduation probabilities in dependence of the spending for education were analysed from a high level perspective. Therefore, the correlation between these two variables assuming several temporal lags of the effect were calculated for each graduation point.

The data on education spending used in this analysis is spending by public and private sector per student, derived from *Eurostat* time series. The detailed references are given in appendix B.5 on page 171. This data is given as nominal purchase power parity figures. These figures were deflated to constant 1995 Euros.

The linear model used for the analysis was equal to equation 4.43 on the facing page, extended by the error term. For this model the parameters were

Table 4.4
Education Spending → Graduation Probability: Correlation Analysis

GradPoint		*18F*				*18M*		
Lag (years)	*0*	*1*	*2*	*3*	*0*	*1*	*2*	*3*
Interception [%]	0.369	0.470	0.581	0.651	0.783	0.766	0.729	0.680
Inclination [%/€]	0.000089	0.000071	0.000051	0.000039	0.000013	0.000017	0.000024	0.000033
Corr. Coeff. [.]	0.70	0.64	0.48	0.37	0.39	0.33	0.45	0.59
GradPoint		*22F*				*23M*		
Lag (years)	*0*	*1*	*2*	*3*	*0*	*1*	*2*	*3*
Interception [%]	-0.043	0.066	0.155	0.116	0.139	0.160	0.187	0.159
Inclination [%/€]	0.000037	0.000025	0.000014	0.000020	0.000013	0.000010	0.000007	0.000011
Corr. Coeff. [.]	0.89	0.84	0.68	0.62	0.77	0.75	0.62	0.61
GradPoint		*31F*				*31M*		
Lag (years)	*0*	*1*	*2*	*3*	*0*	*1*	*2*	*3*
Interception [%]	-0.060	-0.015	0.053	0.040	0.109	0.103	0.092	0.094
Inclination [%/€]	0.000018	0.000013	0.000005	0.000007	0.000001	0.000001	0.000003	0.000002
Corr. Coeff. [.]	0.90	0.78	0.68	0.62	0.11	0.29	0.58	0.45

Results of analysis. Units: Interception [%]. Inclination [%/€].

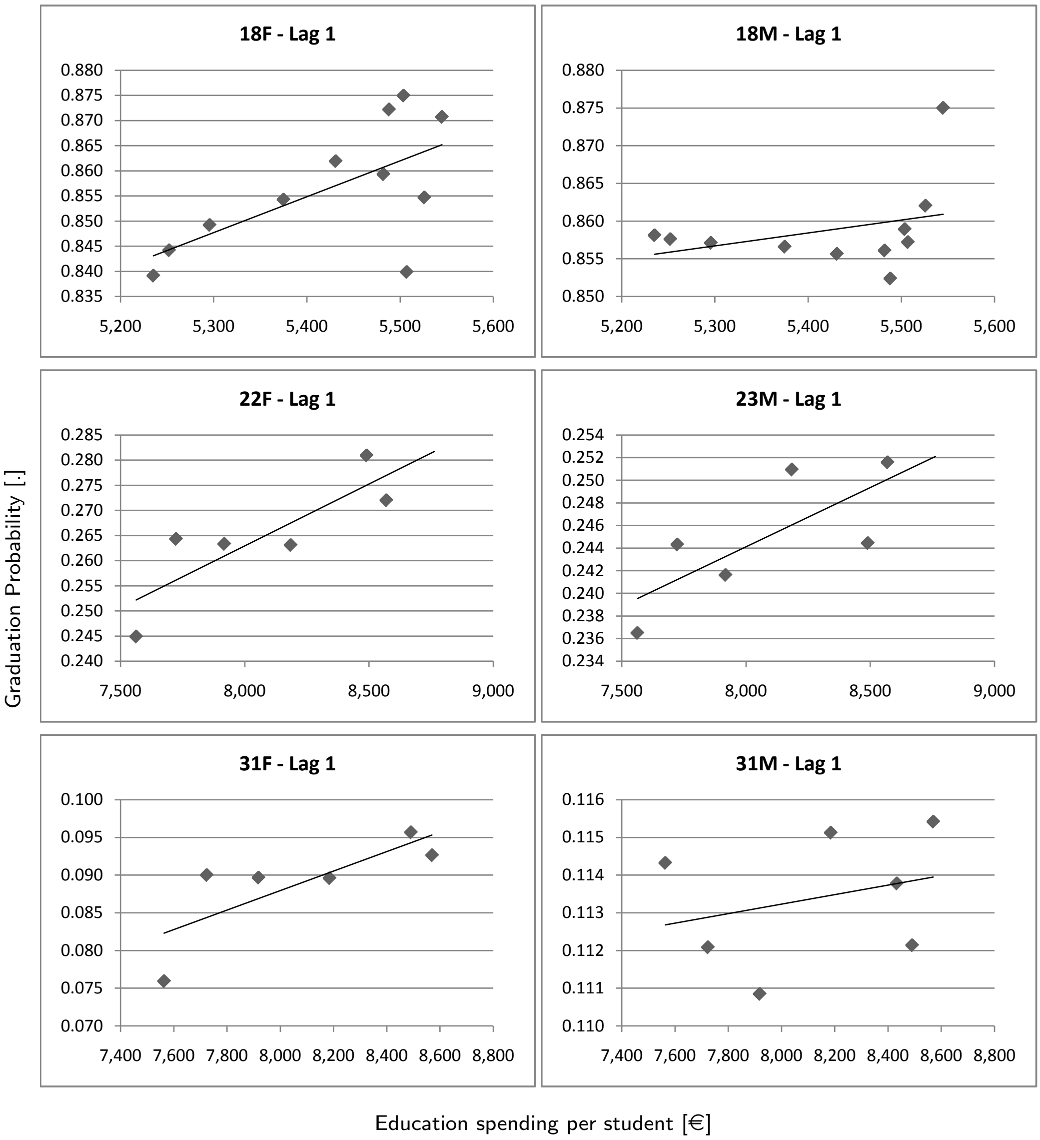
estimated under the assumption of a time lag from 0 to 3 years for the effect of the education spending on the graduation probabilities.

The complete results are compiled in the following, showing the interception as well as the inclination and the according correlation coefficient for each parameter estimation (per graduation point and per time lag). The full set of numerical results are compiled in table 4.4. For each parameter estimation, the according graph was constructed, plotting the graduation probability against education spending per student. The full set of scatter plots is included into the appendix C.3 on page 206. Here, an exemplary subset is given in figure 4.12 on the next page, containting one plot for each graduation point with a time lag of one year.

The plots give a good visual impression of the findings from the correlation analysis. The individual results vary strongly in the clarity of the findings. The correlation coefficients vary broadly. But looking at the set of analysis in total, a clearer picture emerges. The correlations are positive for all estimates. This finding is taken as clear support for the legitimacy of the analysed assumption. Increases in the spending for education raise the probability of the students to achieve a degree.

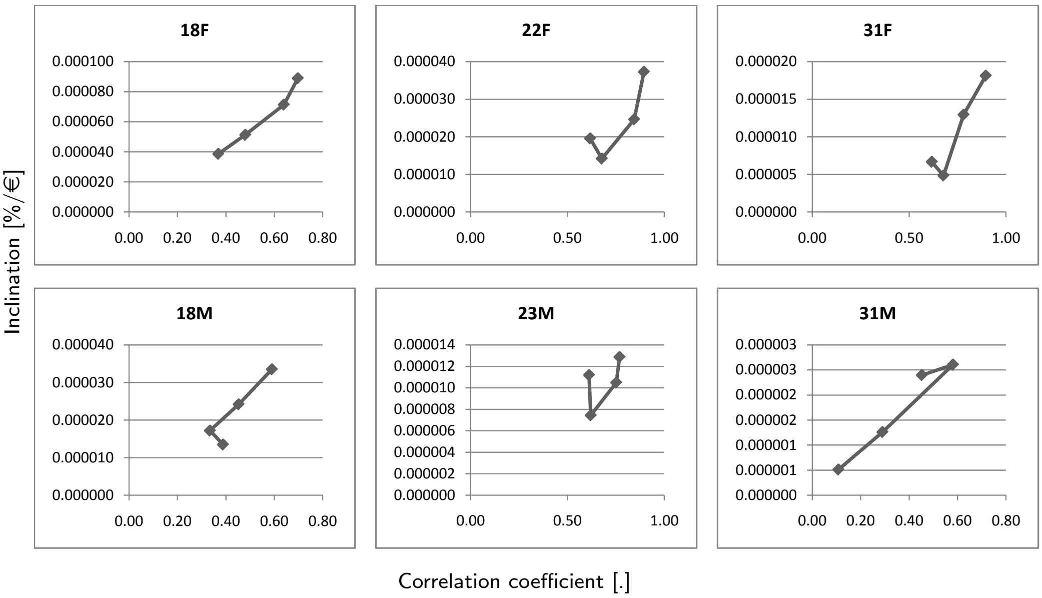
Also, figure 4.13 on page 90 increases the clearity of the findings. It summarizes the results for each graduation point as plots of the inclination

Figure 4.12
Education Spending → Graduation Probability: Scatter Plot Examples



Result of analysis.

Figure 4.13
Education Spending → Graduation Probability: Inclination vs Correlation Coeff



Result of analysis.

vs. the correlation coefficient. This perspective shows clearly that higher inclinations are found in analysis with higher correlation coefficient, and lower inclinations are found in analysis with correlation coefficients closer to zero. This can be interpreted as additional indication that the inclinations are different from zero and positive.

In order to reflect the uncertainty of this analysis, a range of inclination values rather than a single value is used for the scenario calculations with *SEGESD*. In table 4.5 the minimum and maximum values for the inclination parameter per graduation point is given. These values are used as upper and lower bounds in the scenario analysis.

GradPoint	*Inclination [%/€]*	
	min	*max*
18F	0.00386	0.00889
18M	0.00135	0.00335
22F	0.00142	0.00373
23M	0.00074	0.00129
31F	0.00048	0.00181
31M	0.00005	0.00026

Table 4.5
Spending → GradProb: Inclin.

The unit of this inclination is [%/€]. Therefore, for example, additional 1000 € per student per year spent in medium level education programs would lead to an increase of the graduation probabilities between 3.86 and 8.89

percent points of 18 year old girls. Similarly, this additional money spent in high level programs would increase the graduation probabilities of young men at the age of 23 by 0.74 to 1.29 percentage points, but at a lower level of the absolute height of the graduation probabilities on the one hand and at a lower level of absolute numbers of students on the other. The exact quantitative effects are analysed within the scenario analysis.

The significantly higher inclinations in the linear regression models for females than for males in all cases must probably be attributed to a large part to the increased participation of woman in high level education programs due to increasing gender equality over the time period of the analysis.

4.5.2 Spending → Students → Graduates

Additionally to the analysis described in the previous section (4.5.1) a more detailed analysis was carried out. As mentioned in the beginning of section 4.5 on page 85, the effects under analysis are the influence of spending in the education system on student and graduate figures. Therefore, on the most detailed level, it would be of interest how the student numbers are influenced by the amount of money in the education system or by direct students subsidies. And how the shares of students finally graduating from the mass of all students is driven by these spending.

This analysis is principally possible when taking the available variables provided by *Eurostat* or by *Destatis*. Unfortunately, the data availability differs largely depending on the subset of the relevant variable distinguished by ISCED classes. The problems with the data are twofold. Either, numbers are simply not given, or are extremely low and therefore completely implausible. These are not problems with the order of magnitude, since for the classes 5 and 6, the numbers are significantly higher and plausible. Only for the aggregation of ISCED classes 5 and 6 (i.e. level *high* in terms of the aggregation used within this work) this analysis could be carried out. The approach along with the results are laid out in the following.

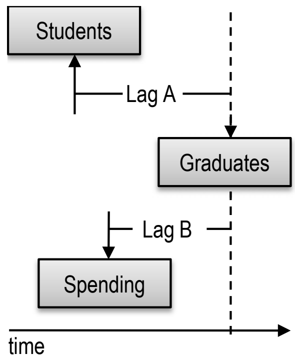


Figure 4.14
Lag Levels

For that aggregation class, a set of 600 combinations of timelines was analysed. This is the permutation of 10 age classes (20 to 29), 5 lag levels (0 to 4 years) for the calculation of graduates per students, 6 lag levels (0 to 5 years) of the effects of spending on graduates, and 2 sexes (10 * 5 * 6 * 2 = 600).

The lag levels are visualized in figure 4.14. *Lag A* refers to the time lag between the student numbers and the graduate numbers used for the calculation of the shares of graduates in all students. *Lag B* refers to the time lag between the spending figures and the graduate figures. So, for example, if $Lag\ A = 2$ and $Lag\ B = 3$, then the three timelines are shifted in the way that the education expenditures of the year 2000, the student numbers of 2001 and the graduate numbers of 2003 are compared to each other.

Those lagged timelines were then analysed in a linear correlation analysis. The linear model estimated was

$$GradsPerStuds = \alpha_{GradsPerStuds} + \beta_{GradsPerStuds} \cdot EducationSpending \quad (4.46)$$

with:	$GradsPerStuds$	Share of yearly graduates per students. [.]
	$\alpha_{GradsPerStuds}$	Interception of linear model. [.]
	$\beta_{GradsPerStuds}$	Inclination of linear model. [1/ €]
	$EducationSpending$	Spending for education. [Mio €]

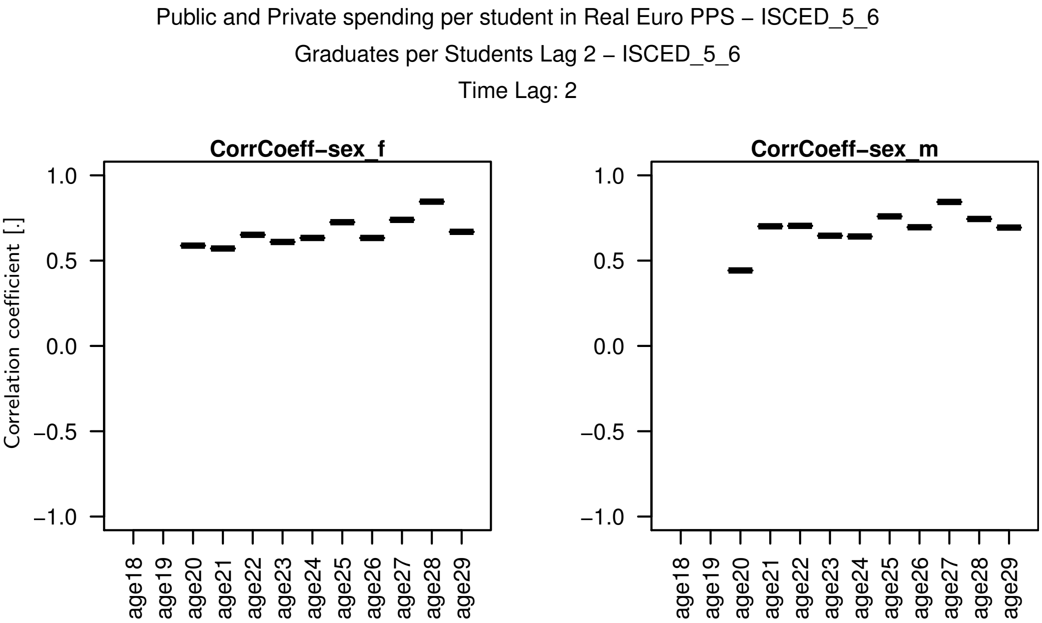
with α denominated the interception and β called inclination in the following in analogy to the previously described analysis. As described above, this analysis could be carried out for 600 cases. The correlation coefficients for each one of these 600 cases was then plotted against the age cohorts for which it was determined, distinguished by sex and both lag levels, resulting in 60 (= 2 * 5 * 6) plots.

An example of the results is given in figure 4.15 on the next page. The full results of this analysis - as plots and as tables of numerical values - are compiled in appendix C.4 on page 210.

The correlation coefficients for all age classes remain clearly in the positive region for almost all analyses. They show a tendency to raise towards the older age classes. Also, for increased lag levels for both *Lag A* as well as *Lag B*, the correlation coefficients appear to increase. Grouping all correlation coefficients by age also shows this tendency (→ fig. 4.16 on page 94). This results are interpreted as support for the existence of a correlation between the spending for education and the probabilities for students to graduate and thereby as support for the findings of the previous analysis described in section 4.5.1 on page 87.

The inclinations obtained through this analysis can be used for the scenario calculations in analogy to the previous section, with the difference that the relative changes of the shares of graduates in all students obtained from the linear model used for the analysis (i.e. $\Delta GradsPerStuds$ obtained from equation 4.46 in analogy to the derivation of equation 4.45 on page 87) have

Figure 4.15
Correlation: Spending per Student against Graduates per Student



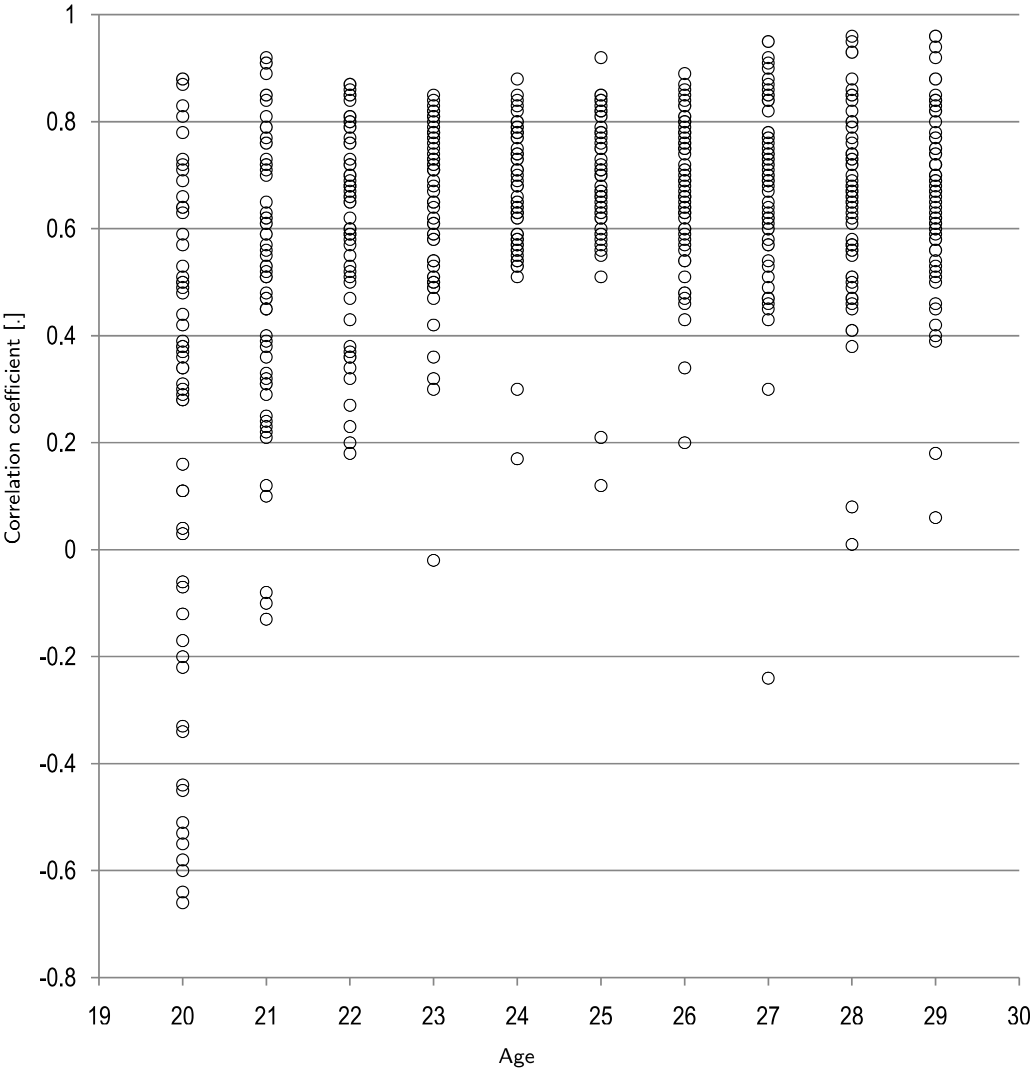
Result of analysis. Correlation Coefficient [.] over age cohort.

to be multiplied with the shares of students in the total population:

$$\begin{aligned} & \Delta GraduationProbability \\ = \quad & \Delta GradsPerStuds \cdot \frac{Students}{Population} \end{aligned} \tag{4.47}$$

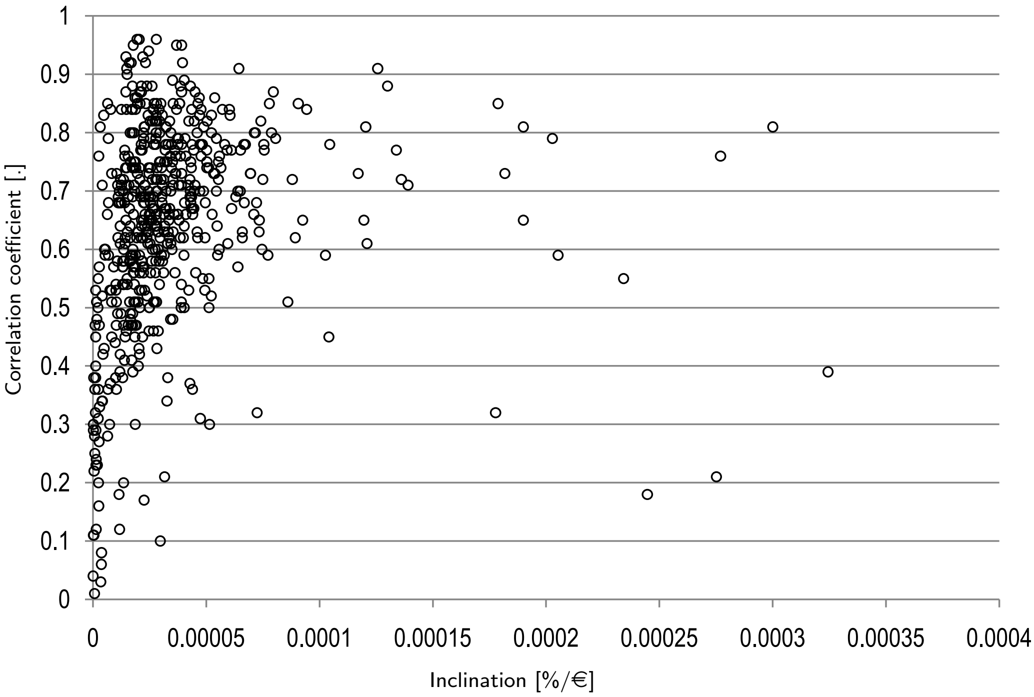
with:	*GraduationProbability*	Share of persons raising to next education level. [.]
	GradsPerStuds	Share of yearly graduates per students. [.]
	Students	Number of students. [#]
	Population	Number of all persons. [#]

Figure 4.16
Correlation of Spending per Student against Graduates per Student: Correlation Coefficients by age



result of analysis

Figure 4.17
Correlation of Spending per Student against Graduates per Student: Correlation Coefficients vs. Inclinations



Result of analysis. Very view observations beyond visible range omitted.

Combining this equation with 4.46 results in the effective formula:

$$\begin{aligned} & \Delta GraduationProbability \\ = \quad & \beta_{GradsPerStud} \cdot \Delta EducationSpending \cdot \frac{Students}{Population} \end{aligned} \tag{4.48}$$

with:	$GraduationProbability$	Share of persons raising to next education level. [.]
	$\beta_{GradsPerStuds}$	Inclination of linear model. [1/ €]
	$EducationSpending$	Spending for education. [Mio €]
	$Students$	Number of students. [#]
	$Population$	Number of all persons. [#]

For example, a value of 0.00001 for $\beta_{GradsPerStud}$ means that additional 1000€ per student spend in the *high* level education programs lead to additional 0.01 graduates per students, i.e. an increase in the probability of students to graduate by 1 percentage point.

Table 4.6
β for Spending $\rightarrow$ Grad. Prob. based on Grads per Studs Correlation

Grad.	*beta GradsPerStuds [% / €]*		*Ratio Studs in Population*		*beta GraduationProbability [% / €]*	
Point	*lower*	*upper*	*lower*	*upper*	*lower*	*upper*
22F	0.00132	0.00611	0.191	0.244	0.000252	0.001493
23M	0.00101	0.00406	0.168	0.210	0.000170	0.000853
31F	0.00132	0.00611	0.063	0.069	0.000084	0.000422
31M	0.00101	0.00406	0.046	0.051	0.000046	0.000207

result of analysis.

Figure 4.17 on the preceding page shows a plot of the inclinations against the according correlation coefficients, showing a strong concentration in the interval [0.00001; 0.00005] for the inclinations. This interval contains ²⁄₃ of all results. The according correlation coefficients are concentrated within the interval [0.51; 0.84], containing 75% of all values.

When the results are analysed separately for woman and men, a picture similar in its tendency to the preceding analysis (sec. 4.5.1) emerges. The values of $\beta_{GradsPerStud}$ are higher for women than for men, probably due to the same reasons mentioned before (increasing participation of women in education and labour market during the analysed time frame, for which increased spending in education can only be part of the explanation). The comparable interval yields [0.0000132;0.0000611] for women and only [0.0000101;0.0000406] for men, i.e. an approximately 30 (lower boundary) to 50 (upper boundary) percent higher inclination of the impact of increased education spending on the graduation probability for women than for men.

Multiplying $\beta_{GradsPerStuds}$ with the shares of students in the total population (age cohort specifically, of course) yields the inclination of the linear model described in equation 4.45 on page 87. The shares of students in the total population were calculated for each year available in the timelines of the data for the correlation analysis. Of these shares the upper and lower boundaries of the covered intervals were used, multiplying the lower boundary of the $\beta_{GradsPerStuds}$ intervals with the lower boundary of the shares of students in the total population and doing the same with the upper boundaries. The results are compiled in table 4.6. They form the equivalent of this analysis to the results of the analysis in the previous section 4.5.1 compiled in table 4.5 on page 90.

Table 4.7
Graduation Probability Ranges for a 10% increase of per student spending

Parameters for a 10% increase of money spent per student.	*Grad Point*	*Baseline Average*	*Impact Scenario*		
			weak	*moderate*	*strong*
Additional Graduation Probability [% points]	*18F*	*0*	*0.372*	*2.102*	*4.843*
	18M	*0*	*0.168*	*0.735*	*1.822*
	22F	*0*	*0.206*	*1.162*	*3.045*
	23M	*0*	*0.139*	*0.608*	*1.052*
	31F	*0*	*0.068*	*0.395*	*1.481*
	31M	*0*	*0.038*	*0.042*	*0.213*
Relative Increase of graduation probability (relative to baseline avg.) [%]	*18F*	*0*	*0.44*	*2.48*	*5.72*
	18M	*0*	*0.20*	*0.85*	*2.12*
	22F	*0*	*0.80*	*4.53*	*11.88*
	23M	*0*	*0.57*	*2.48*	*4.28*
	31F	*0*	*0.80*	*4.61*	*17.26*
	31M	*0*	*0.33*	*0.37*	*1.88*
Graduation Probabilities Scenario Values [%]	*18F*	*84.68*	*85.05*	*86.78*	*89.52*
	18M	*86.08*	*86.25*	*86.81*	*87.90*
	22F	*25.64*	*25.84*	*26.80*	*28.68*
	23M	*24.55*	*24.69*	*25.15*	*25.60*
	31F	*8.58*	*8.65*	*8.98*	*10.06*
	31M	*11.31*	*11.35*	*11.36*	*11.53*

result of analysis.

4.5.3 Combining both correlation analyses

Comparing the results of the two analyses of the previous two section in table 4.6 as well as in table 4.5 shows a significantly lower range for the $\beta_{GraduationProbability}$ parameter in the second analysis. But for each graduation point except for *31F* the intervals are overlapping. In the case of *31F* a small gap between the two intervals remains open. So, two completely independent approaches based on independent statistical data yield overlapping results. This is interpreted as evidence for the validity of the two correlation analysis, which each individually is based on not very long timelines. But the combined picture of the two analyses let the results appear more stable and reliable.

Based on these two analysis, within the scenarios analysed in the following chapter 5 three levels for the parameter $\beta_{GraduationProbability}$ - *weak*, *moderate* and *strong* will be used. *Weak* represent the lower boundary of results of the correlation between education spending the the shares of graduates per students as described within this section (4.5.2). *Moderate* represents the lower boundary of the analysis of the correlation between education spending and the graduation probability (sec. 4.5.1) and *strong* reflects the upper boundaries of the parameter ranges of that analysis. For the two graduation points at age 18, no results could be calculated within the correlation analysis between spending and graduates per student. Therefore, for these graduation points the *weak* parameters are calculated based on the relation between *moderate* and *weak* of the graduation points 22F and 23M.

Based on these ranges for the parameter $\beta_{GraduationProbability}$ the relative changes of the graduation probability are calculated based on spending per students averaged over the available timeframe and on the graduation probabilities averaged over the same timeframe. This relative change is then used within *SEGESD* to vary the time series of the graduation probabilities. For the case of a 10% increase of the money spent per student the results are compiled in table 4.7 on the preceding page.

Chapter 5

Quantitative Behaviour of *SEGESD*

This chapter lays out the quantitative behaviour of *SEGESD*. It starts with a short description of the design of the baseline scenario (sec. 5.1). Then, the global analysis showing the sectoral reaction of the economy to a change in the spending for education (sec. 5.2) is laid out. After that (in sec. 5.3) follows a series of partial analyses demonstrating the elasticities of the individual links of the whole chain of effects as explained in chapter 4.

The sector codes used in *SEGESD* are those provided by the *EUKLEMS* framework. The mixture of numbers and letters is difficult to keep in mind, especially during first time reading. Also the codes of the labour types are often used and might need to be looked up repeatedly. Therefore, the sector code list and the labour types list is included as an A3 page in appendix A.4 on page 163 which can be folded out in order to always have the list next to the main text[1].

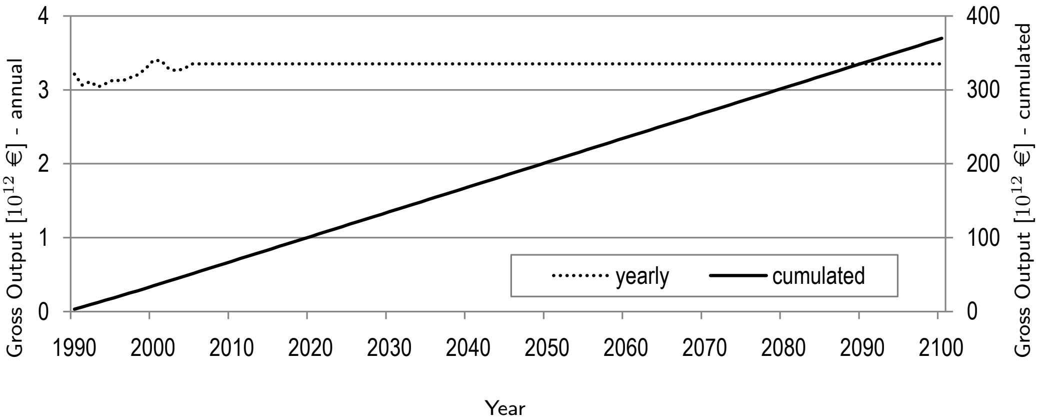
5.1 Baseline

This section gives an overview of the baseline scenario. It describes the assumptions for the development of the economic output, the population and the education spending until 2100.

The baseline was implemented as a constant continuation of the output reported in the latest EUKLEMS data set. Figure 5.1 on the following page shows the total gross output in real values, both as annual values and

[1]This is only the case in the paper version of this thesis. The electronic version (PDF) contains an regular sized page which can be removed from a printout of this PDF in order to facilitate reading.

Figure 5.1
Gross Output Total [Mio * Mio €] Baseline



SEGESD baseline. Based on EUKLEMS data.

cumulated over the complete timeframe relevant to the economic analysis. And table 5.1 on the next page contains the detailed yearly values sectorally disaggregated.

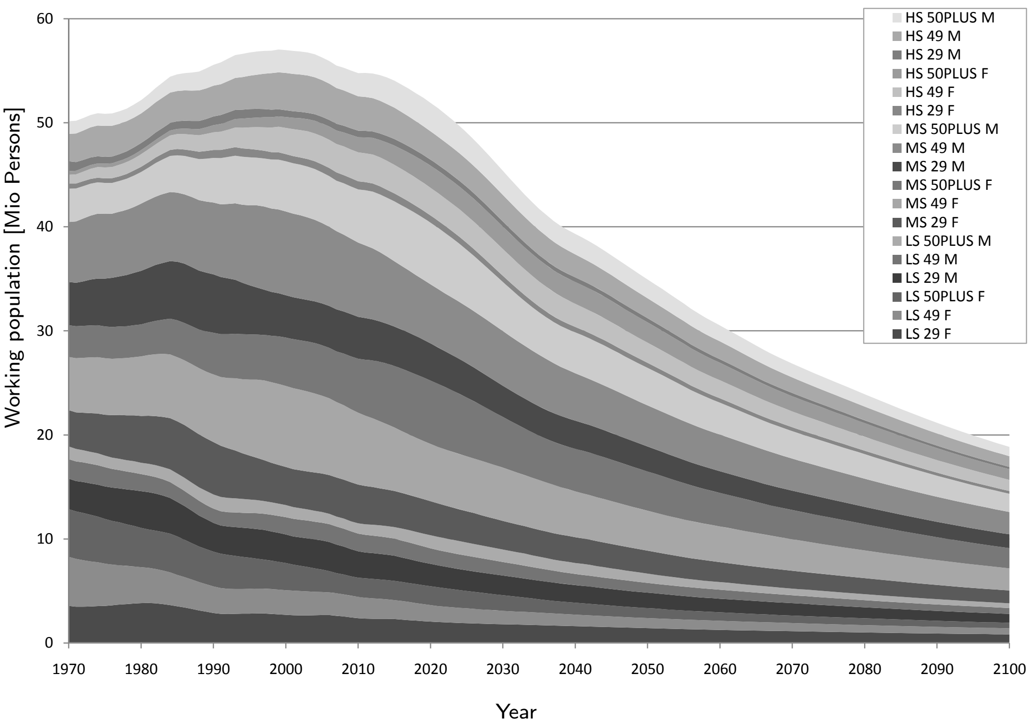
The population development was modelled based on a combination of *Labour Force Survey* data by *DESTATIS* and *Eurostat* data. The details are compiled in section 4.4. For the time beyond the latest available data, the population is endogenously computed based on the birth and morbidity figures of the latest year. This reflects the assumptions of the "moderate" population development scenario in the population forecast by DESTATIS (2009). The resulting population structure differentiated into yearly age cohorts is included in appendix C.2. Figure 5.2 contains aggregated time series for each labour type. This graph shows very well the already diminishing work force (not total population!) due to the demographic change. If current trends in birth and morbidity rates are continued, a strong decrease of the workforce appears inevitable. The development of the birth rate might be subject to political change, especially by the provision of daycare facilities. But a change of the morbidity rates towards dying at older ages would probably not strongly impact the labour force. Most people already die after their retirement, i.e. after 65. Therefore, this will rather impact the ratio of retired to working persons, which does not influence the results within *SEGESD*. And the question of the economic effect of an increase of the retirement age could also be analysed within *SEGESD* as described in the

Table 5.1
Gross Output Sectoral [Mrd €] Baseline

[Mrd €]	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2050	2100
AtB	52.6	50.2	48.3	45.7	45.5	45.9	46.2	46.2	44.3	43.9	45.5	46.2	42.1	38.9	40.5	35.9	35.9	35.9
C	30.4	29.0	26.4	24.7	23.0	22.1	16.4	14.7	14.0	12.1	12.2	10.5	10.6	11.5	10.6	10.1	10.1	10.1
15t16	147.3	140.5	137.1	130.3	127.8	125.2	122.4	123.9	119.4	118.0	120.5	122.7	118.5	118.6	117.5	116.7	116.7	116.7
17t19	49.9	47.6	43.1	38.5	35.4	32.6	30.8	30.4	29.8	28.5	28.5	27.6	24.7	22.7	22.2	21.1	21.1	21.1
20	19.8	18.9	19.5	18.7	21.2	22.5	20.2	20.8	20.2	20.3	20.2	18.5	18.6	17.2	18.0	18.0	18.0	18.0
21t22	83.6	79.7	76.9	71.5	70.5	71.7	71.0	72.1	72.1	74.6	79.4	75.9	71.4	67.0	67.3	67.9	67.9	67.9
23	31.3	29.9	25.8	24.1	25.0	23.3	23.8	21.7	21.5	23.4	36.4	35.3	33.8	36.1	41.6	48.5	48.5	48.5
24	112.7	107.5	101.3	92.9	96.5	105.1	101.2	103.9	102.0	102.7	113.6	113.0	107.2	107.7	108.7	111.0	111.0	111.0
25	50.5	48.1	47.7	43.9	43.1	46.3	44.0	45.4	45.7	45.9	47.9	47.2	46.4	45.4	47.5	48.0	48.0	48.0
26	40.1	38.3	39.6	39.5	41.4	41.6	38.3	37.1	36.1	36.9	36.8	33.8	31.7	29.6	30.0	29.5	29.5	29.5
27t28	154.4	147.3	139.0	122.4	124.2	133.2	124.6	127.9	132.2	126.8	138.6	137.5	128.5	127.4	137.5	146.6	146.6	146.6
29	161.7	154.3	144.3	126.4	124.3	133.6	132.6	132.8	139.2	136.3	145.7	149.0	138.9	139.7	143.8	149.2	149.2	149.2
30t33	157.9	150.6	146.4	134.4	132.7	125.3	122.8	129.8	133.9	139.3	158.3	153.4	139.5	139.9	145.6	145.9	145.9	145.9
34t35	169.3	161.5	160.8	131.1	135.9	147.4	156.0	170.3	191.6	206.5	221.8	235.0	231.9	230.4	236.5	245.6	245.6	245.6
36t37	34.6	33.0	32.8	30.7	29.1	29.7	28.7	29.5	30.5	30.6	32.2	30.8	28.1	26.5	26.5	27.2	27.2	27.2
E	73.9	70.5	69.6	68.3	67.7	67.1	68.6	66.8	69.0	67.0	62.0	64.6	67.4	68.3	76.8	82.1	82.1	82.1
F	209.4	199.7	226.1	233.4	250.2	244.3	233.5	224.9	214.2	215.4	208.4	193.6	175.4	168.3	159.5	152.4	152.4	152.4
50	43.0	41.0	41.4	35.8	37.1	38.6	38.6	39.6	41.4	43.1	41.5	43.4	46.3	46.0	44.7	44.4	44.4	44.4
51	151.1	144.1	143.3	144.8	150.9	148.7	141.4	144.8	149.5	145.3	145.3	141.8	124.7	121.6	128.1	131.2	131.2	131.2
52	115.9	110.6	112.1	110.8	109.3	113.1	115.4	114.4	113.5	117.1	125.7	126.0	121.2	118.5	116.7	117.9	117.9	117.9
H	57.3	54.6	56.3	57.1	58.2	57.5	56.0	55.9	56.0	57.5	59.5	58.6	55.6	53.1	52.3	52.2	52.2	52.2
60t63	135.6	129.3	129.7	127.7	129.5	128.7	127.3	131.8	133.3	141.8	152.5	152.6	147.3	145.1	148.6	156.1	156.1	156.1
64	48.2	46.0	49.6	51.9	52.2	52.0	50.2	52.3	55.1	60.3	64.7	69.1	71.6	71.9	71.7	71.9	71.9	71.9
J	137.1	130.7	131.2	139.6	142.6	142.6	149.0	154.7	154.5	175.9	168.7	169.3	172.5	182.4	186.4	190.0	190.0	190.0
70	209.3	199.6	217.2	233.7	245.9	256.3	263.5	262.1	262.1	261.4	260.7	262.4	259.6	257.8	256.6	257.5	257.5	257.5
71t74	245.2	233.9	247.7	258.5	255.3	260.8	267.9	275.3	285.5	301.4	317.6	323.8	314.5	315.3	312.9	326.8	326.8	326.8
L	160.7	153.3	158.5	158.1	156.7	156.7	155.8	153.6	153.3	157.2	154.4	152.3	153.2	150.6	148.1	148.0	148.0	148.0
M	82.3	78.5	83.5	84.7	84.8	87.2	88.4	89.7	90.9	92.6	94.4	95.3	97.6	96.2	96.1	97.1	97.1	97.1
N	132.1	126.0	137.4	139.5	146.6	153.6	160.1	161.5	162.6	166.1	169.2	169.6	172.4	173.4	172.5	172.1	172.1	172.1
O	115.1	109.7	115.9	118.3	120.6	122.2	123.9	125.8	128.9	133.4	137.6	135.8	130.9	130.0	129.1	128.8	128.8	128.8
Total	3,212.5	3,063.9	3,108.6	3,036.9	3,083.0	3,134.8	3,118.6	3,159.7	3,202.1	3,281.4	3,399.5	3,394.6	3,282.1	3,256.9	3,293.8	3,350.1	3,350.1	3,350.1

SEGESD baseline. Based on EUKLEMS data.

Figure 5.2
Working population structure [Mio Persons] Baseline



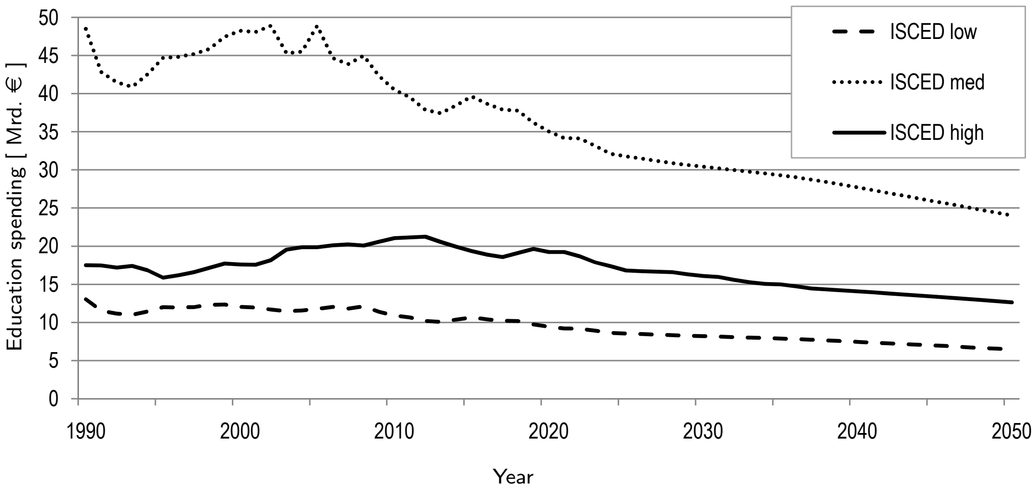
SEGESD baseline. Details on assumptions in section 4.4.

outlook on further research in section 6.7.

The graduation probabilities applied in the baseline are described in section 4.4.4, where the derivation of these figures based on the Labour Force Survey data is described. There, table 4.2 lists the detailed figures, also visualized in figure 4.10. For the baseline, the graduation probabilities were assumed to remain constant for the remaining years after the latest empirically derived values.

The education spending was calculated as the product of student numbers and per head spending for education, distinguished for medium and high level education. The baseline figures for both spending and student numbers are taken from *Eurostat* database (for data details see appendix B.5). For the time frame after the last available data sets, the student numbers are assumed to develop relatively to the total population of the according age cohorts, and the per head spending to remain constant on the level of the

Figure 5.3
Education spending [Mrd. €] Baseline



SEGESD baseline. Total yearly spending per ISCED group.

last reported year, i.e. 2008. Based on this assumption, the total spending per ISCED class results in the numbers visualized in figure 5.3.

The approach of assuming constant economic output in the baseline was chosen in order to reduce the complexity of *SEGESD* and to leave out additional uncertainty about the possibly declining growth rates not relevant to the focus of the analysis. *SEGESD* is designed to analyse the impact of hypothetical change in education spending on historically observed economic output data. It is neither designed nor intended to be a forecast tool. The long time scope to 2100 of the model is only needed to reflect the long temporal lags of the effects under analysis. Therefore the economic output in the baseline is kept constant for the analysis of the dynamics of a change in the education policy with it's extremely long time lags. The design of a baseline scenario until 2100 by itself is a field of high uncertainties. Good reasons can be compiled for both increasing and reducing economic output in real terms. So keeping output constant appears as an acceptable way to avoid additional uncertainties.

The total population does not decrease as strongly as the active labour force (shown in fig. 5.2) due to the overall aging of the population. Still, the tendency, of course, remains the same. So assuming constant gross output implies the assumption of growth of gross output per capita, i.e. growth of total factor productivity. Therefore, the assumptions described above imply that the growth of total factor productivity is compensated by the declining of the population, resulting in constant gross output for the future.

The baseline scenario serves as a basis for comparing the policy determined scenario results to a no-policy alternative. The absolute values of the baseline scenario do not have a high importance for the outcome of the analysis. Relevant are the deviations from the baseline triggered by policy changes, described in the following sections.

Also relevant to the design of the baseline is the question of what effect should later be analysed. Neither the growth nor the contraction of the population is the focus of the analysis, but the effect of changed education spending. And relative rather than absolute education spending change on a per head basis is analysed.

5.2 Education Spending → Gross Output

This section describes the results of the global analysis carried out with *SEGESD*, i.e. the analysis of the complete chain of effects implemented in *SEGESD*. Therefore the reaction of the sectoral gross output to a change in the spending for education is analysed (fig. 5.8 on page 115 shows the full chain of effects). It contains a description of the aggregated economy wide results, relative to the aggregated education spending (sec. 5.2.1). After that, the results disaggregated by 30 economic sectors are laid out (sec. 5.2.2). And finally, a set of analyses showing the strength of the reaction of each sector relative to each other are described using a statistical analysis of a large set of results calculating age group specific effects separately for each graduation point (also sec. 5.2.2).

A change of education spending over a timeframe of fifty years is analysed, starting in 1990 till 2040. For the full effect of this change to show, the simulation needs to be calculated at least for 96 years. The persons of age 18 in the year 1990 turn 66, i.e. they leave the oldest workforce group, after 48 years. This time span needs to be doubled, since it takes the same amount of time for the complete workforce to drop back to the baseline figures after the additional education spending is cut. So for simplicity the education spending is assumed to be on the increased level for 51 years, till 2040. Therefore, in 2088 the population structure dropped back to the baseline level, and with it the additional gross output back to zero, as can be seen in figure 5.4. This long time span is needed to be able to compare the benefits of a policy of increased education spending with its costs.

5.2.1 Economy wide aggregate

In this section the aggregated results for the whole economy are presented. The aggregated additional gross output is compared to the aggregated additional education spending for three different impact scenarios.

For this analysis, various percentage increases in the per student spending were analysed. Higher percentage increase of the per student spending leads to higher cumulated additional output. But the ratio between the cumulated additional gross output and the cumulated additional education spending remains approximately the same. This might mislead to the impression of a linear reaction of the total additional gross output to a homogenous percentage change in the per student education spending for all education levels. But looking at the numbers behind the graph, small deviations of the ratios show. They simply would not show on the scale of the given graph, which is why only one is included here. The reason for that is the design of *SEGESD*, as described in chapter 4. The non-linearities of the population model are linearly scaled up since all graduation probabilities are raised proportionally. And the non-linearities of the *EUKLEMS* framework are minor compared to the scale of the analysis given here. Therefore, the absolute values are shown for the case of a one percent increase as an example. The underlying non-linear relations become clear in the partial analyses following below.

Figure 5.4 on page 107 contains three graphs visualizing these results. The first graph shows the yearly additional education spending for medium and high level programs as well as the yearly total additional gross output for the moderate impact scenario. The second graph shows the cumulated additional education spending for medium and high level programs and the cumulated yearly total gross output also for the moderate impact scenario. The third graph shows the ratio between the cumulated additional total gross output and the cumulated additional education spending (sum of medium and high level spending) for the three impact scenarios weak, moderate and strong.

The 1% additional education spending ranges from 140 to 212 Mio € per year for high level programs and from 277 to 489 Mio € for medium level programs. The additional yearly economy wide gross output peaks at 433 Mio € in 2037. Additional education spending cumulates to 19350 Mio € for medium and to 9040 Mio € for high level programs (28390 together) after 2040. The cumulated additional gross output reaches 12110 Mio € at the same time and keeps rising till 21711 Mio € in the year 2088.

This leads to a ratio between the cumulated additional gross output and the cumulated additional education spending (sum of medium and high level spending) of 0.77 in 2088 and 0.39 in 2037 for the moderate impact scenario. The weak impact scenario reaches a ratio 0.15 and the strong impact scenario climbs up to 1.7.

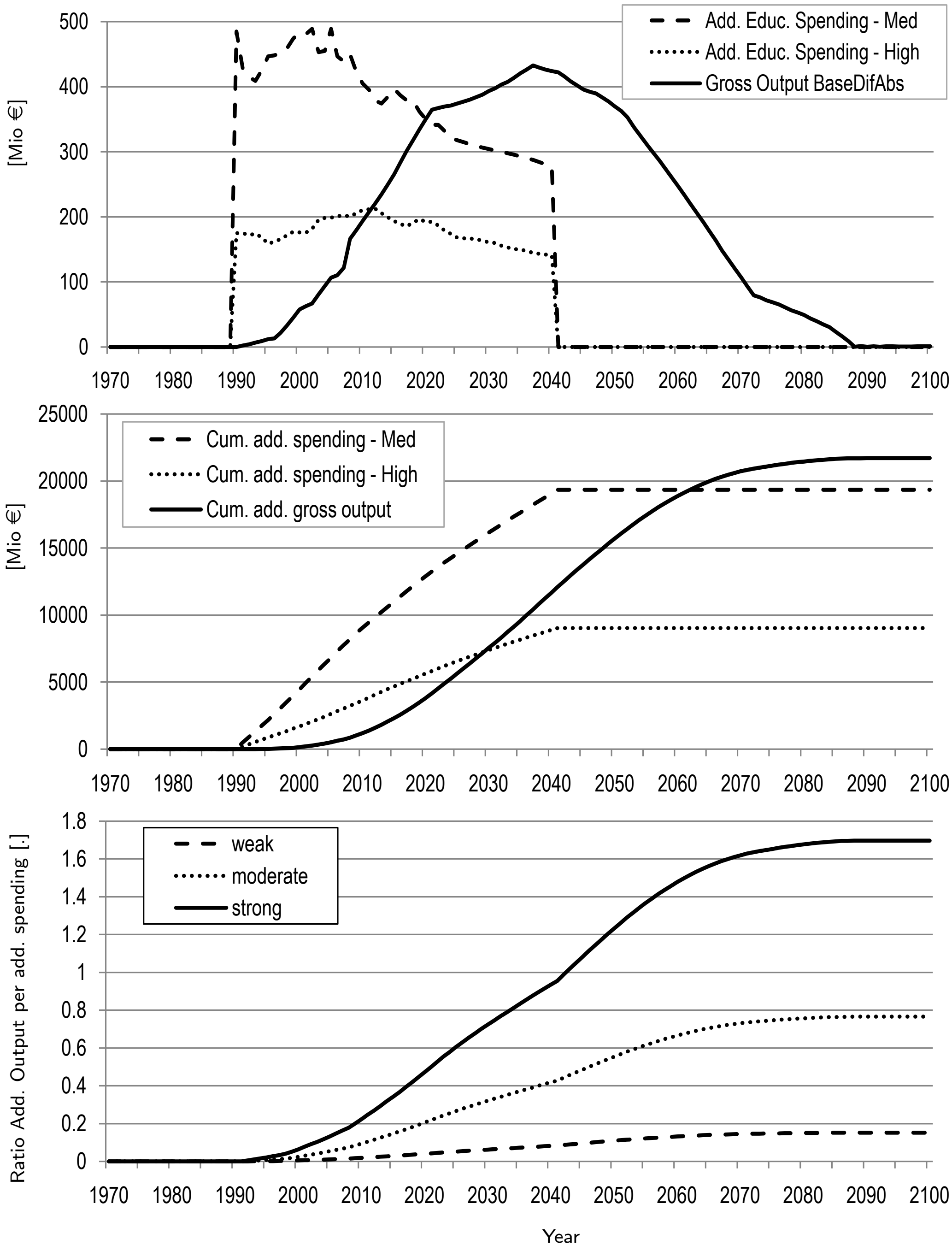
So far, no interest payments have been included in the analysis. Including interests in economic analyses of such long time frames imposes special problems not further discussed here. Still, in order to complete the picture, the above figures have been calculated also by discounting both education spending and additional gross output to the year 1990 with 3% interest (Rothengatter et al., 1984). This leads to a reduction of the previous ratios to 0.39 in 2088 and 0.28 in 2037 in the case of the moderate impact scenario. In the strong impact scenario, the value in 2088 drops to 0.87 and the one for 2037 to 0.63.

As described in section 4.5, the parameters for the correlation between education spending and graduation probability used in the *weak* impact scenario result from a very crude analysis while those used in the *moderate* and *strong* impact scenarios result as the boundaries of the parameter estimates based on a more detailed basis. Therefore, the results of the *medium* as well as the *strong* impact scenario form the boundaries of the more likely result range, while *weak* impact scenario results should be interpreted rather as a minimum possible outcome.

With that in mind, *SEGESD* indicates that additional education spending can lead to positive returns, if the values are not discounted. And the analysis does not include positive feedback loops (or second round effects) from an increased population of higher education, which is especially relevant in Germany due to the high correlation of the education level of the parents with the graduation probability of their children as reported by the OECD's education benchmark reports commonly known as PISA tests (Prenzel et al., 2008). Also, multiplier and accelerator effects from public investments into the education sector are not taken into account within *SEGESD*, since only one chain of effects is modelled. And the structure of the economic sectors is assumed to remain constant, thereby excluding effects of structural dynamics. Therefore, the results on additional gross output presented here as aggregate as well as sectoral disaggregated in the following section can be assumed to mark the lower boundary of possible effects.

Furthermore, the positive cultural effect of additional education can not be quantified at all in an analysis like the one undertaken here. Also, the long term importance of technological leadership for a country like Germany can not be quantified in the analysis within *SEGESD*. To what amount additional education exactly contributes to maintaining the standard of living that was achieved in Germany in the period after the second world war is impossible to quantify exactly. And an exact cost benefit ratio with this long temporal perspective would not be possible. The results presented here simply show a positive effect of additional education spending on the economic output from

Figure 5.4
Additional education spending and gross output: Yearly / Cummulated / Ratios



SEGESD results. Impact: moderate (1st & 2nd graph). 1% add. educ. spending. [Mio €]

the most aggregated perspective. From an empirical point of view there seem to be good reasons that the order of magnitudes of additional spending and additional gross output triggered thereby are the same.

5.2.2 Sectoral growth

The core ability of *SEGESD* is its ability to distinguish the reaction of the economy to an increase of education spending in 30 different sectors. These sectors have been classified into three categories of knowledge intensity - *low / low-high / high* - based on Legler and Frietsch (2006). Their classification was transferred to the sectors used in *SEGESD*, with *low-high* indicating sectors aggregating both originally low and highly knowledge intensive sectors. This is included in the list of economic sectors in appendix A.2. In the following I will present results from *SEGESD* indicating that the additional gross output of a sector is the higher the more knowledge intense that individual sector is.

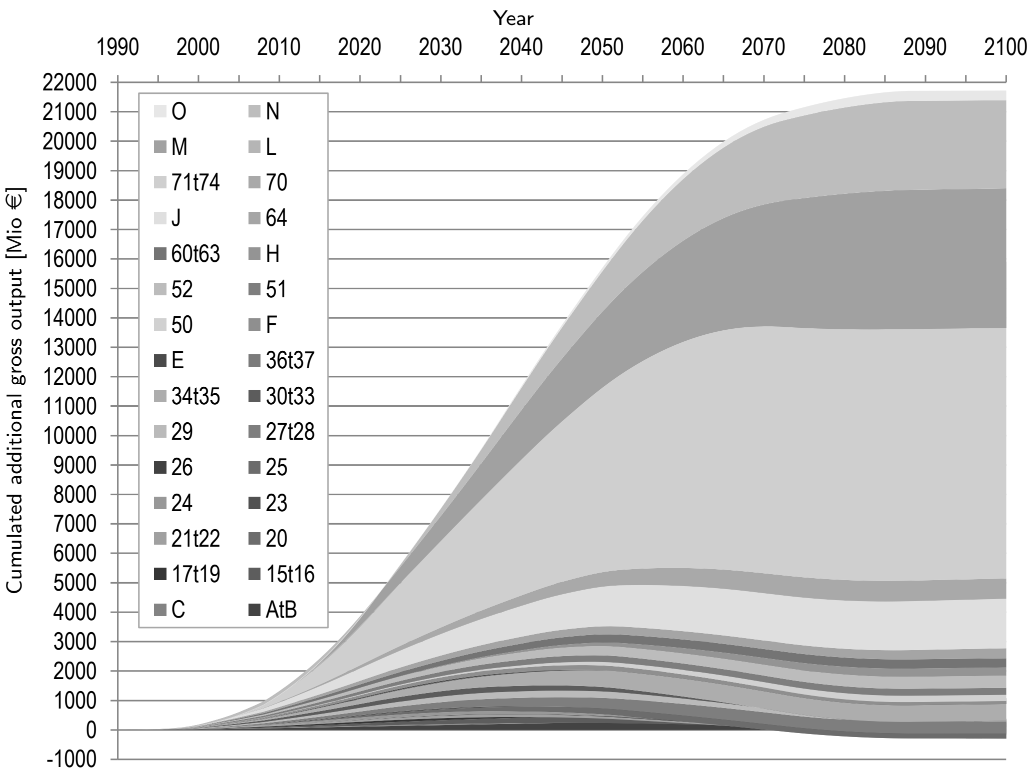
To start, the cumulated additional gross output distinguished by the 30 sectors used in *SEGESD* is plotted in figure 5.5 on the next page for the scenario under analysis. The largest gains can be observed in sector *Health & Social work (N), Education (M), Renting Equipment /Data Processing / IT / R&D / Business Services / Consulting (71t74)* and *Financial Intermediation (J)* (order as in graph - large areas from top to bottom), all knowledge intensive sectors. The absolute values are listed in table 5.2 on page 110. Negative values are possible due to a drop in the numbers of low qualified persons. The output of sectors with a positive correlation in these labour types is reduced, as explained in detail in the partial analysis in section 5.3.7.

Analysing the individual sectoral development shows that highly knowledge intensive sectors profit significantly more from an increase of highly educated persons in the economy than less knowledge intensive sectors. This is laid out in two differing perspectives, both based on the same idea of ordering the 30 sectors according to the additional gross output compared to the baseline scenario. First, the individual sectors are ordered according to the results in the moderate impact scenario of 1% increased education spending affecting all graduation points. Second, a statistical analysis of the results from a set of sensitivity analyses testing the impact of increased graduation probabilities at individual graduation points is undertaken.

The reaction differentiated by knowledge intensity of the sectors is based on the combined effect of the two elementary links *population structure* $\rightarrow$ *labour input* and *labour input* $\rightarrow$ *gross output*, described in section 5.3.8.

The first approach leads to the results shown in table 5.2 on page 110. It shows the 30 sectors sorted by the cumulated additional gross output. The

Figure 5.5
Cumulated additional gross output per sector [Mio €]



SEGESD results. Impact: moderate. 1% additional education spending. Sector order in graph as in legend, from top to bottom. Grey shades are NOT knowledge intensity.

knowledge intensity of each sector is coded in grey shades. Sectors of *low* knowledge intensity are marked dark grey, *low-high* are marked light grey and *highly* knowledge intensive sectors are marked white.

In this way the table visualizes the ability of the methodology implemented in *SEGESD* to let the growth of individual sector be relative to each other according to the expectations based on the knowledge intensity of each sector. Highly knowledge intensive sectors are better in transforming an increased availability of medium and highly educated workforce into additional gross output than those sectors aggregating low as well as highly knowledge intensive industries. And sectors of low knowledge intensity do worst on average. Also, the results reflect the statistical nature of the underlying links in the model. *SEGESD* is not capable of completely and clearly reproducing the splitting of the sectors into three groups according to their knowledge

Table 5.2
Sectors sorted by cumulated additional gross output [Mio €]

Sector		*R&D Intensity*	*Knowledge Intensity*	*2040 Value*
L	public admin and defence	low	low-high	-375
20	wood and of wood and cork	low	low-high	-6
36t37	manufacturing nec	low	low	10
26	other non-metallic mineral	low	low-high	12
C	mining and quarrying	low	low-high	14
23	coke, refined petroleum and nuclear fuel	low-high	low-high	21
17t19	textiles, textile, leather and footwear	low	low	28
E	electricity, gas and water supply	low	low-high	30
O	other community, social and personal services	low	low	58
H	hotels and restaurants	low	low	69
50	sale, maintenance and repair of motor vehicles, motorcycles	low	low	75
21t22	pulp, paper, printing and publishing	low	low-high	78
24	chemicals and chemical	med-high	high	90
F	construction	low	low-high	149
25	rubber and plastics	med	high	159
15t16	food, beverages and tobacco	low	low-high	185
30t33	electrical and optical equipment	high	high	189
51	wholesale trade and com. trade, except of motor vehicles, motorcyc.	low	low-high	194
AtB	agriculture, hunting, forestry and fishing	low	low	214
29	machinery, nec	med	high	219
60t63	transport and storage	low	low-high	231
64	post and telecommunications	low	low-high	233
52	retail trade, except of motor vehicles and motorcycles	low	low-high	250
27t28	basic metals and fabricated metal	low	low-high	296
70	real estate activities	low	high	358
34t35	transport equipment	med-high	high	431
N	health and social work	low	low-high	757
J	financial intermediation	low	high	1,047
M	education	low	high	1,679
71t74	renting of Mach.&Equip., data processing, IT consulting, R&D, business services, consulting	low	high	4,998

SEGESD results. Impact: moderate. 1% additional education spending.

intensity. But the results presented clearly show that the three groups are well separated by the methodology implemented, with overlaps, but still very adequately.

Looking at the results displayed in table 5.2 gives an indication of the problem inherent in this perspective. The values are for one year only (2040). When looking at later years, the details change, i.e. the order of individual sectors change slightly, but the overall picture does not change. Knowledge

Table 5.3
Sensitivity tests: graduation point and age specific - 16 cases

age	*graduation points*					
	Low → Med		*Med → High*			
	18F	*18M*	*22F*	*23M*	*31F*	*31M*
15-29	1990	1990	1990	1990	--	--
30-49	1978	1978	1982	1983	1990	1990
50-65	1970 (2002)	1970 (2002)	1970 (1997)	1970 (1998)	1971	1971

Overview of the 16 sensitivity tests for the analysis of impacts at each graduation point at each age group seperately. Years of start of change of graduation probability. Years in brackets indicate when effect starts (due to time lag).

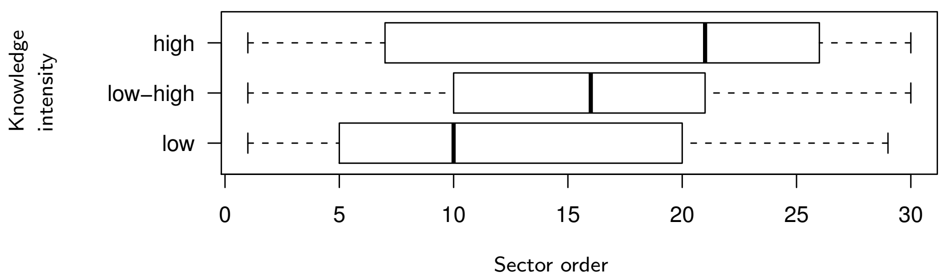
intensity correlates positively with the amount of additional gross output per sector.

In order to give an aggregated view on many differing results all pointing in a similar direction, a second approach was devised. A set of 16 differing sensitivity analyses were carried out, investigating the reaction of *SEGESD* to allowing only effects of the increased graduation probability at one graduation point and isolatedly evaluating the effect on only one of the three age groups distinguished in the model.

Six graduation points and three age groups would make 18 cases, but the youngest age group can not be effected by the oldest graduation points, reducing the total set of cases to 16. In each analysis the start year of the graduation probability change has to be set individually. The goal is to have the effect on the level of the according age group start after 1990, so that the *EUKLEMS* data can reflect the change. Table 5.3 is a schema of this set of sensitivity test carried out, indicating these start years. There, the years in brackets in the oldest age groups are the years when the effect starts. These years are after 1990 because the model can not be started before 1970. And due to the long time lags, the results have to be analysed in a later period. The time lags, of course, stem from the delay in the population development.

Figure 5.6 on the next page shows the result of these tests as histograms of the distribution of the order of the sectors in each of the test grouped by the knowledge intensity category of the sectors. This high level perspective produces two obvious results. On the one hand it confirms that on average a higher knowledge intensity is associated with a higher additional gross output per sector. The median of the order achieved by each of the three groups of

Figure 5.6
Reaction of sectors in sensitivity analyses - grouped by knowledge intensity



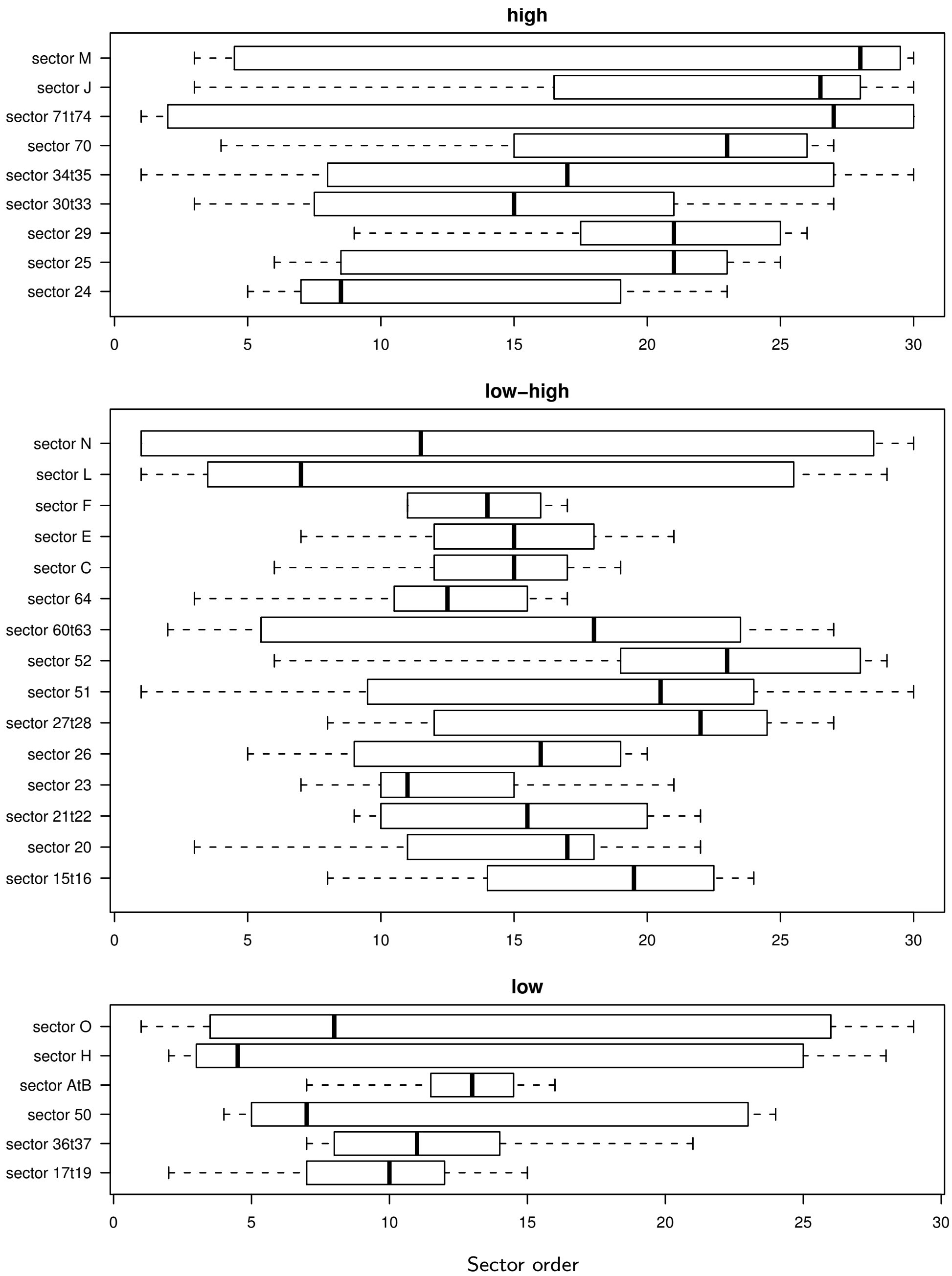
SEGESD results. Impact: moderate. 1% additional education spending.
Sectors ordered by additional gross output in the 16 sensitivity scenarios.
Histogram of sector order in sensitivity analyses grouped by knowledge intensity.

sectors in the 16 cases is higher, the higher the knowledge intensity. On the other hand, it also unveils the stochastic nature of *SEGESD*. Each knowledge intensity group covers almost the full spectrum of available order numbers. This means that all sectors of one group taken together increase their gross output either stronger than most others or less than most other, depending on the analysed case. But the positions of the medians of each group relative to each other indicate that *highly* knowledge intensive sectors gain more gross output than *low-high* knowledge intensive ones, and *low* knowledge intensive sectors gain least - on average over all 16 cases.

When looking at the individual sectors it becomes clear that some sectors remain rather stable in a certain interval of the available orders while others cover a broader range. This is shown in figure 5.7 on the facing page, showing the range of orders obtained by each sector in the 16 cases of the sensitivity analyses. This figure confirms the aggregated picture of figure 5.6. The median of the order number is the higher, the higher the knowledge intensity of the according sector is.

Taking all results presented of the relation of additional gross output among sectors together, I conclude that the methodology described in chapter 4, implemented in *SEGESD*, is able to produce plausible results for the growth of gross output on sectoral level driven by increased spending for education. More heterogeneous results emerge when analysing the results at a more disaggregated level, i.e. when looking at the results differentiated by sector and labour type. But this can be explained by the nature of a statistical simulation model and fits very well with the design of *SEGESD*. Particularly the statistical analysis of the relation between the education

Figure 5.7
Reaction of sectors in sensitivity analyses



SEGESD results. Impact: moderate. 1% additional education spending. Histogram of sector order in 16 sensitivity analyses. Sectors grouped by knowledge intensity.

structure of the population (the labour supply side) and the labour input on sectoral level (the labour demand side) described in section 4.3 induce heterogeneous results on the detailed sectoral level. That analysis showed a clear trend when looking at distributions of the results grouped by education level, as plotted in figure 4.3 on page 61, but individual labour types in individual sectors could well deviate from that aggregated picture. All together, higher knowledge intensity of a sector leads to higher gains in gross output due to increased education spending.

5.3 Partial Analyses

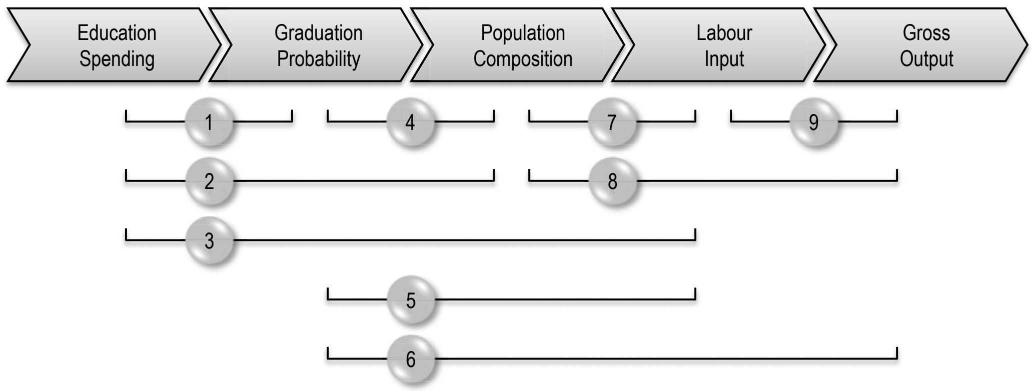
The previous section (5.2) took the *wide-angle* perspective, looking at the complete scope of *SEGESD*. The model is implemented as a chain of 4 elementary links (see figure 5.8): Education spending driving graduation probability (#1). Graduation probability determining population structure (#4). Population composition, i.e. labour supply driving sectoral labour input, i.e. labour demand (#7). Sectoral labour input influencing sectoral gross output (#9).

This section complements the previous perspective with *close-up* views analysing each elementary link and all possible combinations of two and three of these links analysed together. Figure 5.8 on the facing page gives a schematic overview of these combinations. They are described in the following subchapters. The numbers used in the schema correspond with the numbers of the subsections of this section 5.3. So, e.g. the number 1 in the schema indicates the link between the education spending and the graduation probability, described in detail in section 5.3.1. Number 5, described in section 5.3.5, refers to the link between graduation probability and labour input, the combination of the two elementary links 4 and 7. The 4 elementary links are described in the sections 5.3.1, 5.3.4, 5.3.7 and 5.3.9 following below.

The aim of these partial analyses is the demonstration of the model's reaction to a defined change in one part of the chain of effects on all subsequent links in that chain. In some cases, these are given as elasticities, e.g. in the case of the impact of the change of labour input on gross output (sec. 5.3.9). For other cases, rather absolute changes are described, depending on what indicator contains the relevant information.

Each partial analysis reveals particular insights, because the changes triggered by each elementary link are never homogenous over all dimensions of the variable. The effect of a change in the education spending on the various links are analysed in the first three sections (5.3.1 & 5.3.2 & 5.3.3). The

Figure 5.8
Schematic overview of the nine partial analyses



The nine partial analyses. Numbers correspond with subsections 5.3.1 to 5.3.9.

next three sections cover the effect of a change in the graduation probability (5.3.4 & 5.3.5 & 5.3.6). After that, two sections deal with the impact of a change in the population composition (5.3.7 & 5.3.8). Finally the effect of a change in the labour input on the gross output is analysed in section 5.3.9.

The results compiled here in the main part of the thesis have to be presented in an aggregated form, since the complete results computed by *SEGESD* are much too large to be comprehensively described here. For some cases, additional information is put into the appendix C.5. The subsections thereof are structured in the same way as the following subsections, in order to maintain a consistent numbering to better find the relevant detailed data.

5.3.1 Education Spending → Graduation Probability

SEGESD is based on the results of the econometric results compiled in section 4.5. This statistical analysis results in a linear correlation between per student education spending and the graduation probability. The resulting parameters (from table 4.7) are compiled in table 5.4 for a 1% increase as well as for a 10% increase. The linear model results in an absolute increase of the graduation probabilities for each graduation point's percentage values. These absolute values are added to the average values of the graduation probabilities. In the scenario calculations, this leads to parallel shifted graduation probabilities compared to the baseline values (given in table 4.2 as well as in graph 4.10).

Table 5.4
Graduation probabilities dependent on education spending increase

Increase in money spent per student			**1%**			**10%**		
	Grad	*Baseline*	*Impact Scenario*			*Impact Scenario*		
	Point	*Average*	*weak*	*moderate*	*strong*	*weak*	*moderate*	*strong*
Additional Graduation Probability	*18F*	*0*	*0.037*	*0.210*	*0.484*	*0.372*	*2.102*	*4.843*
[% points]	*18M*	*0*	*0.017*	*0.073*	*0.182*	*0.168*	*0.735*	*1.822*
	22F	*0*	*0.021*	*0.116*	*0.305*	*0.206*	*1.162*	*3.045*
	23M	*0*	*0.014*	*0.061*	*0.105*	*0.139*	*0.608*	*1.052*
	31F	*0*	*0.007*	*0.040*	*0.148*	*0.068*	*0.395*	*1.481*
	31M	*0*	*0.004*	*0.004*	*0.021*	*0.038*	*0.042*	*0.213*
Relative Increase of	*18F*	*0*	*0.04*	*0.25*	*0.57*	*0.44*	*2.48*	*5.72*
graduation probability	*18M*	*0*	*0.02*	*0.09*	*0.21*	*0.20*	*0.85*	*2.12*
(relative to baseline avg.)	*22F*	*0*	*0.08*	*0.45*	*1.19*	*0.80*	*4.53*	*11.88*
[%]	*23M*	*0*	*0.06*	*0.25*	*0.43*	*0.57*	*2.48*	*4.28*
	31F	*0*	*0.08*	*0.46*	*1.73*	*0.80*	*4.61*	*17.26*
	31M	*0*	*0.03*	*0.04*	*0.19*	*0.33*	*0.37*	*1.88*
Graduation Probabilities	*18F*	*84.68*	*84.72*	*84.89*	*85.16*	*85.05*	*86.78*	*89.52*
Scenario Values	*18M*	*86.08*	*86.10*	*86.15*	*86.26*	*86.25*	*86.81*	*87.90*
[%]	*22F*	*25.64*	*25.66*	*25.75*	*25.94*	*25.84*	*26.80*	*28.68*
	23M	*24.55*	*24.56*	*24.61*	*24.65*	*24.69*	*25.15*	*25.60*
	31F	*8.58*	*8.59*	*8.62*	*8.73*	*8.65*	*8.98*	*10.06*
	31M	*11.31*	*11.32*	*11.32*	*11.33*	*11.35*	*11.36*	*11.53*

SEGESD parameters. Results of linear regression from section 4.5.

Looking at the resulting values of the graduation probabilities, the absolute values in a scenario of 10% increase of the per student spending reach various percentage points of additional graduation probability. As the assumption of a linear relation between per head education spending and the graduation probabilities of the according students is quite crude and only justifiable with the lack of sufficient data for the estimation of a more complex, non-linear model, these numbers show that it appears as a better idea to carry out the following analyses rather for a one percent change than for a ten percent change of the spending. The reason for that can be seen in table 5.4. In the 10% spending increase scenario, the absolute values for the graduation probabilities deviate up to e.g. 17 percent from the baseline in the case of graduation point 31F in the strong impact scenario. This strong increase in graduation probabilities appears unrealistic, especially since the marginal utility of additional education spending per student is probably rather diminishing than linear (and almost certainly not increasing) with increasing spending. In order to stay in the region of a rather marginal reaction of the model, 1% spending increase was chosen for all subsequent analyses.

Two aspects emerge when looking at the detailed numbers. Females profit more from an increase in education spending. As discussed before, this can be at least partially explained by a relatively low start level for females during the observed time frame. The relative increase of the graduation probability is higher for the step from medium to high than for the one from low to medium qualification level. From this perspective, one could conclude that additional spending is better to be put at high level programs rather than at medium level programs. But as will be shown in below, it is crucial to also increase the basis of medium level qualified people when increasing the share of persons raising to high level degrees. Otherwise, losses of gross output result in the scenario simulations.

5.3.2 Education Spending → Population Composition

In this section the effect of a change in the education spending on the population composition is compiled. The underlying population cohort model distinguishes the population in yearly age cohorts as described in detail in section 4.4. Since the correlation between the population structure and the labour input was analysed based on the 18 labour types (see appendix A.1), the results in this section are also compiled using that aggregation level.

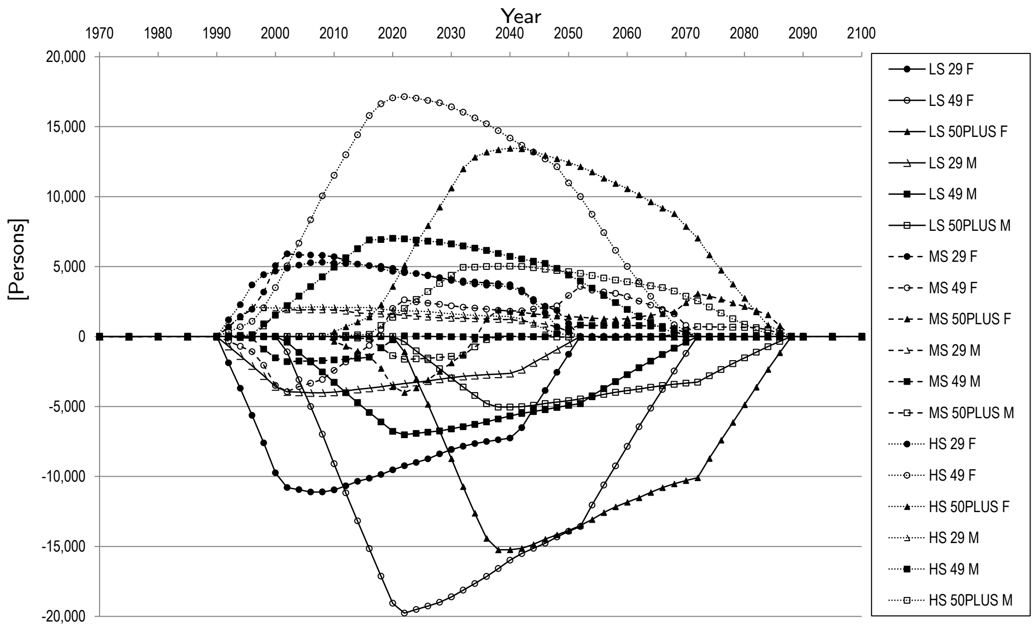
As argued in the previous section 5.3.1, an increase of 1% in the education spending per student is an appropriate order of magnitude for a relevant analysis. Figure 5.9 on the next page shows the effect on the population composition distinguished by all 18 labour types for the complete time scope of *SEGESD*. In appendix C.5.2 the information packed into one graph here is given in individual graphs for better readability, both as absolute values as in figure 5.9 and additionally as relative values.

The first important finding, intuitive but important to keep in mind throughout the following sections, is the reaction in the labour types of low qualification levels. As the graduation probabilities increase, more persons achieve a higher degree, i.e. shift from low to medium level, leading to an increase of the level of persons of medium labour types, but at the same time resulting in a drop of the level in the low qualified labour types. This has significant implications, discussed below in subsequent sections.

Next, the large time lags of education policies on the composition of the population in terms of qualification levels clearly emerges in figure 5.9. The peaks of the individual curves of the change of persons of labour types with equal sex and qualification at different age show the lag between the middle values of the according age groups. Those are 17.5 years between the first and the second age group and 18 years between the second and the third age group (the three age groups are *15 to 29, 30 to 49, 50 to 65*, compare appendix A.1).

Labour types of low qualification only loose persons compared to the

Figure 5.9
Population structure change [Persons] due to education spending increase



SEGESD results. Impact: moderate. 1% additional education spending per student. Difference of persons by labour type [Persons]. Split into individual graphs in appendix C.5.2.

baseline, while those of high qualification only gain persons. The medium qualified labour types show a more heterogeneous behaviour. The youngest age group only gains persons, since the persons additionally shifted to a high level degree because of the increased graduation probability at age 22 & 23 are fewer than those additionally achieving a medium level degree at age 18. For the medium and for the oldest age group, during the first couple of years after the increased spending a loss can be observed before the labour type groups also gain additional persons compared to the baseline. The reason for that is the effect of the graduation points at age 31. Additional persons obtain a high level degree and thereby are removed from the medium groups. And only after 13 years the additional persons of medium qualification level from the change in graduation probability at age 18 appear in the age group *30-49*, then compensating the shift from medium to high at 31, which explains the turning point around 2002. For the oldest age group, this lag lasts 31 (13+18) years, making the turning point 2021.

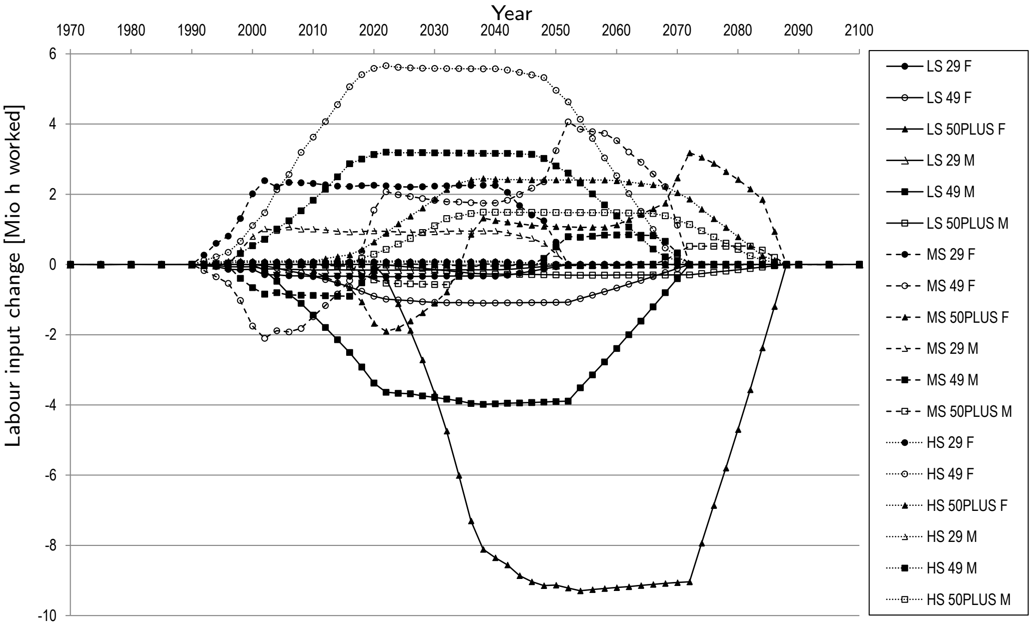
The progress of the individual curves of the change of persons in absolute numbers for each labour type reflect the behaviour of the curves of absolute levels for the according labour types along with the graduation probabilities in the baseline scenario. The relative differences to the baseline (see appendix C.5.2) in turn reflect the change in graduation probabilities as compiled in in table 5.4 on page 116. The relative differences reach their individual level after the time lags as described above and remain quite stable on that level until the end of the policy period plus the same time lags observed in the beginning. The sum of all changes is always zero, as the total population figures are unchanged and individual persons only shift between differing education levels.

5.3.3 Education Spending → Labour Input

In the following, the effect of a 1% increase of the education spending per student on the labour input measured in hours worked is described and explained. Figure 5.10 on the next page shows that effect distinguished by all 18 labour types. These numbers are aggregated figures, i.e. sums of individual figures for each one of the 30 sectors. In appendix C.5.3 the information packed into one graph here (fig. 5.10) is given in individual graphs. There, also the more disaggregated results for each labour type in each sector are compiled in a table.

The first finding is the behaviour of the individual time series. They reflect rather the relative than the absolute change in the population structure. This is contrary to what could be expected, since the correlations between labour input on sectoral level and the population structure are mathematically defined using the absolute changes, not the relative ones, as can be seen in formula 4.28 on page 64. The reason why the observed behaviour reflects the relative change is the definition of the baseline scenario (see section 5.1). The future economic development for the baseline is defined as remaining constant on the levels of the last reported year of the EUKLEMS data. Therefore, the relative change of the education levels in the population model is applied to constant (after the last EUKLEMS data year) population data for the correlation between labour input and population structure. And since the relative changes are quite stable (described in the previous section 5.3.2), also the input of labour remains on a stable level once the initial raise - until all age cohorts of one age group are effected by the changed graduation probabilities - is over. In summary, this means that the changes in the education structure triggered by a change in the per head education spending compared to a population baseline resulting from the continuation of present population trends - particularly declining total numbers - is transferred to an economic baseline which assumes a stable population and stable economic

Figure 5.10
Labour input change [Mio h] due to education spending increase



SEGESD results. Impact: moderate. 1% additional education spending per student. Difference of hours worked by labour type [Mio. h]. Split into individual graphs in appendix C.5.3.

output after the year 2005.

The time lags observable in the results are similar as those visible in the deviation of the population structure described in the previous section 5.3.2. Therefore they are not discussed again.

Looking at the absolute and relative changes in the hours worked for each individual labour type (better distinguishable in appendix C.5.3) reveals evidence for a demand for experienced labour of any qualification level, even low qualified persons. For example, the labour type *LS 50PLUS F* peaks at around -9 Mio hours, while *LS 29 M* looses only 0.15 Mio hours per year at the minimum. When looking at the relative change (also in the appendix C.5.3), it becomes obvious though that for low qualified persons, the losses in hours worked are stronger for older labour types, indicating a need for experienced workers, even though they are only lowly qualified formally. A similar picture emerges from the results for highly qualified persons. The gains in hours worked are the higher, the older the persons are. This also supports the finding that experience is a crucial factor for the economy. In the medium qualified labour types, similar findings emerge for the case of the female labour types. Male labour types of medium qualification level are the only group for which the reactions are strongest in the youngest labour type. But also in there, the oldest labour type shows a stronger reaction than the middle aged labour type.

The results in disaggregated form, split into sectors and ISCED groups, are also compiled in the appendix C.5.3, both in tabular form and as 30 graphs, one for each sector. The change of the sectoral labour input visible there reflects the outcome for the sectoral change of gross output compiled e.g. in figure 5.5 and in table 5.2.

For example sector *71t74*, gaining most in terms of cumulated gross output, shows the highest gains in additional labour input. Additional high level hours worked peak at 5 Mio h and medium level around 2.5 Mio h between 2040 and 2060, i.e. when all changed graduation probabilities are fully effective and before the figures start dropping back to the baseline since the policy is only effective till 2040.

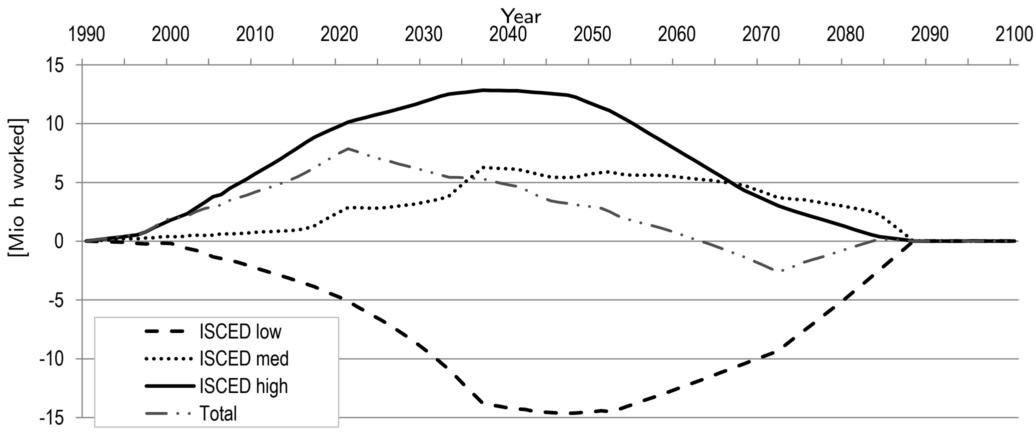
On the other hand, those sectors performing worst in the direct sectoral comparison (*L* and *20*) show strong reductions in the labour input in the low qualified labour types, which can by far not be compensated by the little gains in medium and highly qualified labour. Sector *L* looses most, peaking at almost -5 Mio hours less. The gains for both medium and high qualified labour input, both climbing at maximum to around 300 Tsd hours additional labour input can not compensate for that.

The remaining sectors can be seen as located somewhere between these two extremes. They all vary in the change of the composition of the qualification level of the labour input, explaining the differing gains in terms of monetary gross output.

Additionally, the aggregation of all labour input change by ISCED groups yields important insights. Figure 5.11 on the next page shows these aggregates. The raise of the total hours worked indicate a net gain in employment. The gains are in medium as well as in high qualified jobs, while low qualified labour drops to lower levels. Highly qualified labour gains more in terms of absolute hours worked than medium qualified labour. Especially the medium level curve clearly visualizes the various points as the changes in the different age groups and the impact of the different graduation points come into effect.

These findings stress the importance of the extension of education efforts. They show, on a purely statistical ground, that improving the qualification level of the German population forms an important measure for fighting unemployment. A common insight, underlined by the statistically grounded simulation model *SEGESD*.

Figure 5.11
Labour input change [Mio h] due to education spending increase - ISCED agg.



SEGESD results. Impact: moderate. 1% additional education spending per student. Difference of hours worked by ISCED group [Mio. h].

5.3.4 Graduation Probability → Population

This section focuses on the effect of a change in the graduation probabilities on the population structure. This forms the second elementary link of *SEGESD*. Contrary to section 5.3.2 above, here the effect of a 1% point increase of the graduation probability for each graduation point separately is analysed. This enables the demonstration of the sensitivity of this elementary link in contrary to the higher aggregated perspective in section 5.3.2, where the effect of a change in the education spending was analysed, leading to different changes of the graduation probabilities for each graduation point. Also, in that perspective, the effects of each graduation point were all analysed together, thus not showing individually.

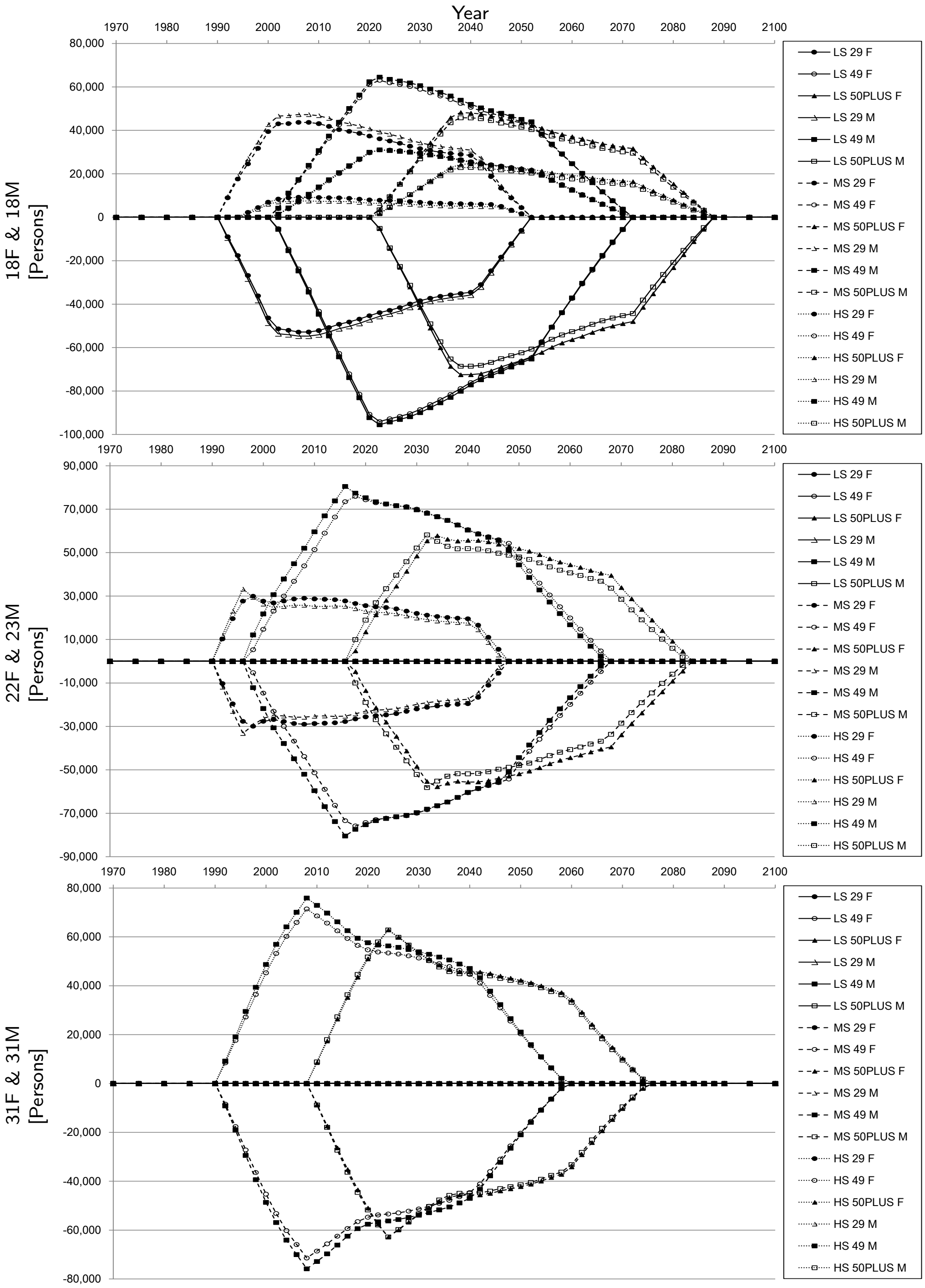
Figure 5.12 on the facing page shows the change in the population structure (in absolute numbers) distinguished by labour type as a reaction to a 1% point increase of the graduation probability. The reaction is compiled separately for each graduation point pair at similar ages, i.e. 18F+18M, 22F+23M and 31F+31M. This leads to three graphs. These results are split to more graphs in appendix C.5.4.

This elementary analysis reveals particularly well the details of the temporal lags. In the graphs here in the main part, and especially clear in the graphs in the appendix (C.5.4), the lags are very well depicted.

The first graph (in fig. 5.12) visualizes the impact of an increase of the

Figure 5.12

Population structure change [Persons] due to graduation probability increase



SEGESD results. Reaction to 1% point increase of graduation probability distinguished by labour type. One plot per two graduation points: 18F+18M / 22F+23M / 31F+31M.

graduation probability at the graduation points *18F & 18M*. It shows the lag of 11 years till the additional graduates become visible in the age group *30 to 49* and the 31 years until it effects the group *50 to 65*. An additional effect of the education system, reproduced by *SEGESD*, can be perceived very well in this case. The *cumulative effect of education*. An increase of the graduation probability at age 18, i.e. at the point of achieving a medium level degree, leads to a lagged increase in the persons of high level degrees as the according age cohorts pass the graduation points at age 22/23 and at age 31. The reason for that is that the base of persons having a medium level degree is increased, and since the graduation probabilities reflect shares of persons achieving a degree of a higher level this leads to more graduates with high level degrees later on.

In the second graph (in fig. 5.12) the impact of an increase of the graduation probability at the graduation points *22F & 23M* can be well seen. Females graduate at age 22, which becomes effective at age 23. For seven years, till age 29, the increased graduate numbers are visible only in the age group *15 to 29*. In the eighth year, the age group *30 to 49* starts getting effected. And twenty years later, the change becomes visible also in the oldest age group *50 to 65*. For males, the same picture emerges, with the effect starting one year later at age 24 due to the graduation at age 23.

And the third graph (in fig. 5.12) visualizes the impact of an increase of the graduation probability at the graduation points *31F & 31M*. The age group *15 to 29* is not effected, of course. And the lag of 18 years till the change effects the age group *50 to 65* can be seen.

The symmetry in the graphs, especially in the second and third graph, reflects the shift from medium to high level degrees. Every person obtaining a high level degree is removed from the group of medium level persons. This is a trivial finding, but important to show the validity of the population model within *SEGESD*.

Even though the different curves of the same sex and education level represent the same age cohorts at different points in time, it is obvious that the absolute levels in the changes are significantly different. The reason for that is the difference in the amount of yearly age cohorts aggregated in the three age groups used for the labour types aggregations. Also, the age at which the graduation probability change is analysed, i.e. the graduation point under analysis, determines the absolute level of the change in that age group. E.g. for the case of the graduation point 22F, the according age group is *15 to 29*. This means that the absolute change in persons of a given sex and education level is the aggregate of 7 years (23 till 29). In the middle age group, these are 20 years (30 to 49), and in the oldest group 16 years (50 to 65).

On the one hand this explains the difference in the absolute level reached by the youngest age group in the differing analyses. On the other hand it explains the difference in the time needed for the individual curves to reach their maximums. In the start phase, the inclination is determined by the yearly addition of an extra age cohort to the aggregate. Once all yearly age cohorts of an age group are effected, the curve reflects the development of the absolute level of the according labour type in the population baseline.

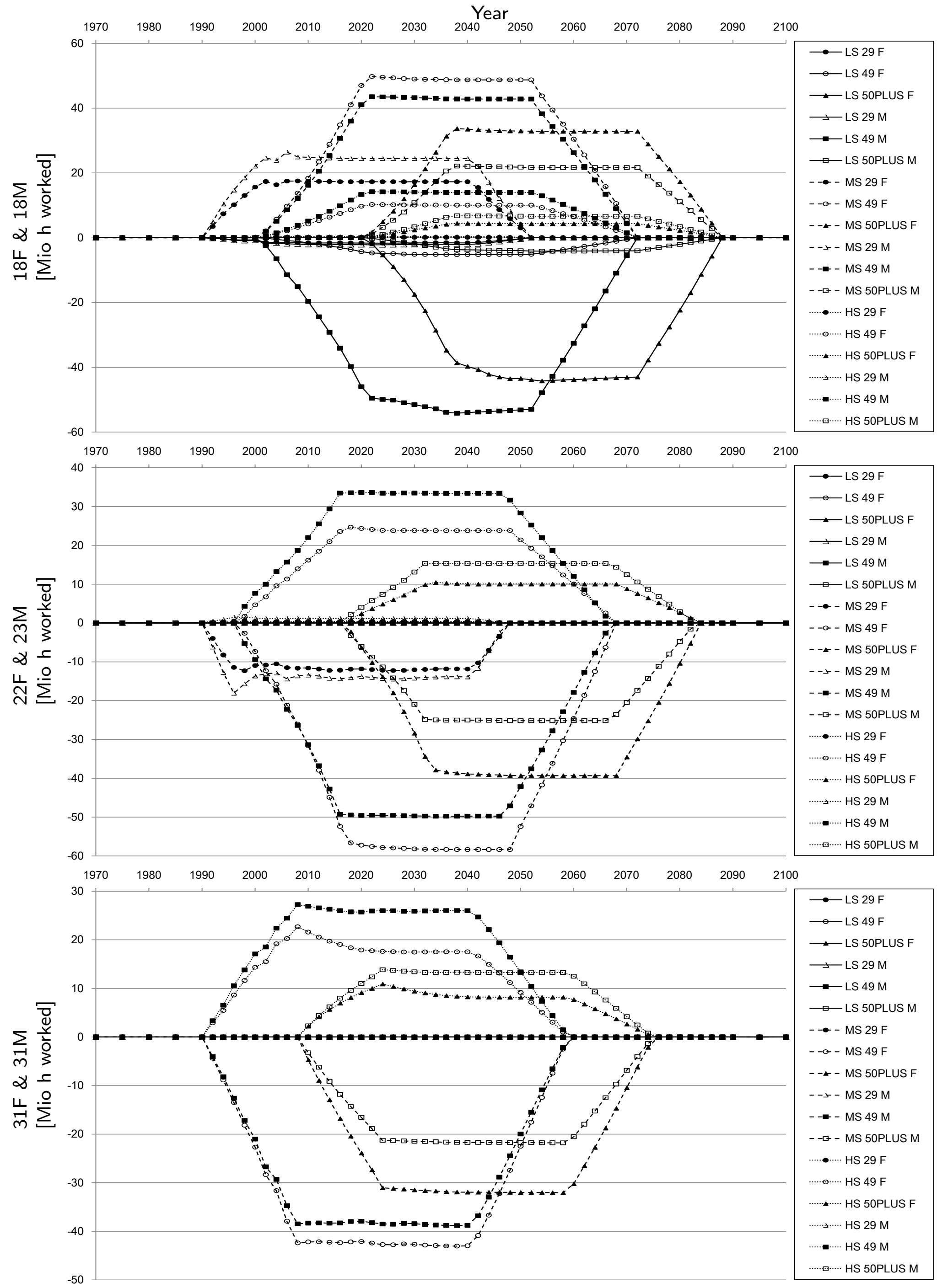
5.3.5 Graduation Probability → Labour Input

Here the details of the effect of a change in the graduation probability on the labour input is laid out. This analysis contains the combined effect of the link between the graduation probability and the population composition (sec. 5.3.4) as well as the effect of the population composition on the labour input (sec. 5.3.7). Figure 5.13 on the next page shows these changes, compiled separately for each graduation point pair at similar ages, i.e. 18F+18M, 22F+23M and 31F+31M. Similarly to the previous analysis, this results in three graphs. These results are split into more graphs in appendix C.5.5.

The observable time lags are equal to those described for the link between graduation probability and the population composition in sec. 5.3.4. This follows from the linear regression model of the link between the change in population composition and the labour input, analysed in more detail in section 5.3.7

The results stress the importance of the increase of the medium level education base. Comparing the first graph to the second and third one reveals the strong loss in low as well as medium level labour input if only the high level graduates at the graduation points 22F / 23M / 31F / 31M are increased without appropriately increasing the medium level graduates as well. A significant lack of labour input would be the result.

Figure 5.13
Labour Input change [Mio h] due to graduation probability increase



SEGESD results. Reaction to 1% point increase of graduation probability distinguished by labour type. One plot per two graduation points: 18F+18M / 22F+23M / 31F+31M.

5.3.6 Graduation Probability → Gross Output

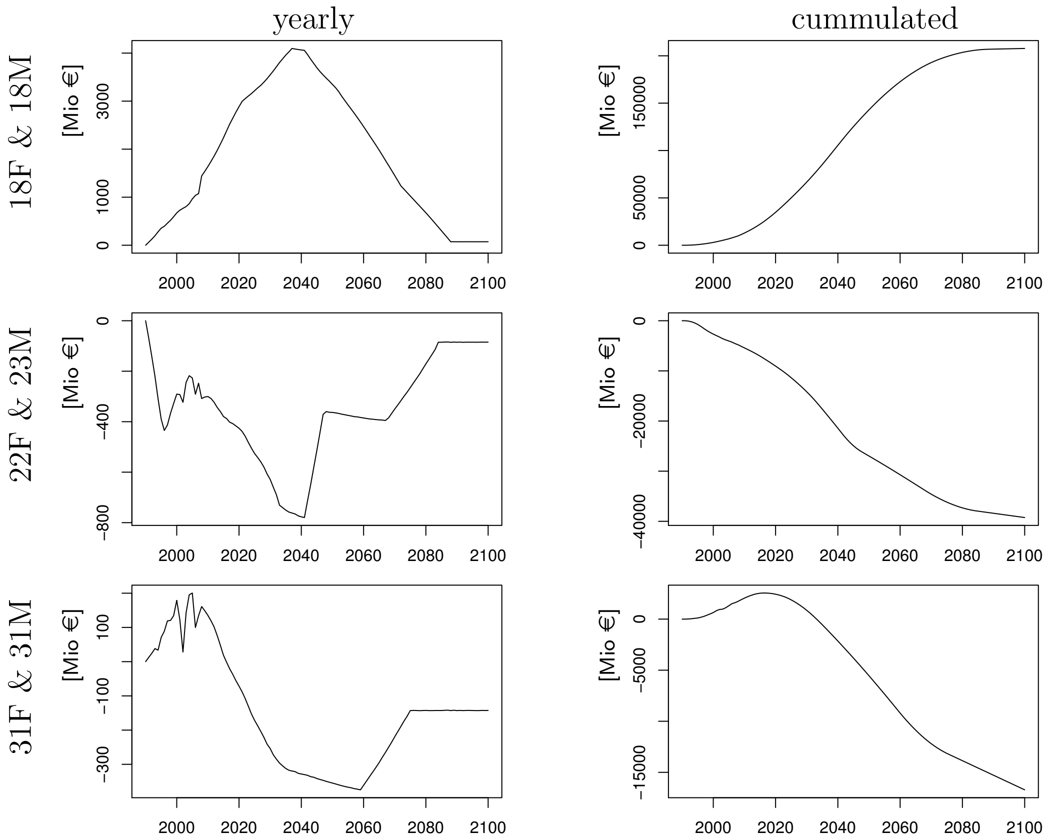
Figure 5.14 on the following page shows the change of gross output (in Mio €) compared to the baseline resulting from a 1% point increase of the graduation probability. The reaction is compiled separately for each graduation point pair at similar ages, i.e. 18F+18M, 22F+23M and 31F+31M. Both the yearly values (left column) as well as the cumulated values (right column) are plotted. This results in six graphs.

The results plotted here are aggregated values of all sectors and all labour type. They represent the combined effects of all labour type specific results laid out in the previous section (5.3.5). The economic results stress the effect of the reduction of labour input of medium and low education level described in the previous section. Analysing the three graduation point pairs isolated, a positive economic impact only results from the increase of the graduates at age 18, since this results in an implicit increase of graduates at 22F / 23M as well as 31F / 31M, as described before. The isolated increase of the graduation probability at 22F / 23M or at 31M / 31F would lead to a loss of cumulated gross output relative to the baseline.

The important result of this perspective is the order of magnitude of the different effects. The economic gains from the change at age 18 peak at around 4 Bil € yearly in 2040 and cumulate to approximately 200 Bio € over the total time frame. But the losses of a change at 22F / 23M peak only at around -800 Mio € and add up to around -40 Bio €. And the loss of gross output triggered by a change at age 31 is even less severe. After a positive development the curve drops to about -350 Mio € in 2060 and the losses cumulate to around -16 Bio €. The slightly positive development in the beginning and the lagged minimum 20 years after the end of the graduation probability change stress the dominance of older labour types in this development.

Looking at these results, one has to keep in mind that they are sensitivity analysis, designed to demonstrate the reaction of *SEGESD* on a partial link. In the analysis of the total chain of effects in section 5.2 the changes of the graduation probabilities are differing for each graduation point. There, the per student spending is increased on a percentage basis for *all* graduation points. In that combined analysis, the reduction in medium level labour input due to the increase of graduates at high level is more than compensated by additional graduates at medium level due to the increase of the graduation probability at age 18.

Figure 5.14
Gross Output [Mio €] change due to graduation probability increase



SEGESD results. Reaction to 1% point increase of graduation probability. Two plots (yearly on the left, cumulated on the rigth) per pair of graduation points: 18F+18M / 22F+23M / 31F+31M, each in one line.

5.3.7 Population Composition → Labour Input

Within this section, the impact on the labour input of a change in the population composition is analysed. This forms the third elementary link in *SEGESD* (fig. 5.8). For consistency with the results in previous sections, the labour types of low qualification level are analysed using a reduction by 1000 persons, while for those of medium and high level an increase by 1000 persons is analysed. This approach was chosen due to the fact that in simulated scenarios the amount of low qualified persons can only be reduced, never increase, as explained before. Due to the linearity of the correlation between population structure and labour input this only effects the sign of the result number, not the absolute value.

Table 5.5 on the next page shows the reaction of the labour input to a change of 1000 persons in the population separately for each labour type. On the one hand, all 18 labour types are distinguished. On the other hand the effects are given as aggregates of low, medium and high qualified persons. The results are constant for the complete period of the assumed change, i.e. for 1990-2040, because the parameters of the underlying linear regression model are assumed to be constant over the complete timeframe of *SEGESD*. Therefore, only one figure for this time frame has to be reported. Before and after that timeframe, the change in labour input is zero as the change in the population is assumed to be zero.

The aggregation by ISCED group yields an important result. The strongest effect on the labour input, measured in hours worked, comes from the medium qualified persons, followed by the highly qualified ones. Labour input from low qualified persons reacts least to the change in the labour force, but in a similar order of magnitude as medium qualified persons. But the effect for medium qualified labour is almost three times as strong as for highly qualified input. This relation forms the basis for the finding in other partial analyses that it is of crucial importance to maintain and to increase the medium qualified labour force and to make sure that those persons additionally obtaining a high level degree are at least substituted by additional graduates at medium level.

Also, this aggregation level yields the important finding that the additional medium and highly qualified labour more than substitutes the loss in low qualified labour. This perspective therefore provides significant indication that additional education clearly leads to higher employment figures, as described in the broader analysis of the impact of a change of education spending on labour input in section 5.3.3 and visualized in figure 5.11 on page 122.

Looking at the effect of age in the more disaggregated perspective on labour type level also reveals important insights. In the labour types of medium qualification level a decreasing reaction with increasing age can be observed. This is an indication for the decreasing demand of older persons of this qualification level, reflecting the increasing difficulty of older persons to find a job appropriate to their training. For the highly qualified labour types, a slightly different picture emerges. In the youngest age group the reaction to an increased supply of labour is extremely low. This can be explained with the aggregation of many age cohorts too young for the according degrees together with very few age cohorts able to achieve these degrees, which leads to a relatively small amount of persons of high volatility. The relation between the medium aged and the oldest age group appears similar to the one in the medium qualified persons, and probably reflects similar difficulties. But the

Table 5.5
Labour Input change [Tsd h] due to population structure change - by labour type

[Tsd Hours]	*per labour type*																		*per ISCED group*		
	LS 29 M	*LS 29 F*	*LS 49 M*	*LS 49 F*	*LS 50PLUS M*	*LS 50PLUS F*	*MS 29 M*	*MS 29 F*	*MS 49 M*	*MS 49 F*	*MS 50PLUS M*	*MS 50PLUS F*	*HS 29 M*	*HS 29 F*	*HS 49 M*	*HS 49 F*	*HS 50PLUS M*	*HS 50PLUS F*	*ISCED low*	*ISCED med*	*ISCED high*
1970-1989	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
1990-2040	-29	-25	-492	-41	-28	-101	659	465	509	560	222	333	51	15	349	320	144	183	-715	2,748	1,061
2041-2100	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Reaction to a change of 1000 persons in the population distinguished by labour types.
- 1000 in low, + 1000 in medium and high qualified labour types.

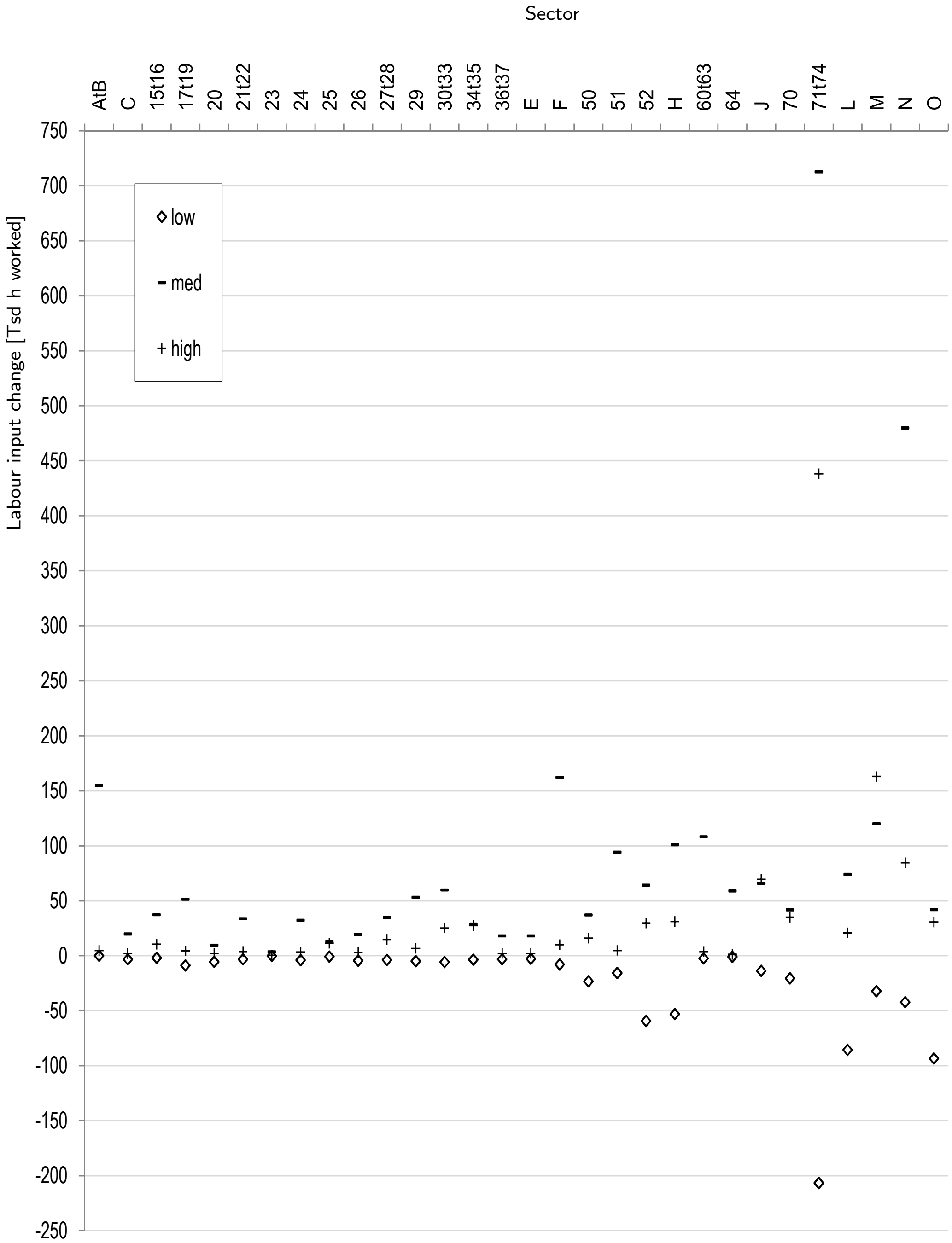
strong difference between the medium and the youngest age group can also be interpreted as an indication for the need of experienced highly qualified persons rather than extremely young highly qualified ones, which is often an issue in the public debate on unemployment. In the low qualified subset, the results are less clear, but aggregating both sexes the same tendency shows up. There is less demand for older persons than for those of medium age. The weakest reaction is found in the youngest group. This can be interpreted as an quantification of the difficulties of young, low qualified persons to find a job.

Looking at sectoral disaggregated results brings forth further insights. The changes of labour input for each ISCED group in every sector of *SEGESD* is compiled in table 5.6 on page 132 as well as in figure 5.15 on the facing page. The order of the strength of impact in the three different ISCED groups discussed before on aggregated level (medium > high > low) also becomes apparent for each individual sector, with two exceptions. Sector J (Financial Intermediation) as well as sector M (Education) are the only ones in which the high ISCED level labour input reacts stronger than the medium level one. And for sector J the difference is not particularly strongly pronounced. Only sector M comes up with a 35% higher labour input increase for highly educated persons compared to medium level ones. These reactions can well be explained with the particularly high share of academic staff in the education field and to a smaller extend in the financial intermediation sector.

Furthermore, the sectoral results reflect the differences in additional sectoral output described in section 5.2.2 before, visualized in figure 5.5 on page 109. The sectors gaining most (*N, M, 71t74, J*)[2] account for relatively high gains in medium and high qualified labour combined with relatively low losses in the low qualified labour input. Contrary to that, those sectors in

[2]compare sector list in appendix A.4 on page 163 (foldout page).

Figure 5.15
Labour input change [Tsd h] due to population structure change (sectoral)



Reaction to a change of 1000 persons in the population distinguished by sector and ISCED group. - 1000 in low, + 1000 in medium and high qualified labour types.

Table 5.6
Labour input change [Tsd h] due to population structure change - sectoral

	AtB	C	15t16	17t19	20	21t22	23	24	25	26	27t28	29	30t33	34t35	36t37
low	-0.1	-3.3	-2.0	-8.9	-5.6	-3.3	-0.3	-4.0	-0.9	-4.5	-3.9	-4.9	-5.8	-3.6	-3.2
med	154.7	19.8	37.3	51.3	9.6	33.7	3.5	32.1	13.1	19.3	34.8	53.0	59.8	28.7	18.1
high	4.7	1.9	10.3	4.4	2.0	3.8	0.3	3.4	11.4	2.8	14.7	6.6	25.2	27.4	2.3
	E	F	50	51	52	H	60t63	64	J	70	71t74	L	M	N	O
low	-2.8	-8.0	-23.3	-15.8	-59.4	-53.1	-2.5	-1.1	-13.8	-20.6	-206.8	-85.7	-32.3	-42.2	-93.5
med	18.0	162.0	37.1	94.1	64.2	100.9	108.2	59.0	65.9	41.9	712.7	74.0	120.1	479.8	42.0
high	2.1	10.0	15.9	4.8	29.7	31.1	3.8	1.2	69.5	35.0	438.1	20.7	162.9	84.6	30.6

Reaction to a change of 1000 persons in the population distinguished by sector and ISCED group. - 1000 in low, + 1000 in medium and high qualified labour types.

which output increases least (e.g. *36t37, 26*), the additional labour input triggered by the increase labour supply is significantly lower. And those sectors in which output is even lower than in the baseline scenario (i.e. *L* and *20*), the losses in the low qualified labour input can not be compensated by the gains in medium and high level input.

5.3.8 Population Composition → Gross Output

This section analyses the impact on the gross output of a change of the population structure individually for each labour type. The change was calculated as reaction to a *one-year* change of 1000 persons in each labour type in the population preceding the reported year. The results are aggregated by ISCED group, for 4 years within the timeframe determined by the EU-KLEMS data. Table 5.7 on the next page shows these results as absolute numbers. And table C.7 on page 265 (in the appendix) contains the same results as relative changes.

Looking at the absolute as well as at the relative numbers, it becomes clear that neither way the results remain stable over time. The reasons for that are the changing absolute levels of sector and labour type specific labour input as well as the changes in the composition of the input factors determining gross output,i.e. labour services, capital services and intermediate inputs as explained in section 4.2.

The general picture of the order of the absolute value of the reaction to the population change found in the previous section 5.3.7 also emerges from this perspective. Additional labour supply of medium education level induces more additional gross output than high level input. And low level input induces least. This can be summarized in short as *medium* > *high* > *low*.

Table 5.7
Sectoral output change [Tsd €] due to population structure change

[Tsd €]	*1992*			*1995*			*2000*			*2005*		
	low	*med*	*high*	*low*	*med*	*high*	*low*	*med*	*high*	*low*	*med*	*high*
AtB	0	1,533	56	0	1,707	70	0	1,814	76	0	1,455	61
C	-47	402	60	-57	439	66	-57	452	70	-54	394	59
15t16	-34	428	265	-8	461	313	-14	492	347	-26	465	336
17t19	-94	617	86	-102	723	113	-110	795	126	-110	739	105
20	-75	152	49	-74	152	53	-63	139	45	-66	136	47
21t22	-43	488	86	-39	602	109	-36	578	101	-32	497	97
23	-2	64	9	-4	78	8	-7	155	22	-6	132	16
24	-69	762	120	-78	898	148	-87	961	152	-103	878	142
25	-13	295	420	-8	305	457	-11	296	426	-13	274	436
26	-60	325	73	-63	344	78	-65	365	83	-65	332	77
27t28	-51	694	531	-63	781	641	-72	781	607	-26	684	607
29	-69	1,045	188	-94	1,203	234	-72	1,315	260	-77	1,213	284
30t33	-86	1,130	668	-86	1,195	734	-116	1,359	867	-90	1,265	839
34t35	-69	839	976	-47	906	1,141	-72	1,026	1,402	-77	1,007	1,575
36t37	-34	278	47	-39	301	53	-43	318	61	-39	255	52
E	-43	407	64	-47	414	70	-51	434	80	-52	432	77
F	-103	2,535	223	-109	2,500	234	-116	2,356	202	-90	2,220	194
50	-377	711	527	-410	754	590	-426	759	578	-465	720	620
51	-308	1,541	154	-313	1,656	188	-361	1,749	202	-387	1,678	219
52	-1,028	908	1,028	-1,055	945	1,117	-1,142	983	1,142	-1,162	839	1,149
H	-736	1,661	891	-742	1,680	938	-716	1,554	857	-703	1,358	833
60t63	-43	1,422	77	-47	1,516	94	-29	1,634	116	-52	1,639	77
64	-9	1,130	34	-12	1,258	43	-14	1,431	36	-6	1,246	32
J	-197	1,422	2,269	-203	1,500	2,406	-188	1,475	2,429	-258	1,471	2,698
70	-411	1,028	1,319	-406	1,031	1,375	-347	954	1,359	-465	826	1,291
71t74	-3,528	15,535	14,935	-3,469	15,672	15,641	-3,816	16,422	17,405	-4,440	15,385	17,683
L	-976	1,216	599	-984	1,281	672	-1,026	1,359	651	-1,071	1,304	658
M	-668	2,929	5,609	-594	2,977	5,977	-600	3,079	6,296	-542	2,723	5,640
N	-617	9,172	2,475	-609	9,188	2,563	-578	9,151	2,544	-581	8,390	2,530
O	-1,644	694	839	-1,547	727	930	-1,532	838	1,070	-1,304	749	994
Total	-11,433	51,364	34,677	-11,307	53,193	37,055	-11,770	55,025	39,612	-12,363	50,706	39,426
Ratios	-4.5	1.5	-3.0	-4.7	1.4	-3.3	-4.7	1.4	-3.4	-4.1	1.3	-3.2

Reaction to a change of 1000 persons in the population distinguished by sector and ISCED group. - 1000 in low, + 1000 in medium and high qualified labour types.

But, additionally to the exception identified previously, more sectors show a deviation of this general pattern in this analysis. The difference between these two levels of analysis reflect the sectoral difference of the additional gross output gained from additional labour supply distinguished by labour type. These are described specifically in the following section 5.3.9.

5.3.9 Labour Input → Gross Output

This last partial analysis covers the fourth and final elementary link within *SEGESD* as sketched in figure 5.8. It covers the relation between additional labour input and additional gross output. The results are compiled as sensitivities, i.e. the relative changes of gross output due to a relative change of the labour input. The values are the results of a single *one-year* increase within the reported year. As in previous sections, the results of the low qualified labour types show the reaction to a reduction of the low qualified labour input by 1% while the medium and highly qualified labour types show the reaction to a 1% increase.

Within *SEGESD*, the underlying results were compiled for 18 labour types for each sector. The data covers the timeframe 1992 to 2005, the timeframe provided by the EUKLEMS data. After 2005, these values remain stable as the last reported year from the EUKLEMS database was used for the remaining time of *SEGESD* as explained before.

Table 5.8 on the next page shows these results. The changes are listed separately for each one of the 30 sectors and for each ISCED group for four distinct years. The sectors are grouped by their knowledge intensity and the average values per knowledge intensity group are also included. The same values without grouping and sorting are compiled in table C.8 on page 266. Additionally, the absolute gross output figures are put in table C.9 on page 267.

As explained in the previous section 5.3.8, the results differ through time due to changing input compositions reported by the EUKLEMS database. Looking at the differences between sectors of different knowledge intensity (well perceivable in the averages of each ISCED group listed within table 5.8), important findings emerge, relevant for the explanations on the other partial analyses within this section (5.3). The sensitivity of the gross output to the labour input of low and medium qualified persons decreases with an increase in knowledge intensity of the according sectors. And at the same time, the sensitivity of gross output to labour input of high qualification level increases with more knowledge intensity of the according sector.

The sensitivities are valuable to understand the relative performance of the individual labour types within the different sectors. They reveal clear evidence that highly qualified labour input is the more important the higher the knowledge intensity of the according sector is. At the same time, they show that medium qualified labour is extremely important in all sectors, but the more, the lower the knowledge intensity is. And they indicate that also low qualified labour input is a necessary component for economic output, also less important for highly knowledge intensive sectors than for low knowledge intensive ones, and clearly less important than medium level input.

Table 5.8
Sectoral output change [‰] due to labour input change - by ISCED group

[‰]	1992			1995			2000			2005			Knowledge
	low	*med*	*high*	*low*	*med*	*high*	*low*	*med*	*high*	*low*	*med*	*high*	*Intensity*
AtB	-1.02	4.11	0.44	-1.06	3.80	0.45	-1.30	2.99	0.35	-1.35	2.49	0.33	low
17t19	-0.77	1.72	0.11	-0.75	1.85	0.13	-0.68	1.75	0.15	-0.64	1.60	0.15	low
36t37	-0.85	2.40	0.38	-0.75	2.69	0.49	-0.55	2.35	0.43	-0.52	1.95	0.52	low
50	-0.81	3.77	0.29	-0.92	4.25	0.37	-1.11	4.17	0.40	-1.25	3.81	0.45	low
H	-0.79	3.66	0.28	-0.83	3.82	0.34	-0.97	3.64	0.35	-1.16	3.53	0.41	low
O	-0.71	2.09	0.81	-0.71	2.11	0.87	-0.81	2.12	0.80	-0.84	2.14	0.87	low
Avg	*-0.83*	*2.96*	*0.39*	*-0.84*	*3.09*	*0.44*	*-0.90*	*2.84*	*0.41*	*-0.96*	*2.59*	*0.46*	low
C	-0.89	2.51	0.40	-0.70	2.52	0.46	-0.78	3.34	0.62	-0.66	2.48	0.66	low-high
15t16	-0.51	1.14	0.07	-0.51	1.27	0.09	-0.52	1.35	0.12	-0.50	1.27	0.12	low-high
20	-1.00	2.44	0.36	-0.85	2.31	0.38	-0.69	1.99	0.34	-0.55	1.68	0.34	low-high
21t22	-0.74	1.79	0.26	-0.72	1.98	0.32	-0.56	1.61	0.28	-0.49	1.52	0.31	low-high
23	-0.16	0.39	0.06	-0.13	0.34	0.06	-0.12	0.36	0.06	-0.06	0.20	0.04	low-high
26	-0.81	1.97	0.29	-0.71	1.93	0.32	-0.67	1.95	0.34	-0.60	1.84	0.37	low-high
27t28	-0.88	2.14	0.31	-0.81	2.22	0.36	-0.72	2.08	0.36	-0.55	1.70	0.34	low-high
E	-0.57	1.60	0.26	-0.46	1.65	0.30	-0.36	1.55	0.29	-0.30	1.12	0.30	low-high
F	-0.71	2.83	0.24	-0.68	2.73	0.25	-0.71	2.61	0.27	-0.84	2.54	0.32	low-high
51	-0.67	3.08	0.24	-0.65	3.02	0.27	-0.80	3.01	0.29	-0.94	2.86	0.34	low-high
52	-1.05	4.85	0.38	-1.10	5.10	0.45	-1.19	4.50	0.43	-1.32	4.03	0.47	low-high
60t63	-0.72	2.72	0.21	-0.70	2.67	0.22	-0.65	2.30	0.19	-0.74	1.91	0.20	low-high
64	-0.83	3.14	0.24	-0.74	2.82	0.23	-0.55	1.94	0.16	-0.47	1.22	0.13	low-high
L	-0.76	4.08	1.08	-0.74	4.16	1.13	-0.63	4.22	1.06	-0.54	4.08	1.11	low-high
N	-0.72	3.81	1.12	-0.65	3.78	0.99	-0.60	3.76	1.01	-0.65	3.68	1.01	low-high
Avg	*-0.74*	*2.57*	*0.37*	*-0.68*	*2.57*	*0.39*	*-0.64*	*2.44*	*0.39*	*-0.61*	*2.14*	*0.40*	low-high
24	-0.77	1.87	0.27	-0.66	1.80	0.29	-0.53	1.54	0.27	-0.44	1.34	0.27	high
25	-0.77	1.88	0.27	-0.71	1.95	0.32	-0.65	1.90	0.33	-0.55	1.70	0.34	high
29	-0.92	2.23	0.33	-0.84	2.30	0.38	-0.74	2.14	0.37	-0.63	1.95	0.39	high
30t33	-0.65	2.30	0.59	-0.56	2.33	0.69	-0.45	2.02	0.61	-0.39	1.90	0.70	high
34t35	-0.48	1.70	0.44	-0.43	1.79	0.53	-0.32	1.46	0.44	-0.26	1.30	0.48	high
J	-0.29	3.10	0.41	-0.24	2.96	0.46	-0.20	2.45	0.46	-0.19	2.09	0.44	high
70	-0.06	0.24	0.11	-0.06	0.24	0.11	-0.09	0.25	0.13	-0.09	0.22	0.12	high
71t74	-0.42	1.64	0.72	-0.47	1.75	0.83	-0.68	1.91	0.96	-0.80	1.95	1.12	high
M	-0.66	3.72	3.21	-0.61	3.70	3.62	-0.63	3.72	3.64	-0.61	3.44	3.54	high
Avg	*-0.56*	*2.08*	*0.71*	*-0.51*	*2.09*	*0.80*	*-0.48*	*1.93*	*0.80*	*-0.44*	*1.77*	*0.82*	high

SEGESD results. Reaction to a 1% change in the labour input by sector and ISCED group. - 1% in low, + 1% in medium and high qualified labour types. These are the same as the ungrouped values in C.8.

Chapter 6

Summary & Conclusion

Within this thesis a contribution to quantifying elements of the *endogenous growth* literature in a system dynamics simulation model was described.

In a *data-driven approach* - combining system dynamics and econometrics under consideration of what data sets are available - the model *SEGESD* (**S**ectoral **E**ndogenous **G**rowth driven by **E**ducation in **S**ystem **D**ynamics) was developed. It covers the German economy, split into 30 sectors, between 1970 and 2100. The model constitutes the result of a reduction of the broad field of endogenous growth theory to one variable driving economic growth: national education spending.

The work presented within this thesis forms the theoretical and empirical basis for an extension of the existing *ASTRA* model - a tool for the economical, ecological and social assessment of climate protection policies developed by Schade (2005b) - by incorporating economic effects of changes in education spending. So, once *SEGESD* is included in *ASTRA*, it will form a contribution to an improved assessment of climate protection policies. But currently, *SEGESD* is technically independent of *ASTRA*, but is designed to be integrated in *ASTRA*. Since *ASTRA* is defined of many European countries, this involves highly repetitive tasks. Therefore, this integration is not part of this thesis.

This is the final chapter. It summarises the four main chapters (sec. 6.1 to 6.4) of this thesis. After that some policy recommendations are drawn (sec. 6.5), the contribution to the literature is described (sec. 6.6) and an outlook for further research is provided (sec. 6.7).

6.1 Theoretical Background Summary

Starting point for this thesis was the question *in what way could the concepts of the broad field of 'endogenous growth theory' be included into a system dynamics simulation model on a sectoral level for all European Countries.* Therefore, first an overview of the development of endogenous growth theory is compiled (→ sec. 2.1), showing its roots in the extension of the neoclassical growth theory by considering human capital stocks in the 1980s. The various drivers of economic growth considered by the large amount of models that were published in the wave of endogenous growth theory are compiled afterwards, and for the main drivers details on the findings of the according publications are compiled (→ sec. 2.2). And the related research field of *endogenous technological change*, particularyly the *experience curve theory* is covered (→ sec. 2.3). First, these theoretical elements were tried to be combined in one system dynamics model. But due to endogeneity and collinearity problems with this model specification under the constraints of available data, this design was reduced to a model driving sectoral gross output only with one factor - education spending. It isolates one chain of effects, i.e. it assumes mono-causality. This is described in section 2.4.

6.2 Methodological Summary

The methodology applied within this thesis was partly determined by the goal to develop an extension to the existing model *ASTRA*, which is a system dynamics model. The consequent orientation of the model design towards available data and the inclusion of econometrically estimated links as well as the avoidance of the *mental creativity* part of the system dynamics methodology was the decision of the author, driven by the goal to produce a simulation model with a firm empirical basis.

System dynamics focuses on the development of complex systems over time. Its main elements are stocks and flows, with flows forming the derivative of stocks with respect to time (→ sec. 3.1). Econometrics refers to the application of statistical and mathematical methods to the analysis of economic data. It forms a huge field by itself. For the development of *SEGESD*, large sets of simple regression analyses have been used to estimate functional relations for parts of the model (→ sec. 3.2). Both system dynamics as well as econometrics have been applied jointly to implement *SEGESD*, as described in section 3.3.

6.3 Model Summary

SEGESD connects changes in the education spending with changes in sectoral gross output (the *long link*), combining four *short links* into one simulation model. Combining an educated population age cohorts model with the *EUKLEMS* framework (growth accounting framework decomposing economic growth into the growth of the input factors capital, labour, energy, materials and services), a model was implemented which connects the qualification of the population via the labour market with the economic output of the economy. The four *short links* are:

1. The relation between education spending and graduation probability was estimated statistically.
2. That link drives changes in the distribution of education levels within the population, calculated in a population age cohort model.
3. These changes in the population lead to changes in the hours worked differentiated by age, sex and education level on sectoral level according to a simple regression model. These changes lead to changes in the sectoral monetary labour input.
4. And finally, that change of labour input *ceteris paribus* leads to a change of gross output within the sectoral growth accounting framework *EUKLEMS*.

Via this chain of effects, the impact of a change of the spending for education on sectoral gross output is modelled for Germany.

The core of the mathematical representation of the economic activity is formed by the growth accounting framework *EUKLEMS* implemented in *SEGESD*. There, sectoral gross output growth is decomposed into a *value-weighted* sum of the growth of various capital stock types, labour input types, intermediate input types and the growth of the total factor productivity. Important to mention at this point is the fact that this growth decomposition formula is *not* a Cobb-Douglas production function (→ sec. 4.2).

The labour input, measured as hours worked, distinguished into 18 labour types categorizing the workforce by education level, age and sex constitutes the connection of the growth accounting framework with the population cohort model. This labour input on sectoral level - i.e. the labour demand - within the *EUKLEMS* growth accounting framework is assumed to depend on the labour supply, i.e. the amount of persons of a certain education level, age and sex in the population. This relation was estimated as a linear regression in 540 cases, for 18 labour types in 30 sectors. In the implementation of *SEGESD*, the correlation coefficient of these linear regressions were also taken into account. A strong correlation between supply and demand was taken as an indication that the according sector needs additional labour of that type, absorbing additional persons of that labour type if available. In the case of weak correlation, no additional labour is demanded if supply rises. These values for the hours worked, changed in the scenario calculations, multiplied with the unchanged wages per hour result in the scenario specific monetary labour input, which is used as one input in the *EUKLEMS* framework. The shift towards higher qualified labour, which yields higher wages per hour, implies an increase of the labour productivity. (→ sec. 4.3).

The population cohort model represents the complete population between 0 and 85 years, distinguished by sex and education level. The qualification structure of the population is determined by the education system. The implementation of the education system and the estimation of its parameters from historical data is described in detail in section 4.4. Better conditions lead to more graduates at each qualification level. And the changes in the amount of persons of the individual labour types drive changes in the sectoral labour input, as described above.

The conditions in the education system are assumed to be determined by its funding. This is the result of another linear regression estimation, laid out in section 4.5. It puts the graduation probabilities at various ages in relation to the the education spending in the according education programs. With this relation, the increase of education spending leads to higher graduation probabilities, increasing the amount of persons of medium and high education level.

Both statistically estimated relations had to be specified as linear models, since the time series were too short for a significant parameter estimation of a non-linear model. Non-linear relations are implemented within *EUKLEMS* growth accounting framework, particularly through the definition of the aggregation of sectoral growth from the growth of labour, capital and intermediate inputs. Also, the population model, implemented using system dynamics stocks and flows, produces complex non-linear relations with temporal lags, since the shifting of persons between education levels triggers additional shifting at later points of time. And the long temporal lags between the changes of the graduation probabilities at age 18, 22, 23 and 31 and the according effect on the population structure at higher ages induces non-linear effects.

In this way, the effects of additional education investments on growth rates of economic output were modelled on a sectoral level, quantifying the positive effects of schooling on the gross output described in section 2.2.2 from a macroeconomic perspective.

6.4 Results Summary

In this section the results obtained from *SEGESD*, described and explained in detail in chapter 5, are summarized. The model calculates results on various aggregation levels. The German economy is split into 30 sectors. The labour input for each sector is differentiated into 18 groups distinguishing by age, sex and education level, the so called *labour types*. The population model calculates the composition of the population split into yearly age cohorts, separated into three ISCED (International Standard Classification of Education) levels - the so called *ISCED groups* - and distinguished by sex. Additionally, the graduation process, i.e. the shift to a higher ISCED level of the individual persons, is implemented to happen at three different ages.

The large set of results produced by the simulation model due to this high disaggregation was compiled in various aggregation levels in order to reveal the relevant mechanisms inherent in the model. This was done for the complete chain of effects within the global analyses (→ sec. 5.2), as well as for all sub-chains indicated in the schema of the model in figure 5.8 within the partial analyses (→ sec. 5.3).

SEGESD computes results for the years 1970 till 2100. Within this timeframe, an increase of 1% of the per student education spending between 1990 and 2040 was analysed. The 20 years forerun are needed in order to have the relevant parts of the population model endogenously calculated. And the 60 years trail after the end of the spending change are needed in order to get the complete picture of the effects in all age groups and to be able to compute a cost-benefit ratio.

All results are given as differences to the baseline scenario. There are two reasons for that. On the one side, the uncertainties common to the baseline as well as the scenario results are removed by calculating the differences of the two. And on the other side, the differences in the order of magnitude of the changes compared to the absolute scenario results make it difficult to interpret the absolute values. The relevant information is contained in the changes between baseline and scenario results.

From the global and partial analyses, the quantitative behaviour of the model emerges. The complete picture is impossible to compile within a written document. Also, looking at all result tables does not give a quickly perceivable picture. But with this combination of various perspectives, the relevant mechanisms and implications become clear. And based on this set of results, various relevant policy conclusions can be drawn.

Increasing the spending for education is likely to result in a positive net effect, i.e. the gross output of the economy is increased more than the education spending in real monetary terms, in the case of not discounting the monetary figures. With a 3% discount rate, the details of the results change, but the order of magnitudes are still the same and the general picture remains unchanged. And since various positive effects of additional education or additional education spending - cultural improvements, technological advances, multiplier effects, accelerator effects, dynamics of the sectoral structure - are not explicitly included (since these would be difficult to quantify, especially over the long time frame of the presented analysis), the calculated benefits appear to mark the lower boundary of possible outcomes and a positive total effect appears likely. This emerges from the analysis of the results on the highest aggregation level, i.e. comparing the total additional education spending with the total effect for the complete economy (→ sec. 5.2.1).

The higher the knowledge intensity of a sector, the higher the gains in additional gross output due to an increase of education spending. This can be perceived in the analysis of the sectoral results (→ sec. 5.2.2). First, the additional gross output per sector for a global increase of the education spending were analysed. And second, the sectoral impact of each individual graduation point on each age group were analysed. Both analyses indicate the ability of *SEGESD* to differentiate the sectors by their knowledge intensity statistically.

Women profit more than men from an increase of the education spending. As discussed before, this can be at least partially explained by a relatively low level of educated females at the beginning of the time frame of the available data and a stronger increase during that period, leading to a higher inclination of the estimated linear model. *And students aspiring high level degrees profit more than those working for a medium level degree.* This follows from the statistical analyses of the relation between per student education spending and graduation probability described in section 4.5, used for the scenario computation in *SEGESD* (→ sec. 5.3.1).

The dynamics of the system incorporate very long time lags, since secondary and tertiary education happens mostly between 18 and the early thirties, but the outcome effects the economy till the retirement age at 65. Also, an increase of persons of higher education level always implies a reduction of the amount of persons on the lower level. Both effects are crucial for the understanding of other results from *SEGESD*. They are laid out in detail in the section on the effect of the education spending on the population composition (→ sec. 5.3.2).

Increasing education efforts raises overall employment figures. This follows from the shift towards more persons of medium and high qualification level in the population (the supply side) which leads to a net increase of the labour input aggregated over all sectors (the demand side). And demand for experienced persons, i.e. older ones, is higher than for unexperienced persons.

The analysis of the effect of additional per student education spending on the sectoral labour input delivers these results (→ sec. 5.3.3).

An increase of the level of persons of medium qualification leads to a lagged increase of graduates at high level. This cumulative effect of education is extracted in the analysis of the change in the graduation probability on the population composition (→ sec. 5.3.4).

Those persons achieving a high level degree must be substituted with additional persons achieving a medium level degree. Increasing the graduation probability for high level degrees isolatedly would decrease the total gross output. The analysis of the effect of changed graduation probabilities on sectoral labour input carried out separately for each graduation point comes up with this finding (→ sec. 5.3.5). And extending that analysis to also include the effect on gross output (→ sec. 5.3.6) supports the same conclusion. The results differ on the sectoral level, since the relation between labour input and gross output differs for each sector. But on the economy wide aggregate, the same picture emerges and the policy recommendations remain the same.

The sectoral reaction of both labour input as well as gross output to a change in the supply structure of labour differs by ISCED level. *On average, medium level reaction is stronger than high level reaction and low level reaction is the weakest (medium > high > low).* Also, an age specific reaction can be identified. *The demand for labour appears to be weaker the older the according persons are in general, with some ISCED specific differences.* These findings emerge from the analyses of the effect of a change in the population structure on the sectoral labour input (→ sec. 5.3.7) and subsequently on the sectoral gross output (→ sec. 5.3.8).

The sensitivity of the sectoral gross output to the labour input increases with the knowledge intensity of the sector in the case of high qualified labour. For medium and low qualified labour input, it decreases with increasing knowledge intensity. This is visually summarized in the schema in figure 6.1. The details of the analysis resulting in these findings are compiled in section covering the sensitivity of gross output to labour input (→ sec. 5.3.9).

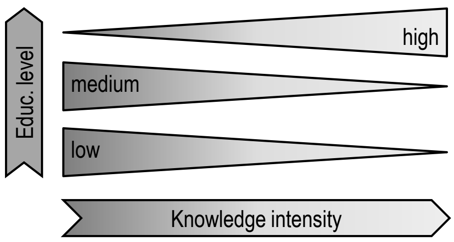


Figure 6.1
Sensitivity of gross output to labour input (schematic)

6.5 Policy recommendations summarized

From the previously summarized quantitative results, two essential policy recommendations can be drawn.

Raising per head education spending is likely to produce net positive effects for the German economy. Even when discounting costs and benefits with 3%, the picture does not change fundamentally. Total benefits remain in the order of magnitude of total costs. Gross output can be increased as well as employment figures. Additionally, the effects of keeping a technological leadership position, at least in some fields, is difficult to predict and to quantify. But it is clear that this is essential for the future of the high-tech nation Germany. And it is clear that in order to achieve this, well qualified persons are needed. One finding clearly emerges from the quantitative results: the more well qualified persons of medium and high level, the better.

Spending increases have to be introduced simultaneously in both medium and high level education programs. This is clearly stressed by the model results. An increase of the high level programs alone would reduce the amount of persons of medium level degree, which would lead, in total, to a loss of gross output.

The clear drawback from a decision maker's perspective is that the positive effects show with a large temporal lag, well beyond the time politicians remain in power, while the higher spending show without any temporal lag.

6.6 Contribution to the literature

This work extends the large stream of endogenous growth literature with a system dynamics simulation model using the education level of the population as explaining variable for economic growth - *SEGESD*. It particularly emphasizes the long temporal lags of the education system with a detailed yearly age cohort model of the population, representing the population distinguished by education level and sex. The changes within the population structure triggered by a change in the spending in the education system cause changes in the sectoral gross output of the German economy. This chain of effect, on that level of detail, has not yet been quantitatively analysed and described.

As described in section 2.2.2, the most detailed analysis found so far by the author comes up with econometric cross country analyses for a set of 21 OECD countries (Fuente and Domenech, 2006), finding a range of 0.15 to 2 % annual growth per year of schooling. A detailed study for Germany alone is not available.

This also shows the advantage of the chosen methodology. Estimating the *shortest* direct links for which data is available and then building a simulation model on these links enables the analysis of more distant relations on a more disaggregated level than the direct estimation of the *long-distance* connection with an econometric approach. One major reason for that is the consideration of the large time lags in *SEGESD*. An econometric model could not take into account these long time lags simultaneously with the available data, since every lag level adds an extra addend to the model, increasing the parameters to be estimated and with that the degrees of freedom. Therefore, the econometric models are bound to a few lag levels within one model and because of that are subject to a strong simplifying assumption.

Therefore, in total this work forms a significant extension of the existing literature in the field of economic effects of increased education spending.

6.7 Outlook - Further research

SEGESD is already a highly complex system of formulas using a large set of exogenous data. Yet, further extensions, well beyond the scope of this work, are imaginable. And, also the set of possible analyses using the existing version of the model is larger than what has been described within this work. In this work, only the main characteristics could be summarized, due to limitations of space and time.

With the existing version of *SEGESD* as described within this thesis, the following analysis could be realized.

Currently, *SEGESD* assumes a continuation of historic migration patterns in the baseline scenario. The model could be used to analyse the effect of a change of the education level structure of immigrants as well as of changes in the total numbers of immigrants accepted by Germany. E.g. the currently often discussed proposal recommending the invitation of highly skilled immigrants to Germany could be analysed with respect to its sectoral economic impacts. The model can be expected to react similar as to the increased education spending, with the major difference of no temporal lags for the older age cohorts, since in those the levels of highly and medium skilled persons could be stocked up immediately.

Also the impact of an increased retirement age could be analysed with *SEGESD*. This would lead to an increase of persons of the oldest labour types, at no costs within the model. Therefore, the model would show additional gross output for all sectors. And in a second step, that analysis could be further extended with additional implementations. The model structure could be changed to take the additional benefits of belated retirement - reduced cost of labour - into account, producing additional positive effects.

Additionally to these analyses, *SEGESD* could be extended with various additional features, enabling further analyses.

The main driver for the reduction of the analytical scope of *SEGESD* to education spending only was the shortness of the available time series (→ sec. 2.4.2). As more data becomes available in the coming years, the model could be extended to include more variables, since more parameters could be included and models of higher degrees of freedom will be possible to be estimated.

Also, with longer time series, more complex econometrical test can be devised, particularly leaving the assumption of a linear relation between labour demand and supply, testing various non-linear relations and deciding based on the data which functional relation is the most suitable.

And *SEGESD* could be extended to incorporate *intergenerational path dependency of education*, i.e. the dependency of the graduation success of children on the achieved degrees of their parents. This would imply a major change of the model structure, adding an additional dimension of complexity. It could be implemented using education level specific birth rates and a population model which not only distinguishes the population by education degree, but which would additionally need to differentiate for the graduation degree of the parents. The necessary parameters for the development of the baseline scenario might possibly be derived from the detailed results of OECD's PISA study (Prenzel et al., 2008).

And finally, *SEGESD* can be extended to cover various European countries. When the decision for the model design was taken, the availability of data was a main driver, as stressed before. But not only the availability for Germany was kept in mind, but also the availability for further countries, due to the need to incorporate the developed concept in *ASTRA*. All data used is avaiable for various EU countries. Not for all, of course, but for many of the larger ones.

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Appendices

Appendix A

Dimensions used in *SEGESD*

A.1 Labour types

Table A.1
Model dimension: labour types

labour type	*isced*	*age*	*sex*
LS_29_F	low	15 - 29	f
LS_29_M	low	15 - 29	m
LS_49_F	low	30 - 49	f
LS_49_M	low	30 - 49	m
LS_50PLUS_F	low	50 - 65	f
LS_50PLUS_M	low	50 - 65	m
MS_29_F	med	15 - 29	f
MS_29_M	med	15 - 29	m
MS_49_F	med	30 - 49	f
MS_49_M	med	30 - 49	m
MS_50PLUS_F	med	50 - 65	f
MS_50PLUS_M	med	50 - 65	m
HS_29_F	high	15 - 29	f
HS_29_M	high	15 - 29	m
HS_49_F	high	30 - 49	f
HS_49_M	high	30 - 49	m
HS_50PLUS_F	high	50 - 65	f
HS_50PLUS_M	high	50 - 65	m

A.2 Economic sectors

Table A.2
Model dimension: economic sectors

NACE 1	*Description*	*R&D intensity*	*Knowledge int.*
AtB	agriculture, hunting, forestry and fishing	–	low
C	mining and quarrying	–	low-high
15t16	food, beverages and tobacco	–	low-high
17t19	textiles, textile, leather and footwear	–	low
20	wood and of wood and cork	–	low-high
21t22	pulp, paper, printing and publishing	–	low-high
23	coke, refined petroleum and nuclear fuel	low-high	low-high
24	chemicals and chemical	med-high	high
25	rubber and plastics	med	high
26	other non-metallic mineral	–	low-high
27t28	basic metals and fabricated metal	–	low-high
29	machinery, nec	med	high
30t33	electrical and optical equipment	high	high
34t35	transport equipment	med-high	high
36t37	manufacturing nec	–	low
E	electricity, gas and water supply	–	low-high
F	construction	–	low-high
50	sale, maintenance and repair of motor vehicles and motorcycles	–	low
51	wholesale trade and commission trade, except of motor vehicles and motorcycles	–	low-high
52	retail trade, except of motor vehicles and motorcycles	–	low-high
H	hotels and restaurants	–	low
60t63	transport and storage	–	low-high
64	post and telecommunications	–	low-high
J	financial intermediation	–	high
70	real estate activities	–	high
71t74	renting of Mach.&Equip., data processing, IT, R&D, business services, consulting	–	high
L	public admin and defence	–	low-high
M	education	–	high
N	health and social work	–	low-high
O	other community, social and personal services	–	low

R&D intensity as well as knowledge intensity based on Legler and Frietsch (2006) transferred to the sector aggregates.

A.3 Capital types

Table A.3
Model dimension: capital types

capital type	*description*
IT	Computing equipment
CT	Communications equipment
Soft	Software
TraEq	Transport Equipment
OMach	Other Machinery and Equipment
OCon	Total Non-residential investment
RStruc	Residential structures
Other	Other assets
ICT	ICT assets
NonICT	Non-ICT assets
GFCF	All assets

A.4 Main Codes of *SEGESD*

Economic sectors

Code	*Description*
AtB	agriculture, hunting, forestry and fishing
C	mining and quarrying
15t16	food, beverages and tobacco
17t19	textiles, textile, leather and footwear
20	wood and of wood and cork
21t22	pulp, paper, printing and publishing
23	coke, refined petroleum and nuclear fuel
24	chemicals and chemical
25	rubber and plastics
26	other non-metallic mineral
27t28	basic metals and fabricated metal
29	machinery, nec
30t33	electrical and optical equipment
34t35	transport equipment
36t37	manufacturing nec
E	electricity, gas and water supply
F	construction
50	sale, maintenance and repair of motor vehicles and motorcycles
51	wholesale trade and commission trade, except of motor vehicles and motorcycles
52	retail trade, except of motor vehicles and motorcycles
H	hotels and restaurants
60t63	transport and storage
64	post and telecommunications
J	financial intermediation
70	real estate activities
71t74	renting of Mach.&Equip., data processing, IT, R&D, business services, consulting
L	public admin and defence
M	education
N	health and social work
O	other community, social and personal services

Labour Types

code	*isced*	*age*	*sex*
LS_29_F	low	15 - 29	f
LS_29_M	low	15 - 29	m
LS_49_F	low	30 - 49	f
LS_49_M	low	30 - 49	m
LS_50PLUS_F	low	50 - 65	f
LS_50PLUS_M	low	50 - 65	m
MS_29_F	med	15 - 29	f
MS_29_M	med	15 - 29	m
MS_49_F	med	30 - 49	f
MS_49_M	med	30 - 49	m
MS_50PLUS_F	med	50 - 65	f
MS_50PLUS_M	med	50 - 65	m
HS_29_F	high	15 - 29	f
HS_29_M	high	15 - 29	m
HS_49_F	high	30 - 49	f
HS_49_M	high	30 - 49	m
HS_50PLUS_F	high	50 - 65	f
HS_50PLUS_M	high	50 - 65	m

Appendix B

Data used in *SEGESD*

This section describes the sources tapped for obtaining the exogenous data for *SEGESD*. The technical steps conducted in order to make the data technically available for the model varied case by case, but these steps were mostly large efforts making up for a significant part of the total time of the modelling effort. A detailed description of these work steps is omitted, since they do not contribute to the understanding of *SEGESD*.

B.1 Classifications

Here details on the classifications of the data used are compiled.

B.1.1 ISCED 1997

The *International Standard Classification of Education (ISCED)* was designed by UNESCO in the early 1970s to serve 'as an instrument suitable for assembling, compiling and presenting statistics of education both within individual countries and internationally'. It was approved by the International Conference on Education (Geneva, 1975) and was subsequently endorsed by UNESCO's General Conference. The present classification, now known as ISCED 1997, was approved by the UNESCO General Conference at its 29th session in November 1997. (Text from *http://en.wikipedia.org/wiki/ISCED*)

On the following pages the details of the *ISCED 97* (→ tab. B.1) are included as well as an overview of the corresponding programs in Germany (→ tab. B.3) along with the mapping to the *low, medium, high* groups of education used for the statistical analysis as well as in *SEGESD*.

Table B.1

ISCED 97 Details, p. 1

0	Pre-primary level of education	Main criteria	Auxiliary criteria		Sub-categories		
	Initial stage of organised instruction, designed primarily to introduce very young children to a school-type environment.	Should be centre or school-based, be designed to meet the educational and development needs of children at least 3 years of age, and have staff that are adequately trained (*i.e.* qualified) to provide an educational programme for the children.	Pedagogical qualifications for the teaching staff; implementation of a curriculum with educational elements.				
1	Primary level of education	Main criteria	Auxiliary criteria				
	Normally designed to give students a sound basic education in reading, writing and mathematics.	Beginning of systematic studies characteristic of primary education, e.g. reading, writing and mathematics. Entry into the nationally designated primary institutions or programmes. The commencement of reading activities alone is not a sufficient criteria for classification of an educational programmes at ISCED 1.	In countries where the age of compulsory attendance (or at least the age at which virtually all students begin their education) comes after the beginning of systematic study in the subjects noted, the first year of compulsory attendance should be used to determine the boundary between ISCED 0 and ISCED 1.				
2	Lower secondary level of education	Main criteria	Auxiliary criteria		Destination for which the programmes have been designed to prepare students		Programme orientation
	The lower secondary level of education generally continues the basic programmes of the primary level, although teaching is typically more subject-focused, often employing more specialised teachers who conduct classes in their field of specialisation.	Programmes at the start of Level 2 should correspond to the point where programmes are beginning to be organised in a more subject-oriented pattern, using more specialised teachers conducting classes in their field of specialisation.	If there is no clear break-point for this organisational change, however, then countries should artificially split national programmes into ISCED 1 and 2 at the end of 6 years of primary education.	A	Programmes designed to prepare students for direct access to Level 3 in a sequence which would ultimately lead to tertiary education, that is, entrance to ISCED 3A or 3B.	1	Education which is not designed explicitly to prepare participants for a specific class of occupations or trades or for entry into further vocational/technical education programmes. Less than 25% of the programme content is vocational or technical.
		If this organisational transition point does not correspond to a natural split in the boundaries between national educational programmes, then programmes should be split at the point where national programmes begin to reflect this organisational change.	In countries with no system break between lower secondary and upper secondary education, and where lower secondary education lasts for more than 3 years, only the first 3 years following primary education should be counted as lower secondary education.	B	Programmes designed to prepare students for direct access to programmes at Level 3C.	2	Education mainly designed as an introduction to the world of work and as preparation for further vocational or technical education. It does not lead to a labour-market relevant qualification. Content is at least 25% vocational or technical.
				C	Programmes primarily designed for direct access to the labour market at the end of this level (sometimes referred to as "terminal" programmes).	3	Education which prepares participants for direct entry, without further training, into specific occupations. Successful completion of such programmes leads to a labour-market relevant vocational qualification.
3	Upper secondary level of education	Main criteria	Modular programmes		Destination for which the programmes have been designed to prepare students		Programme orientation
	The final stage of secondary education in most OECD countries. Instruction is often more organised along subject-matter lines than at ISCED Level 2 and teachers typically need to have a higher level, or more subject-specific, qualification than at ISCED 2.	National boundaries between lower secondary and upper secondary education should be the dominant factor for splitting Levels 2 and 3.	An educational qualification is earned in a modular programme by combining blocks of courses, or modules, into a programme meeting specific curricular requirements.	A	ISCED 3A: programmes at Level 3 designed to provide direct access to ISCED 5A.	1	Education which is not designed explicitly to prepare participants for a specific class of occupations or trades or for entry into further vocational/technical education programmes. Less than 25% of the programme content is vocational or technical.
		Admission into educational programmes usually requires the completion of ISCED 2 for admission, or a combination of basic education and life experience that demonstrates the ability to handle ISCED 3 subject matter.	A single module, however, may not have a specific educational or labour market destination or a particular programme orientation.	B	ISCED 3B: programmes at Level 3 designed to provide direct access to ISCED 5B.	2	Education mainly designed as an introduction to the world of work and as preparation for further vocational or technical education. It does not lead to a labour-market relevant qualification. Content is at least 25% vocational or technical.
	There are substantial differences in the typical duration of ISCED 3 programmes both across and between countries, typically ranging from 2 to 5 years of schooling.		Modular programmes should be classified at Level "3" only, without reference to the educational or labour market destination of the programme.	C	ISCED 3C: programmes at Level 3 not designed to lead directly to ISCED 5A or 5B. Therefore, these programmes lead directly to labour market, ISCED 4 programmes or other ISCED 3 programmes.	3	Education which prepares participants for direct entry, without further training, into specific occupations. Successful completion of such programmes leads to a labour-market relevant vocational qualification.

Table B.2
ISCED 97 Details, p. 2

4	Post-secondary non-terti	Main criteria	Types of programmes that can fit into Level 4		Destination for which the programmes have been designed to prepare students		Programme orientation
	These programmes straddle the boundary between upper secondary and post-secondary education from an international point of view, even though they might clearly be considered as upper secondary or post-secondary programmes in a national context.	Students entering ISCED 4 programmes will typically have completed ISCED 3.	The first type are short vocational programmes where either the content is not considered "tertiary" in many OECD countries or the programme did not meet the duration requirement for ISCED 5B -- at least 2 years FTE since the start of Level 5.	A	Programmes at Level 4, designed to provide direct access to ISCED 5A.	1	Education which is not designed explicitly to prepare participants for a specific class of occupations or trades or for entry into further vocational/technical education programmes. Less than 25% of the programme content is vocational or technical.
	They are often not significantly more advanced than programmes at ISCED 3 but they serve to broaden the knowledge of participants who have already completed a programme at Level 3. The students are typically older than those i n ISCED 3 programmes.	Programme duration: ISCED 4 programmes typically have a full-time equivalent duration of between 6 months and 2 years.	These programmes are often designed for students who have completed Level 3, although a formal ISCED Level 3 qualification may not be required for entry.	B	Programmes at Level 4, designed to provide direct access to ISCED 5B.	2	Education mainly designed as an introduction to the world of work and as preparation for further vocational or technical education. It does not lead to a labour-market relevant qualification. Content is at least 25% vocational or technical.
			The second type of programmes are nationally considered as upper secondary programmes, even though entrants to these programmes will have typically already completed another upper secondary programme (i.e. second-cycle programmes).	C	Programmes at Level 4 not designed to lead directly to ISCED 5A or 5B. These programmes lead directly to labour market or other ISCED 4 programmes.	3	Education which prepares participants for direct entry, without further training, into specific occupations. Successful completion of such programmes leads to a labour-market relevant vocational qualification.
5	First stage of tertiary education	Classification criteria for level and sub-categories (5A and 5B)			Cumulative theoretical duration of tertiary		Position in the national degree and qualifications structure
	ISCED 5 programmes have an educational content more advanced than those offered at Levels 3 and 4.	Entry to these programmes normally requires the successful completion of ISCED Level 3A or 3B or a similar qualification at ISCED Level 4A or 4B.					
5A	ISCED 5A programmes that are largely theoretically based and are intended to provide sufficient qualifications for gaining entry into advanced research programmes and professions with high skills requirements.	The minimum cumulative theoretical duration (at tertiary level) is of three years (FTE). The faculty must have advanced research credentials. Completion of a research project or thesis may be involved.	The programmes provide the level of education required for entry into a profession with high skills requirements or an advanced research programme.	A	Duration categories: Medium: 3 to less than 5 years; Long: 5 to 6 years; Very long: more than 6 years.	A	Categories: Intermediate; First; Second; Third and further.
5B	ISCED 5B programmes that are generally more practical/technical/occupationally specific than ISCED 5A programmes.	Programmes are more practically-oriented and occupationally specific than programmes at ISCED 5A and they do not prepare students for direct access to advanced research programmes. They have a minimum of two years' full-time equivalent duration.	The programme content is typically designed to prepare students to enter a particular occupation.	B	Duration categories: Short: 2 to less than 3 years; Medium: 3 to less than 5 years; Long: 5 to 6 years; Very long: more than 6 years.	B	Categories: Intermediate; First; Second; Third and further.
6	Second stage of tertiary education (leading to an advanced research qualification)						
	This level is reserved for tertiary programmes that lead to the award of an advanced research qualification. The programmes are devoted to advanced study and original research.	The level requires the submission of a thesis or dissertation of publishable quality that is the product of original research and represents a significant contribution to knowledge. It is not solely based on course-work.	It prepares recipients for faculty posts in institutions offering ISCED 5A programmes, as well as research posts in government and industry.				

Source: OECD (1999)

Table B.3
ISCED 97 in Germany

Entfällt/Nicht zuordenbar		▪ ohne Angabe zum Schulabschluss und ohne Angabe zum beruflichen Abschluss ▪ ohne Angabe ob Schulabschluss und ohne Angabe ob beruflicher Abschluss
niedrig	**0** Elementar-bereich	▪ Vorschulbereich: Besuch eines Kindergartens, einer Kinderkrippe bzw. eines Kinderhorts (3-8 Jahre ohne Schulbesuch)
	1B	▪ kein Schulabschluss bzw. ohne Angabe ob Schulabschluss und kein beruflicher Abschluss ODER ▪ kein Schulabschluss und ohne Angabe ob beruflicher Abschluss
	1A Primar-bereich	▪ Schulbesuch der Klassen 1-4 an einer allgemein bildenden Schule (bzw. wenn keine weitere Differenzierung: Personen mit Schulbesuch/in Ausbild.)
	2B Sekundar-stufe I B	▪ Hauptschulabschluss ▪ Schulbesuch der Klassen 5-10 an einer allgemein bildenden Schule ▪ Schulabschluss vorhanden, aber ohne Angabe zur Art des Abschlusses UND ▪ kein beruflicher Abschluss ▪ Anlernausbildung, berufliches Praktikum oder Berufsvorbereitungsjahr ▪ ohne Angabe, ob berufl. Abschluss ▪ beruflicher Abschluss vorhanden, aber keine Angabe zur Art des Abschlusses **ODER** ▪ kein Schulabschluss ▪ ohne Angabe, ob Schulabschluss UND ▪ Anlernausbildung, berufliches Praktikum oder Berufsvorbereitungsjahr ▪ beruflicher Abschluss vorhanden, aber ohne Angabe zur Art des Abschlusses
	2 A Sekundar-stufe I A	▪ Realschulabschluss ▪ Abschluss an einer allgemeinen polytechnischen Oberschule der ehemaligen DDR UND ▪ kein beruflicher Abschluss ▪ Anlernausbildung, berufliches Praktikum oder Berufsvorbereitungsjahr ▪ ohne Angabe ob berufl. Abschluss ▪ beruflicher Abschluss vorhanden, aber keine Angabe zur Art des Abschlusses
mittel	**3 B** Sekundar-stufe II B	▪ Abschluss einer Lehrausbildung bzw. Vorbereitungsdienst für den mittleren Dienst in der öffentlichen Verwaltung ▪ Berufsqualifizierender Abschluss an einer Berufsfachschule/Kollegschule bzw. Abschluss einer einjährigen Schule des Gesundheitswesens
	3A Sekundar-stufe II A	▪ Fach-/Hochschulreife ▪ Schulbesuch der Klassen 11-13 an einer allgemein bildenden Schule UND ▪ kein beruflicher Abschluss ▪ Anlernausbildung, berufliches Praktikum oder Berufsvorbereitungsjahr ▪ ohne Angabe, ob berufl. Abschluss ▪ beruflicher Abschluss vorhanden, aber keine Angabe zur Art des Abschlusses
	4A Nicht-tertiäre Bildung nach dem Sekundar-bereich	▪ Fach-/Hochschulreife ▪ Schulbesuch der Klassen 11-13 an einer allgemein bildenden Schule UND ▪ Abschluss einer Lehrausbildung ▪ Berufsqualifizierender Abschluss an einer Berufsfachschule/Kollegschule bzw. Abschluss einer einjährigen Schule des Gesundheitswesens
hoch	**5B** 1. Stufe der tertiären Bildung (B)	▪ Meister-/Techniker- oder gleichwertiger Fachschulabschluss, Abschluss einer 2- oder 3-jährigen Schule des Gesundheitswesens, Abschluss einer Fach- oder einer Berufsakademie ▪ Abschluss der Fachschule der ehemaligen DDR ▪ Abschluss einer Verwaltungsfachhochschule
	5A 1. Stufe der tertiären Bildung (A)	▪ Fachhochschulabschluss (auch Ingenieurabschluss) ▪ Abschluss einer Universität (wissenschaftliche Hochschule, auch Kunsthochschule)
	6 2. Stufe der tertiären Bildung	▪ Promotion

Source: Schroedter et al. (2006, p. 21)

B.1.2 NACE

B.2 EUKLEMS

Description of EUKLEMS Data.

Available from 1991 on for all 30 sectors.

B.3 Labour Force Survey

Labour Force Survey refers to a standardized survey among private households carried out across the European Union by the individual national statistical offices. The data set used within in this work was obtained from the German *DESTATIS* by colleagues of the author at Fraunhofer ISI, Karlsruhe. It is not publicly available, but rather has to be order and is given only to research institutions.

The original data set distinguishes 6 age classes (*below 14*, *15 to 24*, *25 to 32*, *33 to 49*, *50 to 64*, *above 64*) and 13 education levels classified in using ISCED 97 (International Standard Classification of Education) classes. But this data does not provide a consistent picture on the disaggregated level. Therefore, it appears as common to aggregate the education classes into three levels - *low*, *medium*, *high* - in order to obtain a consistent picture, i.e. stable timelines over the total period for which data is available (from 1993 till 2007). The aggregation mapping is given in table 4.1 on page 43. These aggregations are also used with the *EUKLEMS* framework, probably for the same reason, since the analysis within that project is also based on the *Labour Force Survey*.

This data was used in the *educated population cohort model* described in section 4.4, particularly in subsection 4.4.3 on page 70.

B.4 Population data

Population in yearly age cohorts for West Germany
Indicator 12411-0005 - Bevölkerung: Deutschland, Stichtag, Altersjahre.
DESTATIS. Genesis Data Base. *www-genesis.destatis.de*

Population in 5-year age groups, differentiated by sex, total for East and West Germany
Indicator demo_ppavg - Average population by sex and five-year age groups.
Eurostat. *epp.eurostat.ec.europa.eu*

FertilityRates
Indicator demo_frate - Fertility rates by age.
Eurostat. *epp.eurostat.ec.europa.eu*

DeathProbability
Indicator demo_mprob - Probability of dying by sex and age.
Eurostat. *epp.eurostat.ec.europa.eu*

Migration
Indicator 12511-0001 - Einbürgerungen von Ausländern.
Indicator 12521-0001 - Ausländer in Deutschland aus EU Staten.
Indicator 12711-0003 - Wanderungen Deutschland Ausland.
DESTATIS. Genesis Data Base. *www-genesis.destatis.de*

Used in the *educated population cohort model* described in section 4.4 on page 65.

B.5 Education data

Education Spending
Eurostat. *epp.eurostat.ec.europa.eu*
Expenditure on public and private educational institutions
Indicator Group: educ_fitotin
Annual expenditure on public and private educational institutions per pupil in EUR PPS
- at primary level of education, based on full-time equivalents
- at secondary level of education, based on full-time equivalents
- at tertiary level of education, based on full-time equivalents

Students
Eurostat. *epp.eurostat.ec.europa.eu*
Population and social conditions
Indicator: educ_enrl1tl
Students by ISCED level, age and sex

Appendix C

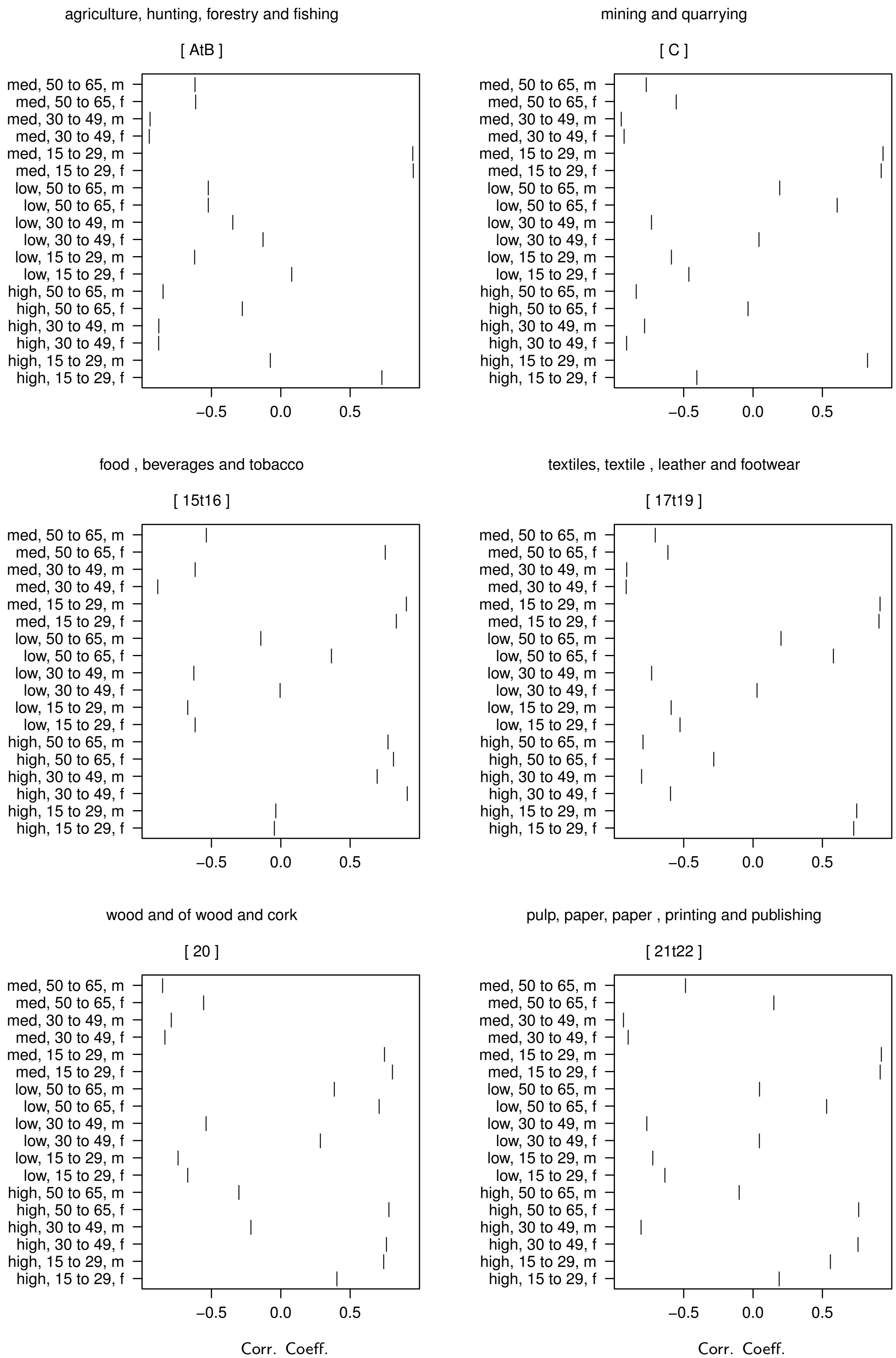
Results

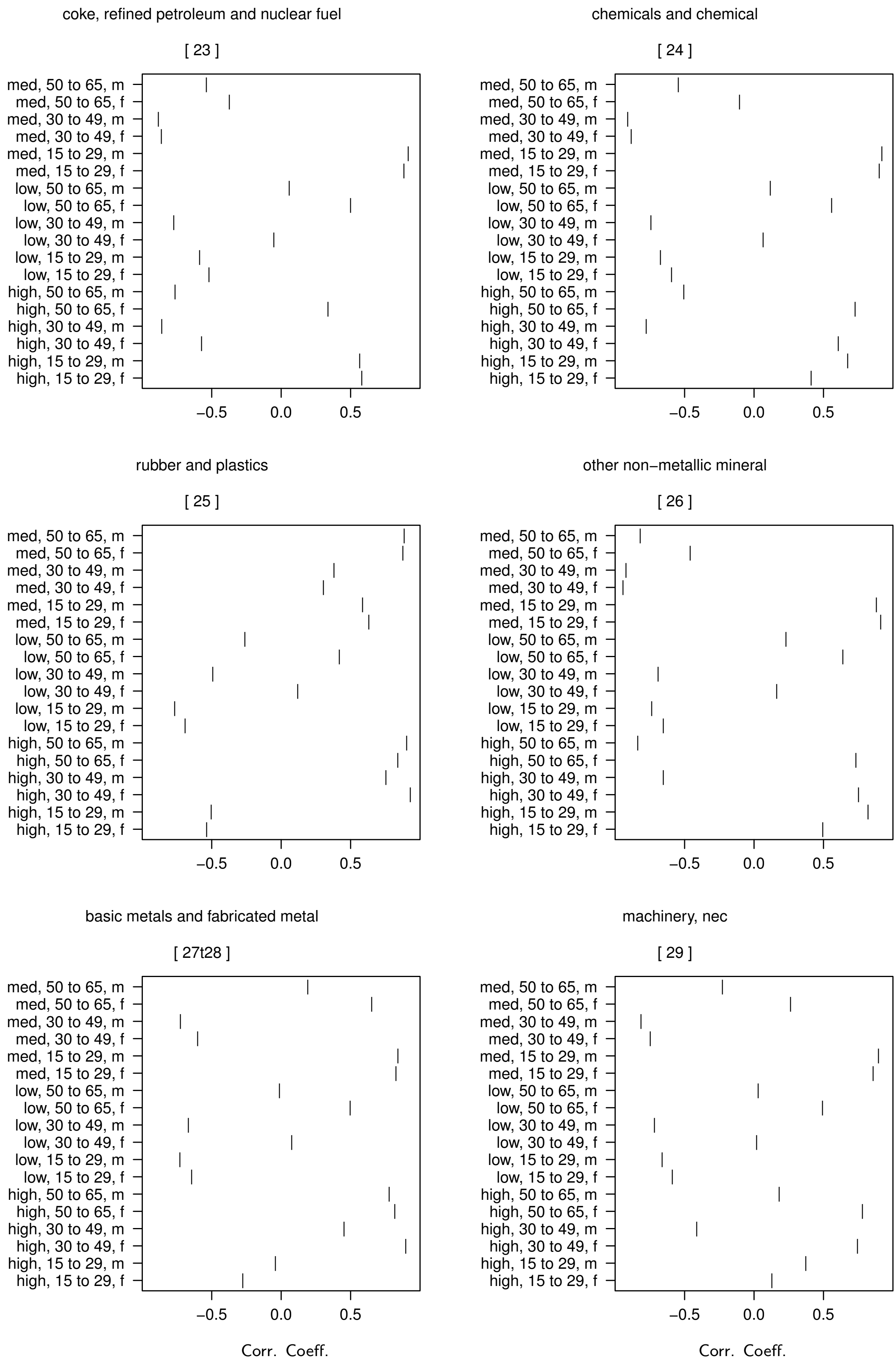
This chapter contains more detailed result data, too comprehensive to be included in the main part of the thesis.

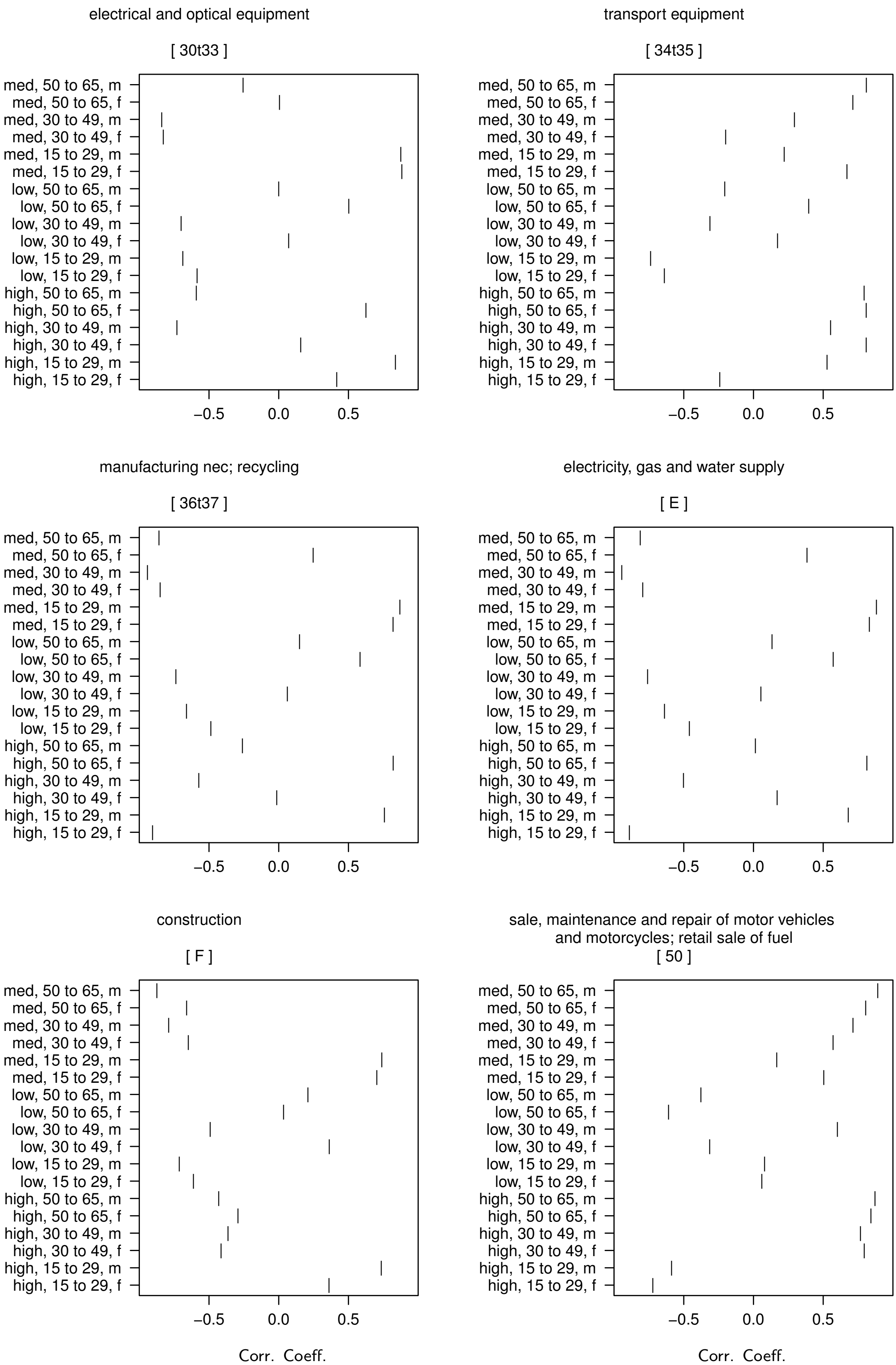
C.1 Education Level - Labour Input Correlation Coefficients

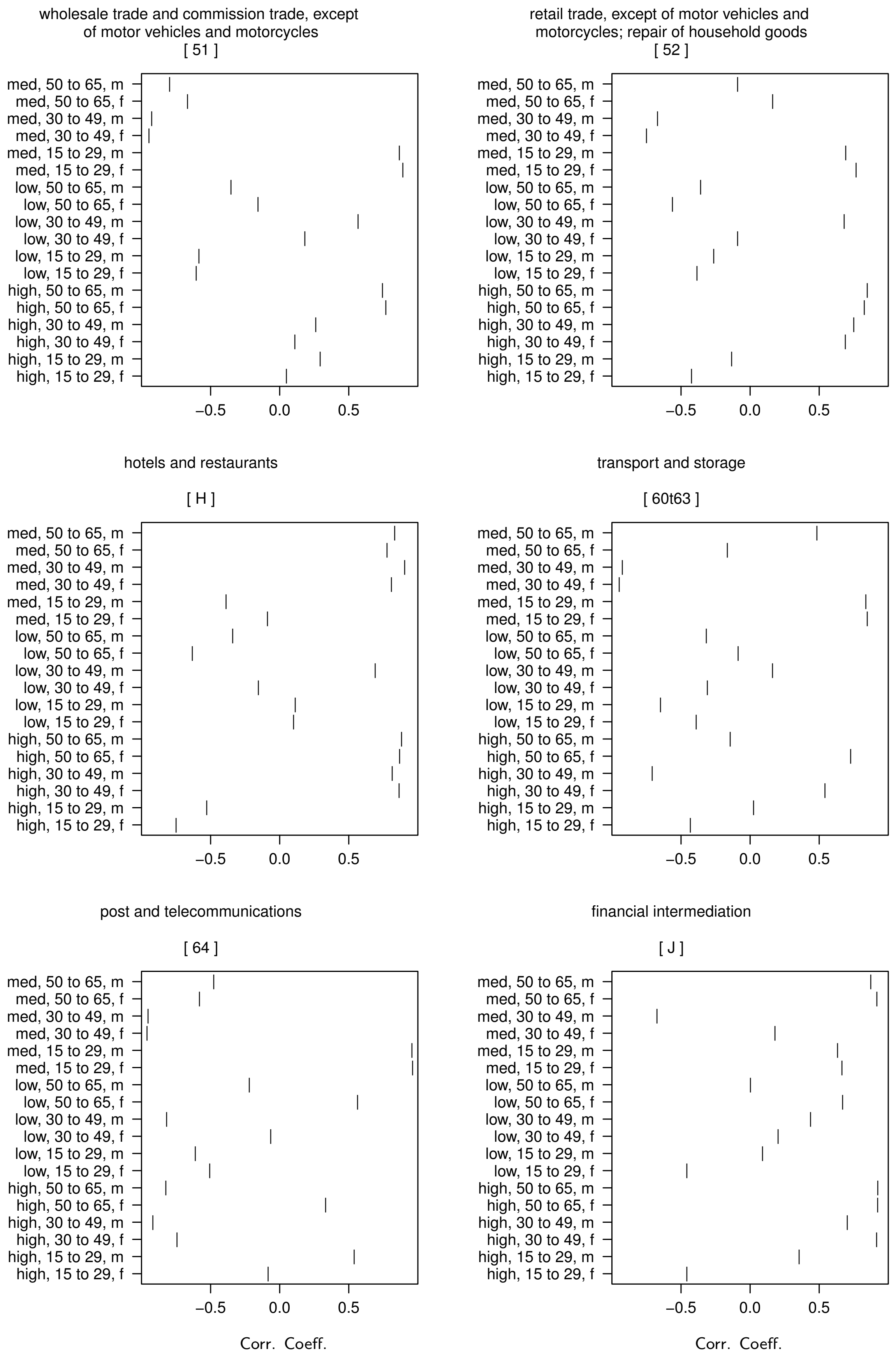
The following pages contain the detailed results of the correlation analysis between the education level in the population and the sectoral labour input described in section 4.3.2 on page 59.

First, the correlation coefficients are plotted as graphs. The complete set of graphs gives a visual impression of the differences of the correlations between industry sectors. Afterwards, the same numbers are also given in a table showing what figures were eventually used in *SEGESD*.


agriculture, hunting, forestry and fishing
[AtB]
mining and quarrying
[C]
food , beverages and tobacco
[15t16]
textiles, textile , leather and footwear
[17t19]
wood and of wood and cork
[20]
pulp, paper, paper , printing and publishing
[21t22]
med, 50 to 65, m
med, 50 to 65, f
med, 30 to 49, m
med, 30 to 49, f
med, 15 to 29, m
med, 15 to 29, f
low, 50 to 65, m
low, 50 to 65, f
low, 30 to 49, m
low, 30 to 49, f
low, 15 to 29, m
low, 15 to 29, f
high, 50 to 65, m
high, 50 to 65, f
high, 30 to 49, m
high, 30 to 49, f
high, 15 to 29, m
high, 15 to 29, f
–0.5
0.0
0.5
Corr. Coeff.
Corr. Coeff.


coke, refined petroleum and nuclear fuel
[23]
chemicals and chemical
[24]
rubber and plastics
[25]
other non−metallic mineral
[26]
basic metals and fabricated metal
[27t28]
machinery, nec
[29]
med, 50 to 65, m
med, 50 to 65, f
med, 30 to 49, m
med, 30 to 49, f
med, 15 to 29, m
med, 15 to 29, f
low, 50 to 65, m
low, 50 to 65, f
low, 30 to 49, m
low, 30 to 49, f
low, 15 to 29, m
low, 15 to 29, f
high, 50 to 65, m
high, 50 to 65, f
high, 30 to 49, m
high, 30 to 49, f
high, 15 to 29, m
high, 15 to 29, f
−0.5
0.0
0.5
Corr. Coeff.

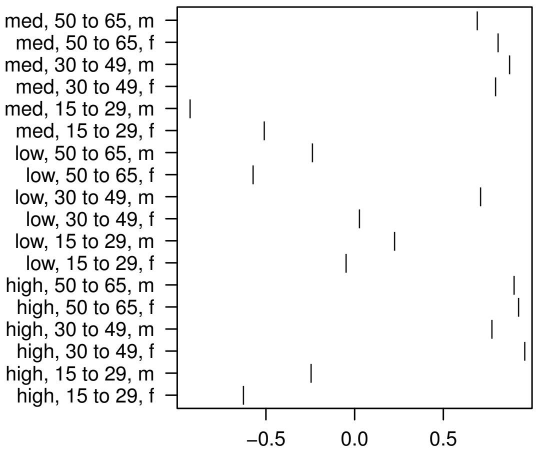

electrical and optical equipment
[30t33]
transport equipment
[34t35]
manufacturing nec; recycling
[36t37]
electricity, gas and water supply
[E]
construction
[F]
sale, maintenance and repair of motor vehicles
and motorcycles; retail sale of fuel
[50]
med, 50 to 65, m
med, 50 to 65, f
med, 30 to 49, m
med, 30 to 49, f
med, 15 to 29, m
med, 15 to 29, f
low, 50 to 65, m
low, 50 to 65, f
low, 30 to 49, m
low, 30 to 49, f
low, 15 to 29, m
low, 15 to 29, f
high, 50 to 65, m
high, 50 to 65, f
high, 30 to 49, m
high, 30 to 49, f
high, 15 to 29, m
high, 15 to 29, f
–0.5
0.0
0.5
Corr. Coeff.



wholesale trade and commission trade, except of motor vehicles and motorcycles
[51]
retail trade, except of motor vehicles and motorcycles; repair of household goods
[52]
hotels and restaurants
[H]
transport and storage
[60t63]
post and telecommunications
[64]
financial intermediation
[J]
med, 50 to 65, m
med, 50 to 65, f
med, 30 to 49, m
med, 30 to 49, f
med, 15 to 29, m
med, 15 to 29, f
low, 50 to 65, m
low, 50 to 65, f
low, 30 to 49, m
low, 30 to 49, f
low, 15 to 29, m
low, 15 to 29, f
high, 50 to 65, m
high, 50 to 65, f
high, 30 to 49, m
high, 30 to 49, f
high, 15 to 29, m
high, 15 to 29, f
–0.5
0.0
0.5
Corr. Coeff.

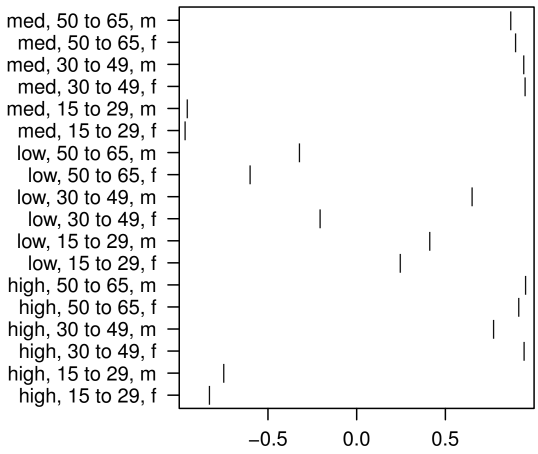
real estate activities

[70]



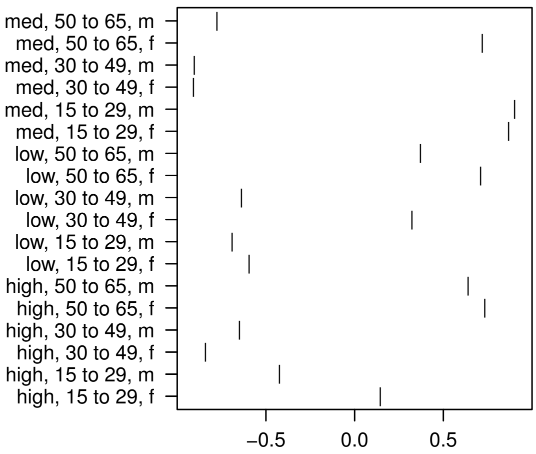
renting of m&eq and other business activities

[71t74]



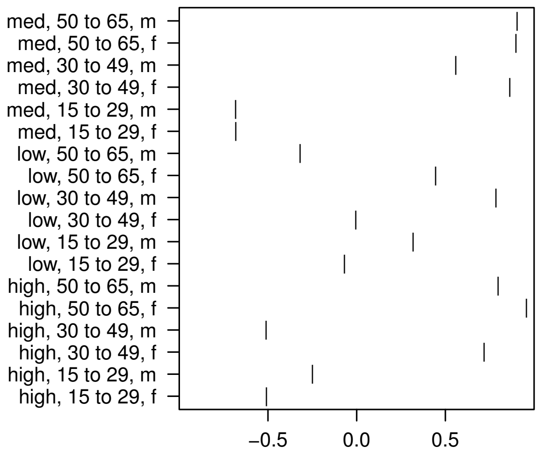
public admin and defence; compulsory social security

[L]



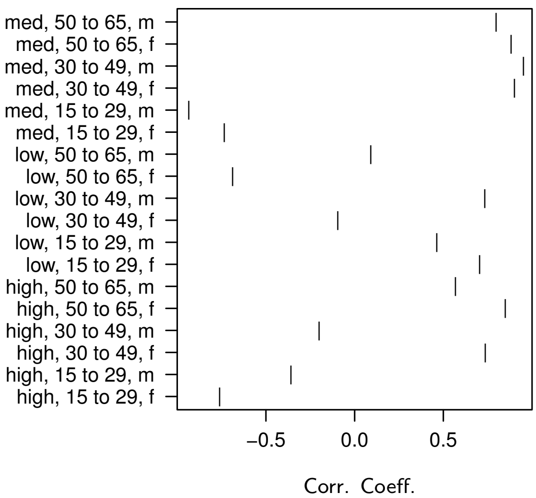
education

[M]



health and social work

[N]



other community, social and personal services

[O]

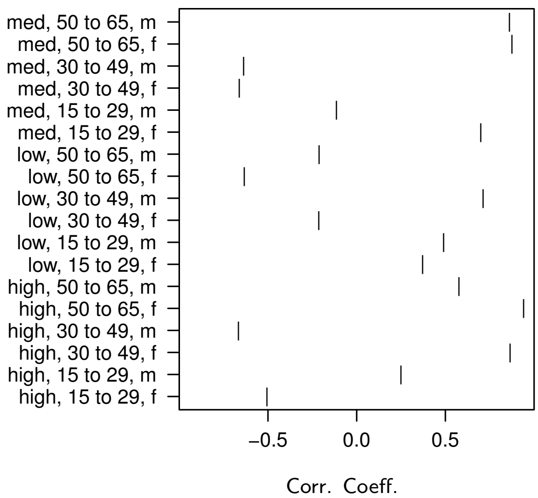


Table C.1
Education Level → Labour Input - Full correlation results

Sector	*Quali*	*Age*	*Sex*	*Cor. Coef.*	*p-Value*	*Inclination (β)*
AtB	low	15 to 29	m	-0.62	0.013552	-0.012993
AtB	low	15 to 29	f	0.08	0.777968	0.001105
AtB	low	30 to 49	m	-0.35	0.207621	-0.021501
AtB	low	30 to 49	f	-0.13	0.649496	-0.009838
AtB	low	50 to 65	m	-0.52	0.045844	-0.011076
AtB	low	50 to 65	f	-0.52	0.045738	-0.005621
AtB	med	15 to 29	m	0.95	0.000000	0.099070
AtB	med	15 to 29	f	0.96	0.000000	0.063153
AtB	med	30 to 49	m	-0.94	0.000000	-0.330058
AtB	med	30 to 49	f	-0.95	0.000000	-0.184525
AtB	med	50 to 65	m	-0.62	0.014081	-0.051990
AtB	med	50 to 65	f	-0.61	0.014969	-0.025253
AtB	high	15 to 29	m	-0.07	0.791100	-0.000537
AtB	high	15 to 29	f	0.73	0.002046	0.006477
AtB	high	30 to 49	m	-0.88	0.000016	-0.034663
AtB	high	30 to 49	f	-0.88	0.000015	-0.008072
AtB	high	50 to 65	m	-0.85	0.000065	-0.009687
AtB	high	50 to 65	f	-0.28	0.317769	-0.000576
C	low	15 to 29	m	-0.59	0.021081	-0.006831
C	low	15 to 29	f	-0.46	0.082776	-0.001670
C	low	30 to 49	m	-0.73	0.001919	-0.051068
C	low	30 to 49	f	0.04	0.877198	0.001568
C	low	50 to 65	m	0.19	0.490720	0.004482
C	low	50 to 65	f	0.61	0.016332	0.003896
C	med	15 to 29	m	0.94	0.000000	0.015526
C	med	15 to 29	f	0.92	0.000001	0.005644
C	med	30 to 49	m	-0.95	0.000000	-0.071764
C	med	30 to 49	f	-0.93	0.000001	-0.014625
C	med	50 to 65	m	-0.77	0.000809	-0.015925
C	med	50 to 65	f	-0.55	0.032348	-0.001790
C	high	15 to 29	m	0.83	0.000150	0.002295
C	high	15 to 29	f	-0.40	0.134640	-0.000371
C	high	30 to 49	m	-0.78	0.000580	-0.013577
C	high	30 to 49	f	-0.91	0.000002	-0.001659
C	high	50 to 65	m	-0.84	0.000084	-0.002799
C	high	50 to 65	f	-0.04	0.899585	-0.000010
15t16	low	15 to 29	m	-0.67	0.006254	-0.007147
15t16	low	15 to 29	f	-0.62	0.014294	-0.013804
15t16	low	30 to 49	m	-0.63	0.012508	-0.015376
15t16	low	30 to 49	f	0.00	0.986860	-0.000512
15t16	low	50 to 65	m	-0.14	0.610836	-0.001398
15t16	low	50 to 65	f	0.37	0.179797	0.005378
15t16	med	15 to 29	m	0.91	0.000003	0.011607
15t16	med	15 to 29	f	0.83	0.000113	0.025521
15t16	med	30 to 49	m	-0.62	0.014256	-0.013855
15t16	med	30 to 49	f	-0.89	0.000011	-0.023239
15t16	med	50 to 65	m	-0.54	0.039477	-0.004141
15t16	med	50 to 65	f	0.75	0.001171	0.007342
15t16	high	15 to 29	m	-0.04	0.901305	-0.000037
15t16	high	15 to 29	f	-0.05	0.870481	-0.000481
15t16	high	30 to 49	m	0.70	0.004019	0.003718
15t16	high	30 to 49	f	0.91	0.000002	0.005682
15t16	high	50 to 65	m	0.77	0.000717	0.001846
15t16	high	50 to 65	f	0.81	0.000230	0.001406
17t19	low	15 to 29	m	-0.59	0.020577	-0.010924
17t19	low	15 to 29	f	-0.53	0.043972	-0.011186
17t19	low	30 to 49	m	-0.73	0.001981	-0.053025

Sector	*Quali*	*Age*	*Sex*	*Cor. Coef.*	*p-Value*	*Inclination (β)*
17t19	low	30 to 49	f	0.03	0.917007	0.004020
17t19	low	50 to 65	m	0.20	0.470577	0.005822
17t19	low	50 to 65	f	0.58	0.023518	0.013066
17t19	med	15 to 29	m	0.92	0.000002	0.022077
17t19	med	15 to 29	f	0.91	0.000003	0.034189
17t19	med	30 to 49	m	-0.91	0.000002	-0.076237
17t19	med	30 to 49	f	-0.91	0.000002	-0.069733
17t19	med	50 to 65	m	-0.70	0.003360	-0.018064
17t19	med	50 to 65	f	-0.61	0.015024	-0.011296
17t19	high	15 to 29	m	0.75	0.001339	0.001260
17t19	high	15 to 29	f	0.73	0.002155	0.004729
17t19	high	30 to 49	m	-0.80	0.000309	-0.006720
17t19	high	30 to 49	f	-0.59	0.019329	-0.000943
17t19	high	50 to 65	m	-0.79	0.000420	-0.000713
17t19	high	50 to 65	f	-0.28	0.308051	-0.000100
20	low	15 to 29	m	-0.74	0.001628	-0.006850
20	low	15 to 29	f	-0.67	0.006241	-0.002718
20	low	30 to 49	m	-0.54	0.038600	-0.018082
20	low	30 to 49	f	0.29	0.301311	0.007156
20	low	50 to 65	m	0.39	0.155085	0.004442
20	low	50 to 65	f	0.71	0.003027	0.002558
20	med	15 to 29	m	0.75	0.001327	0.008500
20	med	15 to 29	f	0.81	0.000294	0.003987
20	med	30 to 49	m	-0.79	0.000474	-0.027321
20	med	30 to 49	f	-0.83	0.000108	-0.007595
20	med	50 to 65	m	-0.85	0.000056	-0.006539
20	med	50 to 65	f	-0.56	0.031430	-0.000642
20	high	15 to 29	m	0.74	0.001520	0.001135
20	high	15 to 29	f	0.41	0.134109	0.000921
20	high	30 to 49	m	-0.21	0.442728	-0.001352
20	high	30 to 49	f	0.76	0.000951	0.000739
20	high	50 to 65	m	-0.30	0.274577	-0.000246
20	high	50 to 65	f	0.78	0.000609	0.000310
21t22	low	15 to 29	m	-0.72	0.002357	-0.017855
21t22	low	15 to 29	f	-0.63	0.011036	-0.007325
21t22	low	30 to 49	m	-0.77	0.000872	-0.070488
21t22	low	30 to 49	f	0.05	0.870823	0.003328
21t22	low	50 to 65	m	0.05	0.868288	0.001540
21t22	low	50 to 65	f	0.53	0.041787	0.005789
21t22	med	15 to 29	m	0.93	0.000001	0.025089
21t22	med	15 to 29	f	0.92	0.000002	0.011289
21t22	med	30 to 49	m	-0.93	0.000000	-0.074650
21t22	med	30 to 49	f	-0.90	0.000005	-0.020426
21t22	med	50 to 65	m	-0.49	0.066163	-0.008992
21t22	med	50 to 65	f	0.15	0.593224	0.000714
21t22	high	15 to 29	m	0.56	0.030583	0.001453
21t22	high	15 to 29	f	0.19	0.500899	0.000794
21t22	high	30 to 49	m	-0.81	0.000276	-0.007091
21t22	high	30 to 49	f	0.76	0.001074	0.002715
21t22	high	50 to 65	m	-0.10	0.725466	-0.000145
21t22	high	50 to 65	f	0.76	0.000957	0.001049
23	low	15 to 29	m	-0.59	0.021458	-0.001308
23	low	15 to 29	f	-0.52	0.047175	-0.000474
23	low	30 to 49	m	-0.77	0.000729	-0.008115
23	low	30 to 49	f	-0.05	0.853015	-0.000341
23	low	50 to 65	m	0.06	0.834681	0.000240
23	low	50 to 65	f	0.50	0.057798	0.000546
23	med	15 to 29	m	0.92	0.000002	0.002655
23	med	15 to 29	f	0.88	0.000012	0.001152
23	med	30 to 49	m	-0.88	0.000012	-0.009988
23	med	30 to 49	f	-0.86	0.000035	-0.002737

Sector	*Quali*	*Age*	*Sex*	*Cor. Coef.*	*p-Value*	*Inclination (β)*
23	med	50 to 65	m	-0.54	0.038517	-0.001609
23	med	50 to 65	f	-0.37	0.170971	-0.000253
23	high	15 to 29	m	0.57	0.027900	0.000240
23	high	15 to 29	f	0.58	0.023197	0.000287
23	high	30 to 49	m	-0.86	0.000041	-0.001868
23	high	30 to 49	f	-0.57	0.025532	-0.000150
23	high	50 to 65	m	-0.76	0.000926	-0.000276
23	high	50 to 65	f	0.34	0.218329	0.000016
24	low	15 to 29	m	-0.67	0.005872	-0.015414
24	low	15 to 29	f	-0.59	0.019690	-0.006150
24	low	30 to 49	m	-0.74	0.001545	-0.068148
24	low	30 to 49	f	0.07	0.816755	0.004417
24	low	50 to 65	m	0.12	0.677604	0.003943
24	low	50 to 65	f	0.56	0.030139	0.005875
24	med	15 to 29	m	0.92	0.000001	0.024273
24	med	15 to 29	f	0.90	0.000004	0.010852
24	med	30 to 49	m	-0.91	0.000003	-0.077983
24	med	30 to 49	f	-0.88	0.000012	-0.021552
24	med	50 to 65	m	-0.55	0.035573	-0.011306
24	med	50 to 65	f	-0.10	0.712086	-0.000502
24	high	15 to 29	m	0.67	0.005784	0.001937
24	high	15 to 29	f	0.41	0.127278	0.001601
24	high	30 to 49	m	-0.78	0.000666	-0.009164
24	high	30 to 49	f	0.61	0.016517	0.001424
24	high	50 to 65	m	-0.51	0.054783	-0.000901
24	high	50 to 65	f	0.73	0.002080	0.000746
25	low	15 to 29	m	-0.77	0.000863	-0.006699
25	low	15 to 29	f	-0.69	0.004352	-0.003238
25	low	30 to 49	m	-0.49	0.062504	-0.009376
25	low	30 to 49	f	0.12	0.670997	0.002861
25	low	50 to 65	m	-0.26	0.346968	-0.001838
25	low	50 to 65	f	0.42	0.119455	0.001252
25	med	15 to 29	m	0.59	0.021555	0.003777
25	med	15 to 29	f	0.63	0.011506	0.001909
25	med	30 to 49	m	0.38	0.161482	0.004299
25	med	30 to 49	f	0.30	0.269738	0.001309
25	med	50 to 65	m	0.89	0.000011	0.005655
25	med	50 to 65	f	0.88	0.000018	0.003005
25	high	15 to 29	m	-0.50	0.055720	-0.000780
25	high	15 to 29	f	-0.54	0.039305	-0.001673
25	high	30 to 49	m	0.76	0.001137	0.006969
25	high	30 to 49	f	0.93	0.000000	0.003808
25	high	50 to 65	m	0.90	0.000004	0.002033
25	high	50 to 65	f	0.84	0.000089	0.000893
26	low	15 to 29	m	-0.74	0.001748	-0.010323
26	low	15 to 29	f	-0.65	0.008308	-0.004041
26	low	30 to 49	m	-0.69	0.004356	-0.037145
26	low	30 to 49	f	0.16	0.559972	0.006458
26	low	50 to 65	m	0.23	0.408800	0.004378
26	low	50 to 65	f	0.64	0.010228	0.003790
26	med	15 to 29	m	0.88	0.000014	0.014867
26	med	15 to 29	f	0.91	0.000002	0.006795
26	med	30 to 49	m	-0.92	0.000001	-0.048622
26	med	30 to 49	f	-0.94	0.000000	-0.013435
26	med	50 to 65	m	-0.82	0.000189	-0.009827
26	med	50 to 65	f	-0.46	0.084664	-0.000969
26	high	15 to 29	m	0.82	0.000173	0.001659
26	high	15 to 29	f	0.49	0.060812	0.001413
26	high	30 to 49	m	-0.65	0.008374	-0.005170
26	high	30 to 49	f	0.75	0.001200	0.000632
26	high	50 to 65	m	-0.84	0.000100	-0.000752

Sector	*Quali*	*Age*	*Sex*	*Cor. Coef.*	*p-Value*	*Inclination (β)*
26	high	50 to 65	f	0.73	0.001829	0.000406
27t28	low	15 to 29	m	-0.73	0.002052	-0.023251
27t28	low	15 to 29	f	-0.64	0.009566	-0.010352
27t28	low	30 to 49	m	-0.67	0.006490	-0.067515
27t28	low	30 to 49	f	0.08	0.786481	0.007158
27t28	low	50 to 65	m	-0.01	0.965223	-0.000441
27t28	low	50 to 65	f	0.50	0.059261	0.006686
27t28	med	15 to 29	m	0.84	0.000086	0.024927
27t28	med	15 to 29	f	0.83	0.000142	0.011482
27t28	med	30 to 49	m	-0.72	0.002229	-0.048725
27t28	med	30 to 49	f	-0.60	0.017908	-0.012986
27t28	med	50 to 65	m	0.19	0.493149	0.003480
27t28	med	50 to 65	f	0.65	0.008421	0.005563
27t28	high	15 to 29	m	-0.04	0.883993	-0.000123
27t28	high	15 to 29	f	-0.28	0.319331	-0.001832
27t28	high	30 to 49	m	0.45	0.089580	0.006678
27t28	high	30 to 49	f	0.90	0.000006	0.008181
27t28	high	50 to 65	m	0.78	0.000629	0.003280
27t28	high	50 to 65	f	0.82	0.000188	0.002210
29	low	15 to 29	m	-0.66	0.007246	-0.027973
29	low	15 to 29	f	-0.59	0.021121	-0.011732
29	low	30 to 49	m	-0.72	0.002631	-0.118739
29	low	30 to 49	f	0.02	0.947902	0.002350
29	low	50 to 65	m	0.03	0.915238	0.001855
29	low	50 to 65	f	0.49	0.061432	0.009769
29	med	15 to 29	m	0.90	0.000006	0.040884
29	med	15 to 29	f	0.86	0.000044	0.018182
29	med	30 to 49	m	-0.81	0.000224	-0.118179
29	med	30 to 49	f	-0.75	0.001384	-0.031980
29	med	50 to 65	m	-0.23	0.415516	-0.008456
29	med	50 to 65	f	0.26	0.343129	0.002855
29	high	15 to 29	m	0.37	0.170680	0.001666
29	high	15 to 29	f	0.13	0.647877	0.000854
29	high	30 to 49	m	-0.41	0.127142	-0.008415
29	high	30 to 49	f	0.75	0.001427	0.005678
29	high	50 to 65	m	0.18	0.517479	0.000774
29	high	50 to 65	f	0.78	0.000588	0.001953
30t33	low	15 to 29	m	-0.69	0.004611	-0.020337
30t33	low	15 to 29	f	-0.58	0.022129	-0.013964
30t33	low	30 to 49	m	-0.70	0.003722	-0.071077
30t33	low	30 to 49	f	0.07	0.800647	0.011245
30t33	low	50 to 65	m	0.00	0.999525	0.000007
30t33	low	50 to 65	f	0.50	0.055998	0.009922
30t33	med	15 to 29	m	0.88	0.000019	0.041699
30t33	med	15 to 29	f	0.88	0.000013	0.026348
30t33	med	30 to 49	m	-0.84	0.000095	-0.138083
30t33	med	30 to 49	f	-0.83	0.000140	-0.042091
30t33	med	50 to 65	m	-0.26	0.358796	-0.009807
30t33	med	50 to 65	f	0.01	0.982932	0.000053
30t33	high	15 to 29	m	0.84	0.000097	0.025484
30t33	high	15 to 29	f	0.42	0.122718	0.007145
30t33	high	30 to 49	m	-0.73	0.002011	-0.057137
30t33	high	30 to 49	f	0.16	0.572909	0.001120
30t33	high	50 to 65	m	-0.59	0.020563	-0.005124
30t33	high	50 to 65	f	0.63	0.012634	0.001153
34t35	low	15 to 29	m	-0.74	0.001711	-0.010608
34t35	low	15 to 29	f	-0.64	0.010354	-0.008533
34t35	low	30 to 49	m	-0.31	0.257553	-0.011316
34t35	low	30 to 49	f	0.17	0.537934	0.013442
34t35	low	50 to 65	m	-0.21	0.461390	-0.003570
34t35	low	50 to 65	f	0.40	0.143070	0.003254

Sector	*Quali*	*Age*	*Sex*	*Cor. Coef.*	*p-Value*	*Inclination (β)*
34t35	med	15 to 29	m	0.22	0.428740	0.002929
34t35	med	15 to 29	f	0.67	0.006180	0.007919
34t35	med	30 to 49	m	0.29	0.286898	0.014823
34t35	med	30 to 49	f	-0.20	0.477222	-0.003146
34t35	med	50 to 65	m	0.81	0.000252	0.018756
34t35	med	50 to 65	f	0.71	0.002861	0.004463
34t35	high	15 to 29	m	0.53	0.043150	0.008292
34t35	high	15 to 29	f	-0.24	0.387091	-0.002463
34t35	high	30 to 49	m	0.55	0.032221	0.021427
34t35	high	30 to 49	f	0.81	0.000258	0.006324
34t35	high	50 to 65	m	0.79	0.000408	0.005978
34t35	high	50 to 65	f	0.81	0.000261	0.001546
36t37	low	15 to 29	m	-0.66	0.007276	-0.009552
36t37	low	15 to 29	f	-0.49	0.065804	-0.002194
36t37	low	30 to 49	m	-0.74	0.001721	-0.057138
36t37	low	30 to 49	f	0.06	0.824222	0.002729
36t37	low	50 to 65	m	0.15	0.594260	0.003685
36t37	low	50 to 65	f	0.58	0.022437	0.004271
36t37	med	15 to 29	m	0.87	0.000026	0.015859
36t37	med	15 to 29	f	0.82	0.000178	0.005054
36t37	med	30 to 49	m	-0.94	0.000000	-0.058528
36t37	med	30 to 49	f	-0.85	0.000061	-0.008620
36t37	med	50 to 65	m	-0.86	0.000042	-0.014697
36t37	med	50 to 65	f	0.25	0.373942	0.000589
36t37	high	15 to 29	m	0.76	0.001049	0.002134
36t37	high	15 to 29	f	-0.90	0.000004	-0.003795
36t37	high	30 to 49	m	-0.57	0.025589	-0.007437
36t37	high	30 to 49	f	-0.01	0.960016	-0.000012
36t37	high	50 to 65	m	-0.26	0.349500	-0.000473
36t37	high	50 to 65	f	0.82	0.000173	0.000780
E	low	15 to 29	m	-0.64	0.010595	-0.008858
E	low	15 to 29	f	-0.46	0.084728	-0.001996
E	low	30 to 49	m	-0.76	0.001030	-0.055793
E	low	30 to 49	f	0.05	0.850681	0.002220
E	low	50 to 65	m	0.13	0.635232	0.003116
E	low	50 to 65	f	0.57	0.025866	0.004030
E	med	15 to 29	m	0.88	0.000014	0.015397
E	med	15 to 29	f	0.83	0.000121	0.004840
E	med	30 to 49	m	-0.94	0.000000	-0.053743
E	med	30 to 49	f	-0.79	0.000416	-0.007452
E	med	50 to 65	m	-0.81	0.000236	-0.013049
E	med	50 to 65	f	0.38	0.157582	0.001083
E	high	15 to 29	m	0.68	0.005232	0.002013
E	high	15 to 29	f	-0.89	0.000009	-0.003931
E	high	30 to 49	m	-0.50	0.057002	-0.006362
E	high	30 to 49	f	0.17	0.544907	0.000232
E	high	50 to 65	m	0.01	0.959966	0.000034
E	high	50 to 65	f	0.81	0.000223	0.000883
F	low	15 to 29	m	-0.71	0.002862	-0.119087
F	low	15 to 29	f	-0.61	0.015418	-0.006096
F	low	30 to 49	m	-0.49	0.063137	-0.123643
F	low	30 to 49	f	0.36	0.184255	0.009930
F	low	50 to 65	m	0.21	0.452938	0.020993
F	low	50 to 65	f	0.04	0.901296	0.000293
F	med	15 to 29	m	0.74	0.001633	0.198657
F	med	15 to 29	f	0.70	0.003389	0.021547
F	med	30 to 49	m	-0.79	0.000478	-0.413854
F	med	30 to 49	f	-0.65	0.009057	-0.036511
F	med	50 to 65	m	-0.87	0.000021	-0.095178
F	med	50 to 65	f	-0.66	0.007359	-0.006879
F	high	15 to 29	m	0.74	0.001756	0.012076

Sector	*Quali*	*Age*	*Sex*	*Cor. Coef.*	*p-Value*	*Inclination (β)*
F	high	15 to 29	f	0.36	0.186048	0.003200
F	high	30 to 49	m	-0.36	0.183775	-0.016147
F	high	30 to 49	f	-0.41	0.125648	-0.002055
F	high	50 to 65	m	-0.43	0.109313	-0.002610
F	high	50 to 65	f	-0.29	0.290990	-0.000281
50	low	15 to 29	m	0.08	0.776845	0.001237
50	low	15 to 29	f	0.06	0.831935	0.000647
50	low	30 to 49	m	0.60	0.017593	0.038500
50	low	30 to 49	f	-0.31	0.254274	-0.017984
50	low	50 to 65	m	-0.38	0.165974	-0.012787
50	low	50 to 65	f	-0.61	0.015966	-0.009272
50	med	15 to 29	m	0.17	0.551655	0.000920
50	med	15 to 29	f	0.50	0.054925	0.003871
50	med	30 to 49	m	0.71	0.002772	0.016359
50	med	30 to 49	f	0.57	0.026236	0.010749
50	med	50 to 65	m	0.89	0.000008	0.010660
50	med	50 to 65	f	0.80	0.000296	0.009532
50	high	15 to 29	m	-0.59	0.021501	-0.002202
50	high	15 to 29	f	-0.72	0.002402	-0.005480
50	high	30 to 49	m	0.77	0.000843	0.011363
50	high	30 to 49	f	0.80	0.000395	0.003871
50	high	50 to 65	m	0.87	0.000023	0.002804
50	high	50 to 65	f	0.84	0.000081	0.001925
51	low	15 to 29	m	-0.58	0.022178	-0.016613
51	low	15 to 29	f	-0.60	0.017210	-0.016242
51	low	30 to 49	m	0.57	0.027332	0.025558
51	low	30 to 49	f	0.18	0.515170	0.006945
51	low	50 to 65	m	-0.35	0.198503	-0.010173
51	low	50 to 65	f	-0.16	0.577510	-0.001548
51	med	15 to 29	m	0.87	0.000029	0.045622
51	med	15 to 29	f	0.89	0.000008	0.061221
51	med	30 to 49	m	-0.93	0.000001	-0.105094
51	med	30 to 49	f	-0.95	0.000000	-0.099085
51	med	50 to 65	m	-0.80	0.000378	-0.018873
51	med	50 to 65	f	-0.67	0.006614	-0.013170
51	high	15 to 29	m	0.29	0.288906	0.001830
51	high	15 to 29	f	0.05	0.862162	0.000591
51	high	30 to 49	m	0.26	0.347305	0.002318
51	high	30 to 49	f	0.11	0.694786	0.000493
51	high	50 to 65	m	0.74	0.001468	0.002201
51	high	50 to 65	f	0.77	0.000812	0.002543
52	low	15 to 29	m	-0.26	0.343477	-0.011134
52	low	15 to 29	f	-0.38	0.157164	-0.011953
52	low	30 to 49	m	0.68	0.005183	0.087253
52	low	30 to 49	f	-0.09	0.748256	-0.007014
52	low	50 to 65	m	-0.36	0.190669	-0.025874
52	low	50 to 65	f	-0.56	0.029319	-0.015482
52	med	15 to 29	m	0.69	0.004199	0.034480
52	med	15 to 29	f	0.77	0.000841	0.051981
52	med	30 to 49	m	-0.67	0.006361	-0.047584
52	med	30 to 49	f	-0.75	0.001308	-0.053922
52	med	50 to 65	m	-0.09	0.748636	-0.000940
52	med	50 to 65	f	0.16	0.561155	0.002435
52	high	15 to 29	m	-0.13	0.636403	-0.001366
52	high	15 to 29	f	-0.42	0.115639	-0.007815
52	high	30 to 49	m	0.75	0.001262	0.021283
52	high	30 to 49	f	0.69	0.004439	0.006523
52	high	50 to 65	m	0.85	0.000063	0.006072
52	high	50 to 65	f	0.83	0.000145	0.004956
H	low	15 to 29	m	0.11	0.688515	0.003431
H	low	15 to 29	f	0.10	0.721900	0.002236

Sector	*Quali*	*Age*	*Sex*	*Cor. Coef.*	*p-Value*	*Inclination (β)*
H	low	30 to 49	m	0.69	0.004303	0.075980
H	low	30 to 49	f	-0.15	0.584069	-0.015477
H	low	50 to 65	m	-0.34	0.215152	-0.019268
H	low	50 to 65	f	-0.63	0.011509	-0.015935
H	med	15 to 29	m	-0.39	0.153433	-0.005864
H	med	15 to 29	f	-0.09	0.754653	-0.001609
H	med	30 to 49	m	0.90	0.000004	0.048884
H	med	30 to 49	f	0.81	0.000258	0.035613
H	med	50 to 65	m	0.83	0.000117	0.018534
H	med	50 to 65	f	0.78	0.000656	0.015913
H	high	15 to 29	m	-0.53	0.043169	-0.003737
H	high	15 to 29	f	-0.75	0.001295	-0.010056
H	high	30 to 49	m	0.81	0.000217	0.022067
H	high	30 to 49	f	0.86	0.000032	0.007096
H	high	50 to 65	m	0.88	0.000013	0.004808
H	high	50 to 65	f	0.87	0.000027	0.003190
60t63	low	15 to 29	m	-0.65	0.008965	-0.011305
60t63	low	15 to 29	f	-0.39	0.151433	-0.003421
60t63	low	30 to 49	m	0.16	0.561738	0.015277
60t63	low	30 to 49	f	-0.31	0.262791	-0.007616
60t63	low	50 to 65	m	-0.32	0.250802	-0.040860
60t63	low	50 to 65	f	-0.09	0.760522	-0.000417
60t63	med	15 to 29	m	0.84	0.000095	0.070110
60t63	med	15 to 29	f	0.85	0.000063	0.048542
60t63	med	30 to 49	m	-0.92	0.000001	-0.151300
60t63	med	30 to 49	f	-0.95	0.000000	-0.070372
60t63	med	50 to 65	m	0.48	0.067452	0.017085
60t63	med	50 to 65	f	-0.16	0.557801	-0.001513
60t63	high	15 to 29	m	0.03	0.928306	0.000242
60t63	high	15 to 29	f	-0.43	0.107552	-0.011603
60t63	high	30 to 49	m	-0.71	0.003153	-0.012801
60t63	high	30 to 49	f	0.54	0.036978	0.003445
60t63	high	50 to 65	m	-0.14	0.610003	-0.000472
60t63	high	50 to 65	f	0.73	0.002103	0.002663
64	low	15 to 29	m	-0.61	0.015628	-0.007020
64	low	15 to 29	f	-0.51	0.054084	-0.002665
64	low	30 to 49	m	-0.82	0.000193	-0.040769
64	low	30 to 49	f	-0.06	0.819862	-0.001352
64	low	50 to 65	m	-0.22	0.431940	-0.005376
64	low	50 to 65	f	0.56	0.028582	0.001915
64	med	15 to 29	m	0.96	0.000000	0.035826
64	med	15 to 29	f	0.96	0.000000	0.025578
64	med	30 to 49	m	-0.95	0.000000	-0.107690
64	med	30 to 49	f	-0.96	0.000000	-0.046962
64	med	50 to 65	m	-0.48	0.072361	-0.010148
64	med	50 to 65	f	-0.58	0.023250	-0.004609
64	high	15 to 29	m	0.54	0.038069	0.002096
64	high	15 to 29	f	-0.08	0.768130	-0.000410
64	high	30 to 49	m	-0.92	0.000001	-0.011988
64	high	30 to 49	f	-0.74	0.001514	-0.001618
64	high	50 to 65	m	-0.82	0.000160	-0.001592
64	high	50 to 65	f	0.33	0.226110	0.000223
J	low	15 to 29	m	0.09	0.749569	0.000153
J	low	15 to 29	f	-0.46	0.086570	-0.002365
J	low	30 to 49	m	0.44	0.102540	0.004216
J	low	30 to 49	f	0.20	0.469011	0.014216
J	low	50 to 65	m	0.00	0.991909	0.000017
J	low	50 to 65	f	0.67	0.006309	0.013450
J	med	15 to 29	m	0.63	0.011250	0.013014
J	med	15 to 29	f	0.66	0.006840	0.040169
J	med	30 to 49	m	-0.67	0.005950	-0.014832

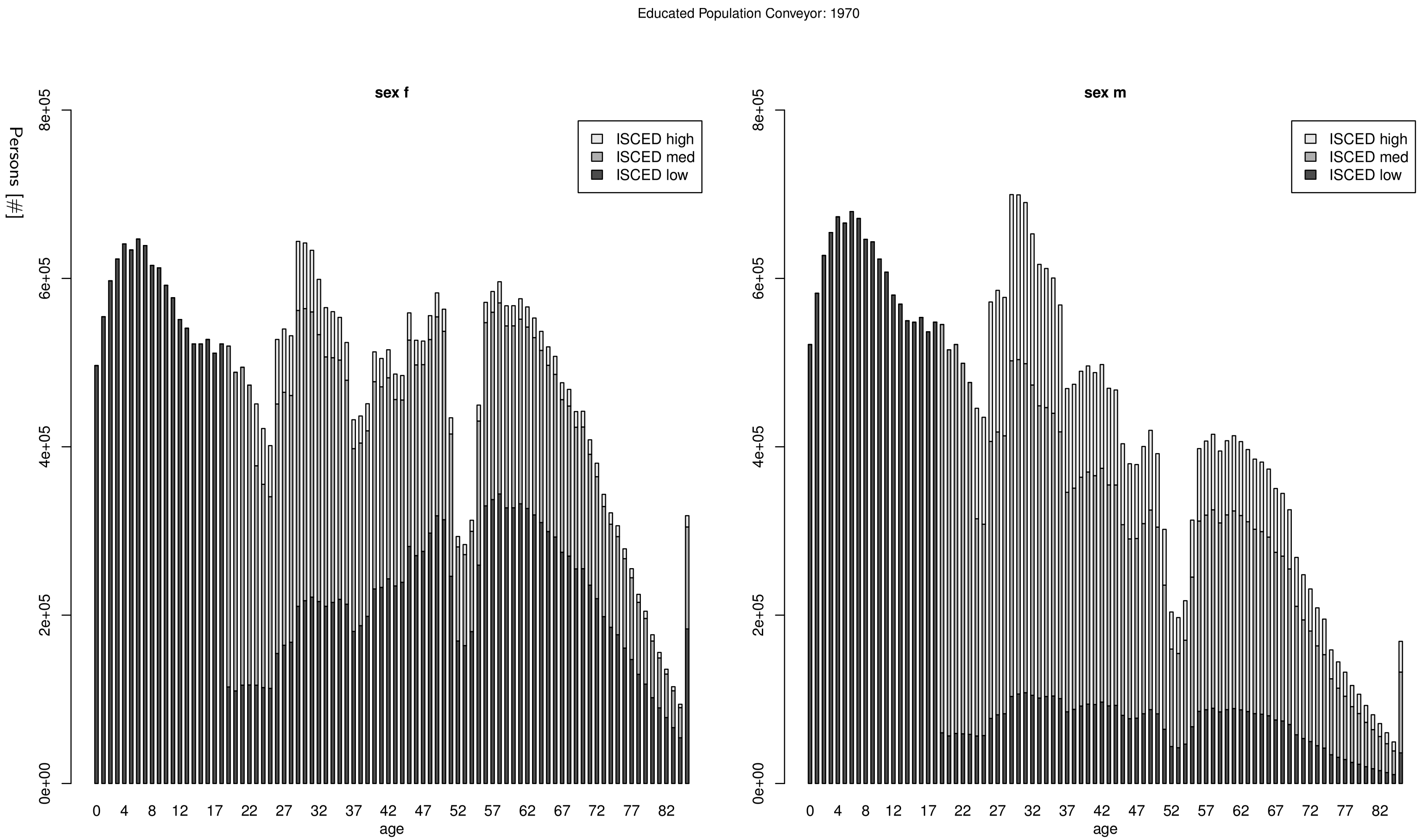
Sector	*Quali*	*Age*	*Sex*	*Cor. Coef.*	*p-Value*	*Inclination (β)*
J	med	30 to 49	f	0.18	0.518948	0.003870
J	med	50 to 65	m	0.87	0.000021	0.009911
J	med	50 to 65	f	0.92	0.000001	0.023538
J	high	15 to 29	m	0.36	0.193836	0.008220
J	high	15 to 29	f	-0.46	0.086356	-0.012985
J	high	30 to 49	m	0.70	0.003401	0.038371
J	high	30 to 49	f	0.92	0.000002	0.025920
J	high	50 to 65	m	0.92	0.000001	0.011002
J	high	50 to 65	f	0.92	0.000001	0.006071
70	low	15 to 29	m	0.23	0.418068	0.001960
70	low	15 to 29	f	-0.05	0.867457	-0.000370
70	low	30 to 49	m	0.71	0.003000	0.028280
70	low	30 to 49	f	0.03	0.922503	0.001471
70	low	50 to 65	m	-0.24	0.394752	-0.005701
70	low	50 to 65	f	-0.57	0.026030	-0.008566
70	med	15 to 29	m	-0.93	0.000001	-0.008786
70	med	15 to 29	f	-0.51	0.052542	-0.004676
70	med	30 to 49	m	0.87	0.000020	0.024826
70	med	30 to 49	f	0.79	0.000399	0.014282
70	med	50 to 65	m	0.69	0.004297	0.006761
70	med	50 to 65	f	0.81	0.000258	0.005107
70	high	15 to 29	m	-0.24	0.379621	-0.002374
70	high	15 to 29	f	-0.63	0.012476	-0.010502
70	high	30 to 49	m	0.77	0.000704	0.024428
70	high	30 to 49	f	0.96	0.000000	0.010392
70	high	50 to 65	m	0.90	0.000005	0.004371
70	high	50 to 65	f	0.92	0.000001	0.002344
71t74	low	15 to 29	m	0.41	0.126793	0.038284
71t74	low	15 to 29	f	0.25	0.376183	0.020470
71t74	low	30 to 49	m	0.65	0.008596	0.285682
71t74	low	30 to 49	f	-0.21	0.462248	-0.144335
71t74	low	50 to 65	m	-0.32	0.241710	-0.090318
71t74	low	50 to 65	f	-0.60	0.018086	-0.116485
71t74	med	15 to 29	m	-0.95	0.000000	-0.112988
71t74	med	15 to 29	f	-0.97	0.000000	-0.091846
71t74	med	30 to 49	m	0.94	0.000000	0.340079
71t74	med	30 to 49	f	0.95	0.000000	0.237703
71t74	med	50 to 65	m	0.87	0.000026	0.109308
71t74	med	50 to 65	f	0.90	0.000006	0.079797
71t74	high	15 to 29	m	-0.75	0.001314	-0.074645
71t74	high	15 to 29	f	-0.83	0.000130	-0.148901
71t74	high	30 to 49	m	0.77	0.000750	0.306805
71t74	high	30 to 49	f	0.94	0.000000	0.125513
71t74	high	50 to 65	m	0.95	0.000000	0.060881
71t74	high	50 to 65	f	0.91	0.000002	0.027078
L	low	15 to 29	m	-0.69	0.004426	-0.009775
L	low	15 to 29	f	-0.59	0.019356	-0.009225
L	low	30 to 49	m	-0.64	0.010545	-0.066234
L	low	30 to 49	f	0.32	0.239774	0.076773
L	low	50 to 65	m	0.37	0.172568	0.047205
L	low	50 to 65	f	0.71	0.003000	0.061021
L	med	15 to 29	m	0.90	0.000004	0.017381
L	med	15 to 29	f	0.87	0.000027	0.046675
L	med	30 to 49	m	-0.90	0.000004	-0.120706
L	med	30 to 49	f	-0.91	0.000003	-0.129116
L	med	50 to 65	m	-0.78	0.000681	-0.048338
L	med	50 to 65	f	0.72	0.002457	0.024697
L	high	15 to 29	m	-0.42	0.116252	-0.007441
L	high	15 to 29	f	0.15	0.605298	0.005737
L	high	30 to 49	m	-0.65	0.008891	-0.027922
L	high	30 to 49	f	-0.84	0.000088	-0.033823

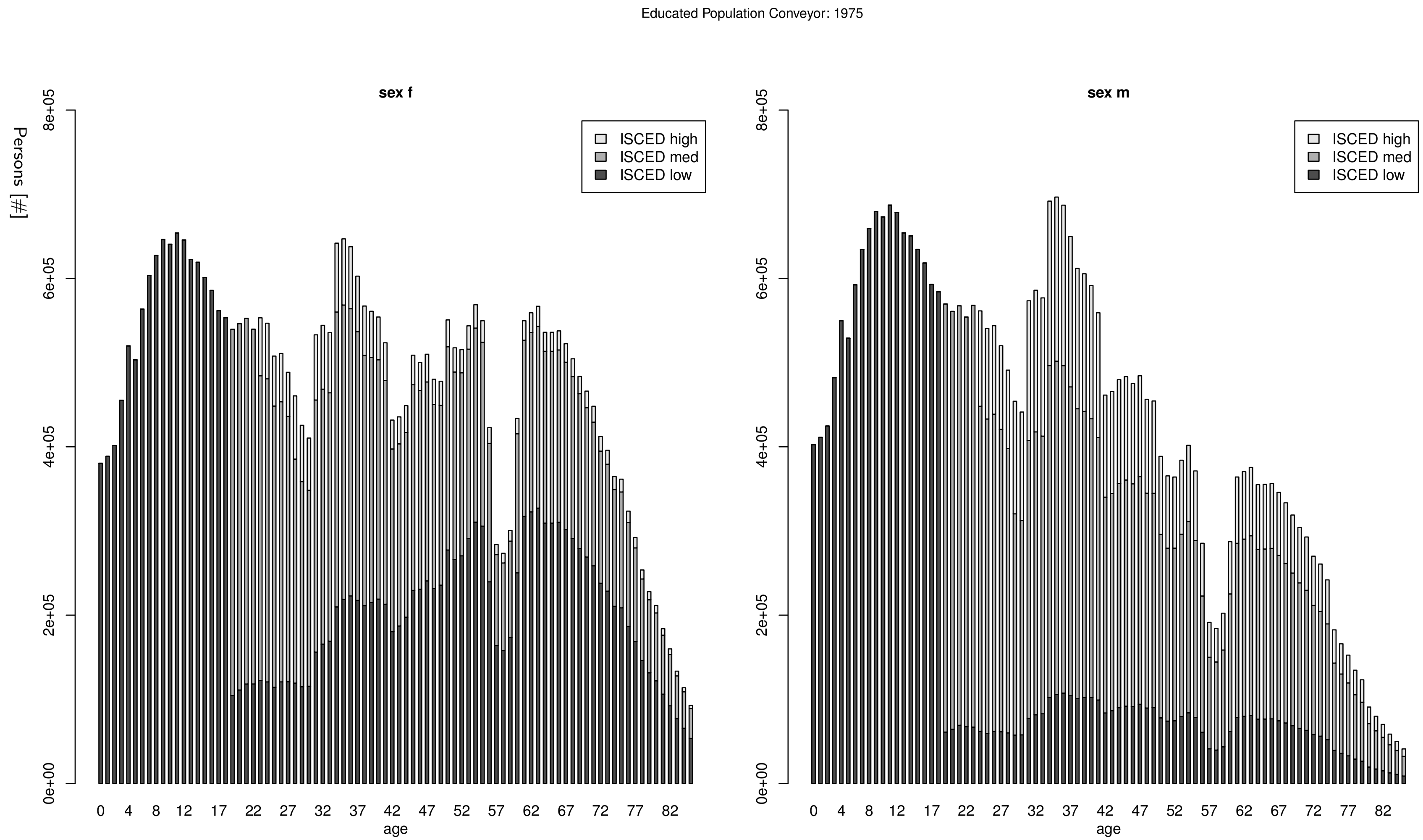
C.1 Education Level - Labour Input Correlation Coefficients

Sector	*Quali*	*Age*	*Sex*	*Cor. Coef.*	*p-Value*	*Inclination* (β)
L	high	50 to 65	m	0.64	0.010235	0.006958
L	high	50 to 65	f	0.73	0.001831	0.021043
M	low	15 to 29	m	0.32	0.246768	0.004628
M	low	15 to 29	f	-0.07	0.807980	-0.000459
M	low	30 to 49	m	0.79	0.000515	0.033439
M	low	30 to 49	f	0.00	0.987047	-0.000273
M	low	50 to 65	m	-0.32	0.247779	-0.016393
M	low	50 to 65	f	0.45	0.095796	0.010248
M	med	15 to 29	m	-0.68	0.005078	-0.008583
M	med	15 to 29	f	-0.68	0.005187	-0.013468
M	med	30 to 49	m	0.56	0.030338	0.010821
M	med	30 to 49	f	0.86	0.000034	0.051231
M	med	50 to 65	m	0.91	0.000004	0.026661
M	med	50 to 65	f	0.90	0.000006	0.050860
M	high	15 to 29	m	-0.25	0.371420	-0.031201
M	high	15 to 29	f	-0.51	0.052911	-0.073904
M	high	30 to 49	m	-0.51	0.052283	-0.039177
M	high	30 to 49	f	0.72	0.002530	0.072353
M	high	50 to 65	m	0.80	0.000371	0.033999
M	high	50 to 65	f	0.96	0.000000	0.087532
N	low	15 to 29	m	0.46	0.081739	0.005597
N	low	15 to 29	f	0.70	0.003332	0.019876
N	low	30 to 49	m	0.73	0.001840	0.034691
N	low	30 to 49	f	-0.09	0.738361	-0.009400
N	low	50 to 65	m	0.09	0.747003	0.001754
N	low	50 to 65	f	-0.69	0.004630	-0.017945
N	med	15 to 29	m	-0.93	0.000000	-0.020213
N	med	15 to 29	f	-0.73	0.001823	-0.074861
N	med	30 to 49	m	0.95	0.000000	0.104281
N	med	30 to 49	f	0.90	0.000005	0.269417
N	med	50 to 65	m	0.80	0.000367	0.027485
N	med	50 to 65	f	0.88	0.000014	0.131333
N	high	15 to 29	m	-0.36	0.189541	-0.011711
N	high	15 to 29	f	-0.76	0.000992	-0.088229
N	high	30 to 49	m	-0.20	0.475618	-0.032267
N	high	30 to 49	f	0.74	0.001744	0.074797
N	high	50 to 65	m	0.57	0.027079	0.020974
N	high	50 to 65	f	0.85	0.000061	0.020740
O	low	15 to 29	m	0.49	0.063426	0.015987
O	low	15 to 29	f	0.37	0.172403	0.014139
O	low	30 to 49	m	0.71	0.002825	0.112764
O	low	30 to 49	f	-0.21	0.444793	-0.052663
O	low	50 to 65	m	-0.21	0.450012	-0.014856
O	low	50 to 65	f	-0.63	0.011224	-0.026706
O	med	15 to 29	m	-0.11	0.685843	-0.000984
O	med	15 to 29	f	0.70	0.003686	0.012377
O	med	30 to 49	m	-0.64	0.010613	-0.011921
O	med	30 to 49	f	-0.66	0.007203	-0.018133
O	med	50 to 65	m	0.86	0.000036	0.015941
O	med	50 to 65	f	0.88	0.000019	0.022374
O	high	15 to 29	m	0.25	0.368156	0.001960
O	high	15 to 29	f	-0.51	0.054839	-0.010049
O	high	30 to 49	m	-0.67	0.006679	-0.017567
O	high	30 to 49	f	0.87	0.000031	0.017518
O	high	50 to 65	m	0.58	0.024246	0.006872
O	high	50 to 65	f	0.94	0.000000	0.011699

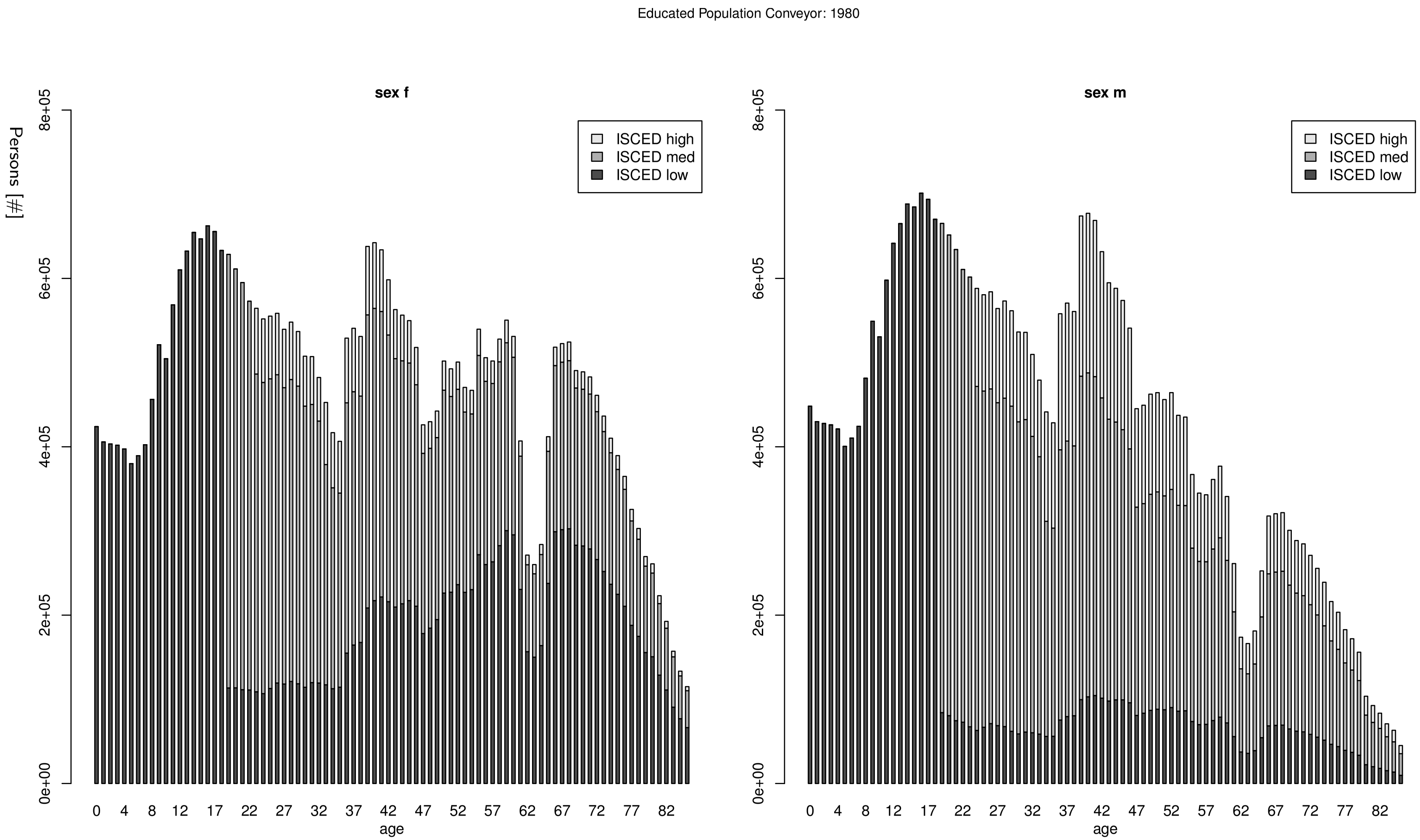
C.2 Educated Population Cohort Model - Baseline

The following pages contain the visualisation of the baseline scenario of the educated population cohort model described in section 4.4 on page 65. The plots show the distribution of education levels for 85 age cohorts for every 5th year, differentiated by sex.

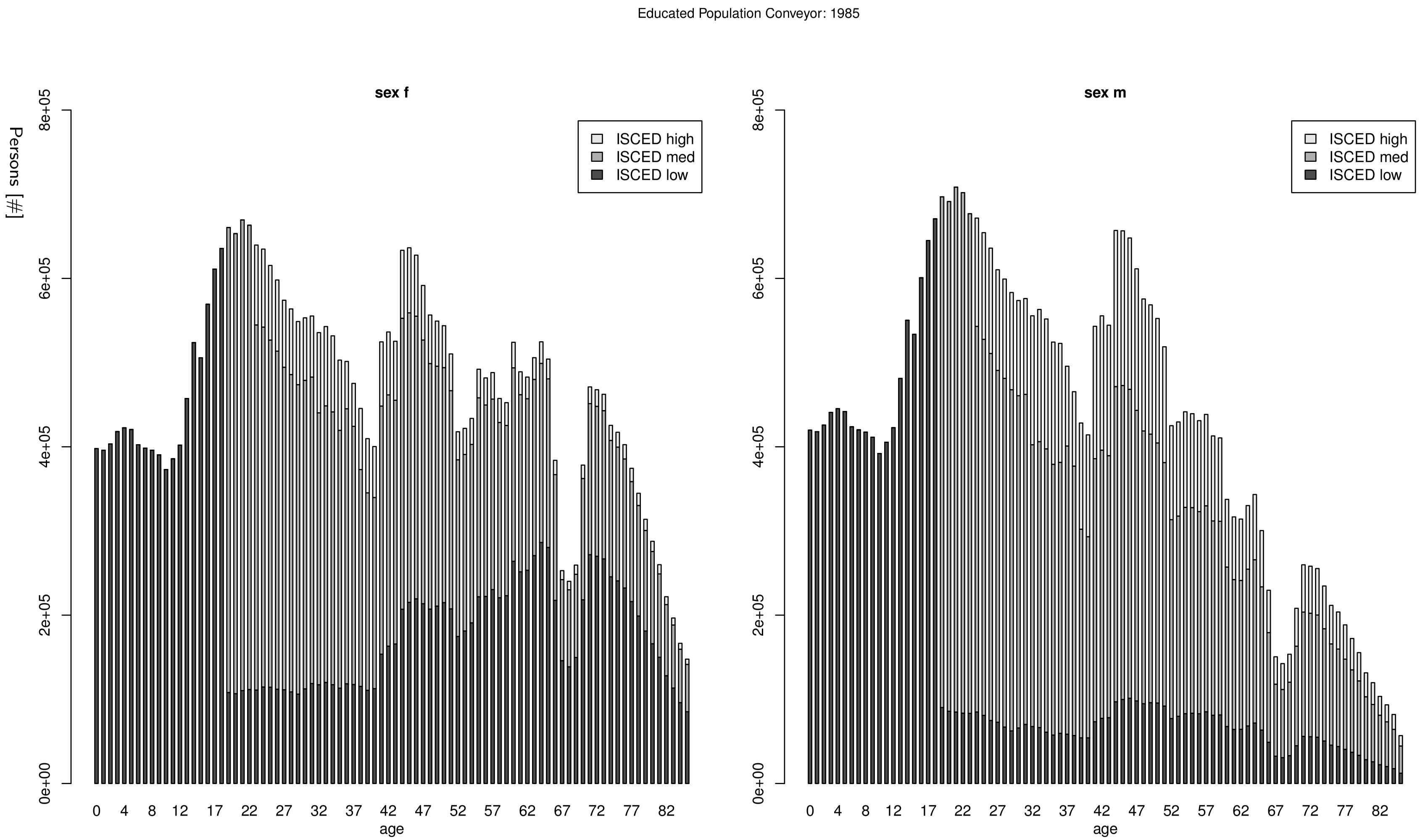

Educated Population Conveyor: 1970
sex f
sex m
ISCED high
ISCED med
ISCED low
Persons [#]
age
0e+00
2e+05
4e+05
6e+05
8e+05
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82

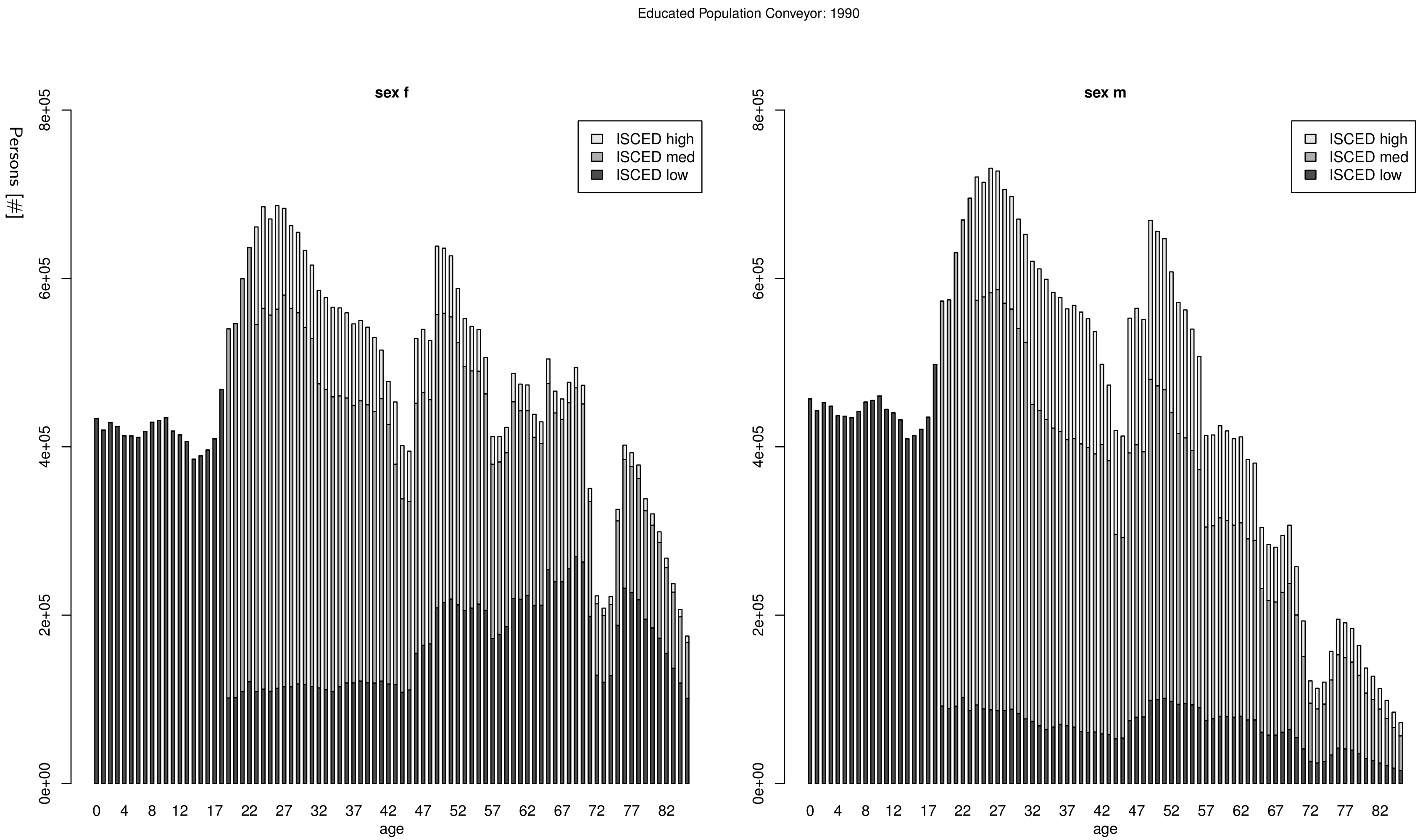


Educated Population Conveyor: 1975
sex f
sex m
ISCED high
ISCED med
ISCED low
Persons [#]
age
0e+00
2e+05
4e+05
6e+05
8e+05
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82

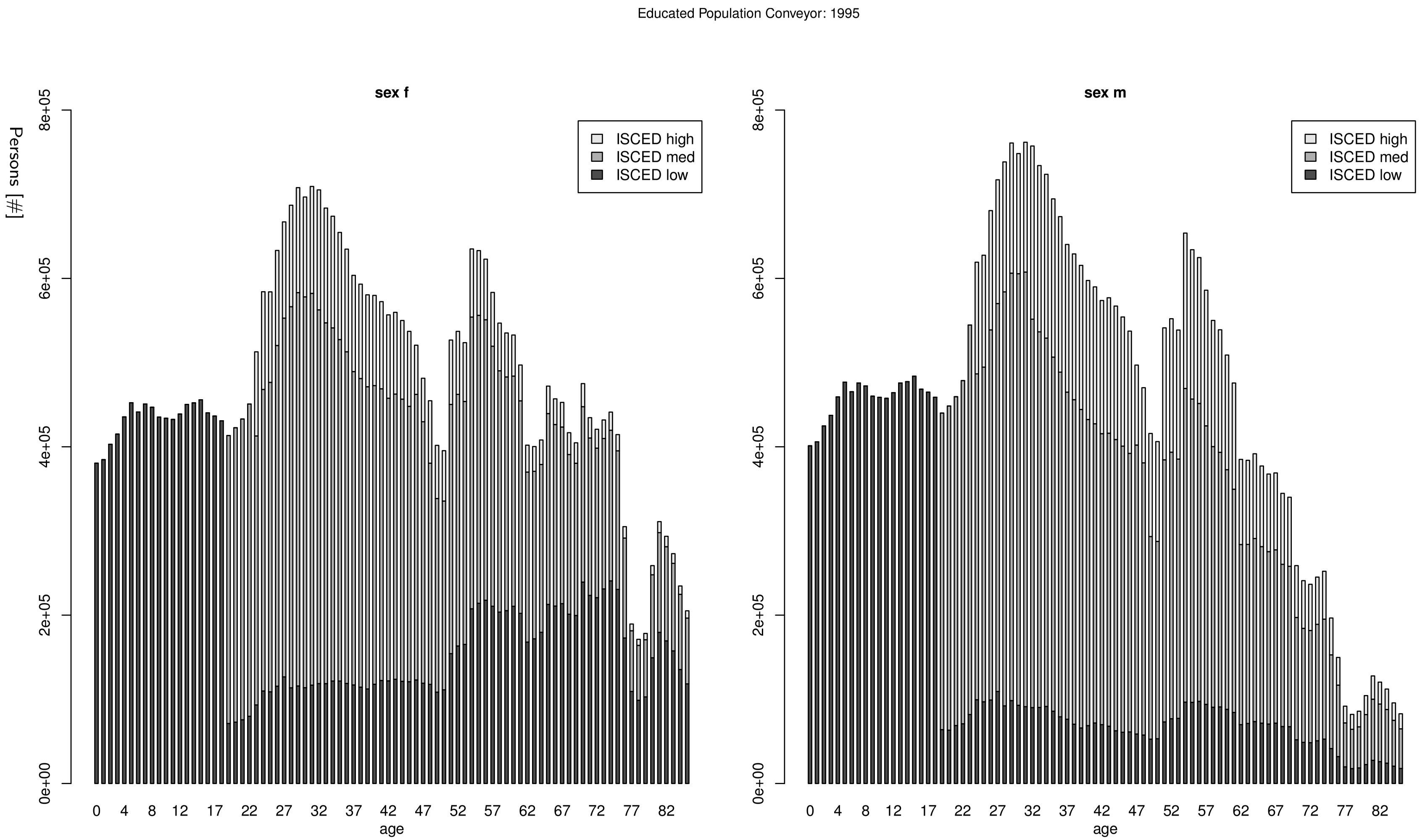


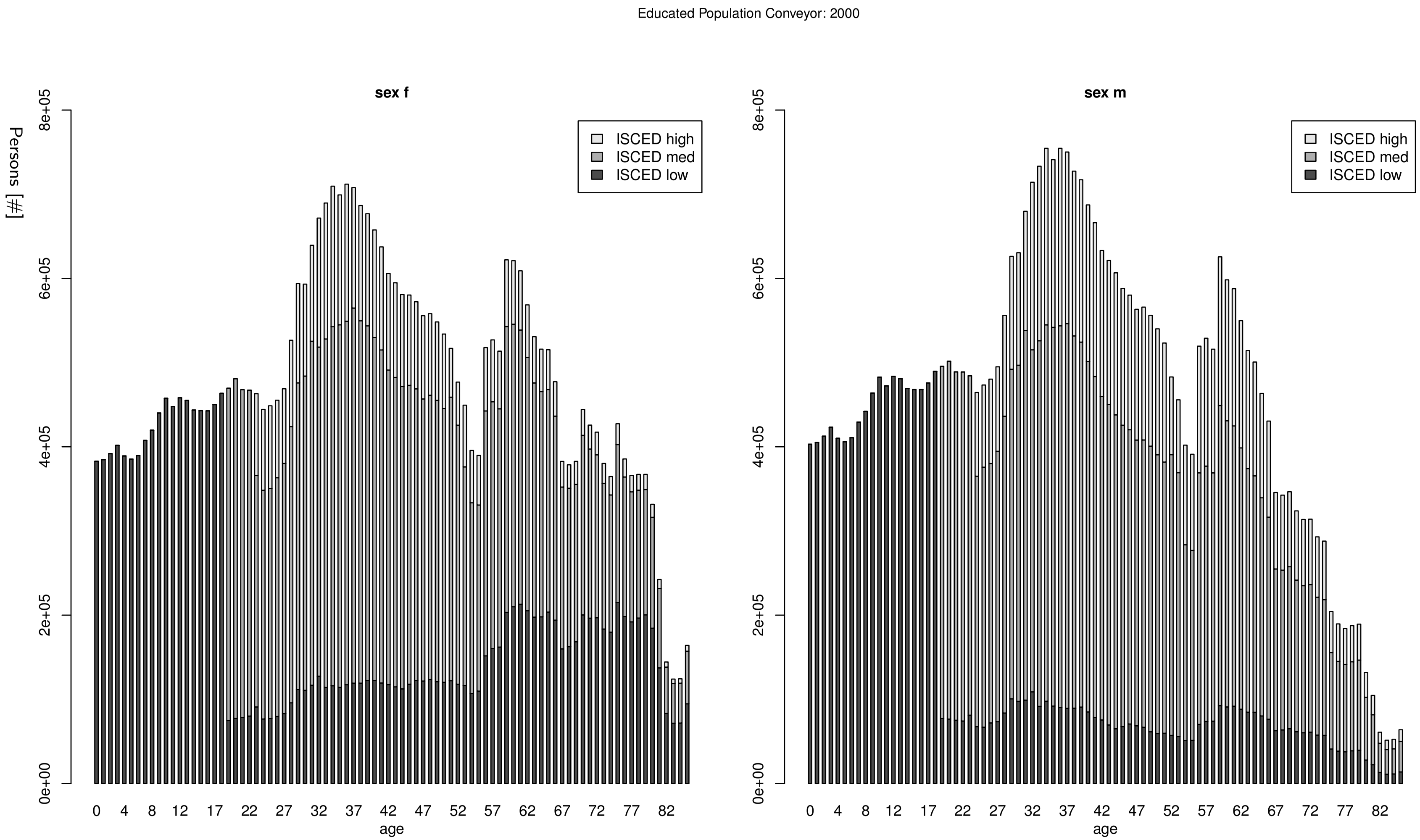
Educated Population Conveyor: 1980
sex f
sex m
Persons [#]
0e+00
2e+05
4e+05
6e+05
8e+05
ISCED high
ISCED med
ISCED low
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82
age


Educated Population Conveyor: 1985
sex f
sex m
Persons [#]
ISCED high
ISCED med
ISCED low
0e+00
2e+05
4e+05
6e+05
8e+05
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82
age



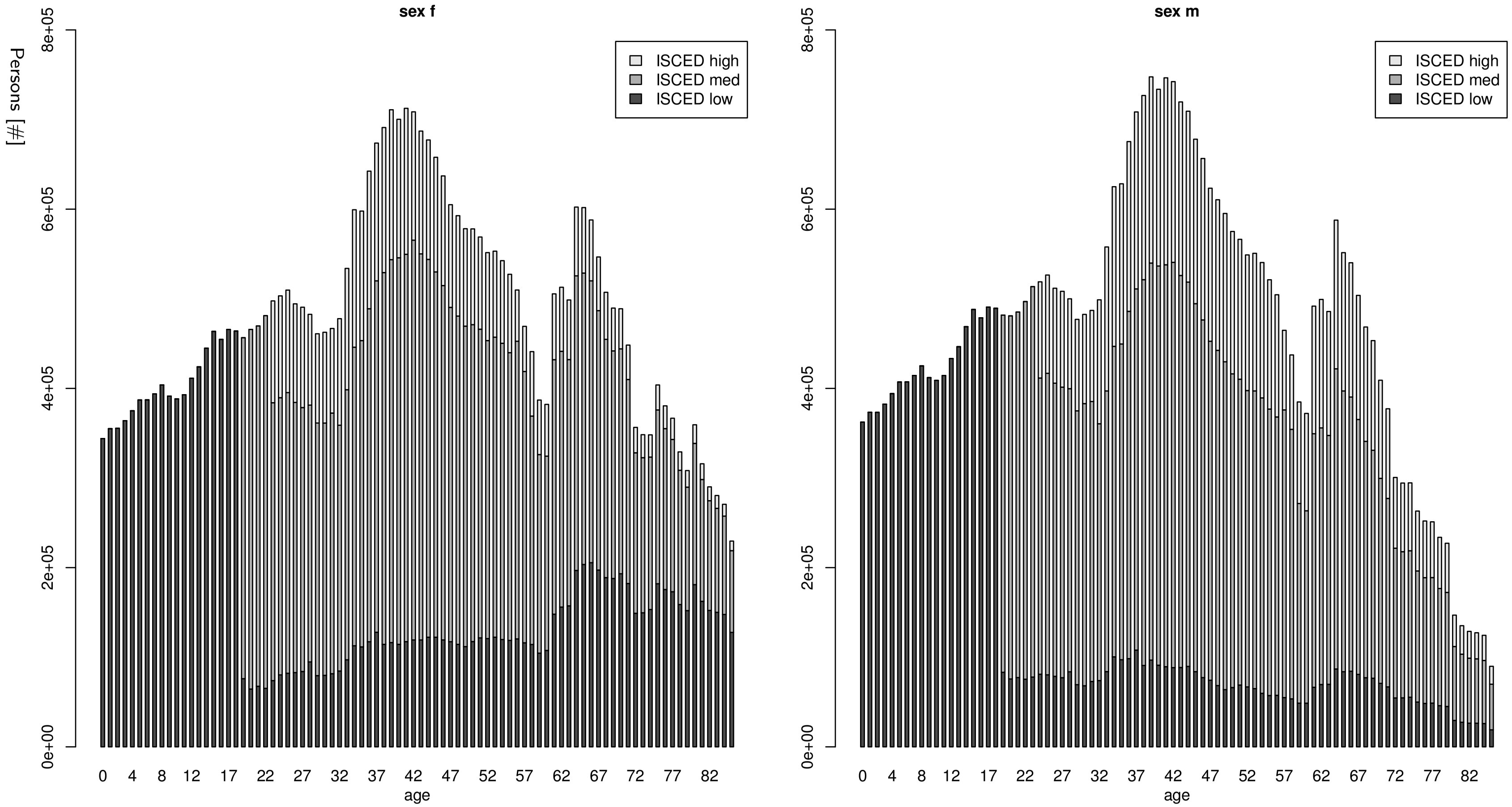
Educated Population Conveyor: 1990
sex f
sex m
Persons [#]
0e+00
2e+05
4e+05
6e+05
8e+05
ISCED high
ISCED med
ISCED low
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82
age

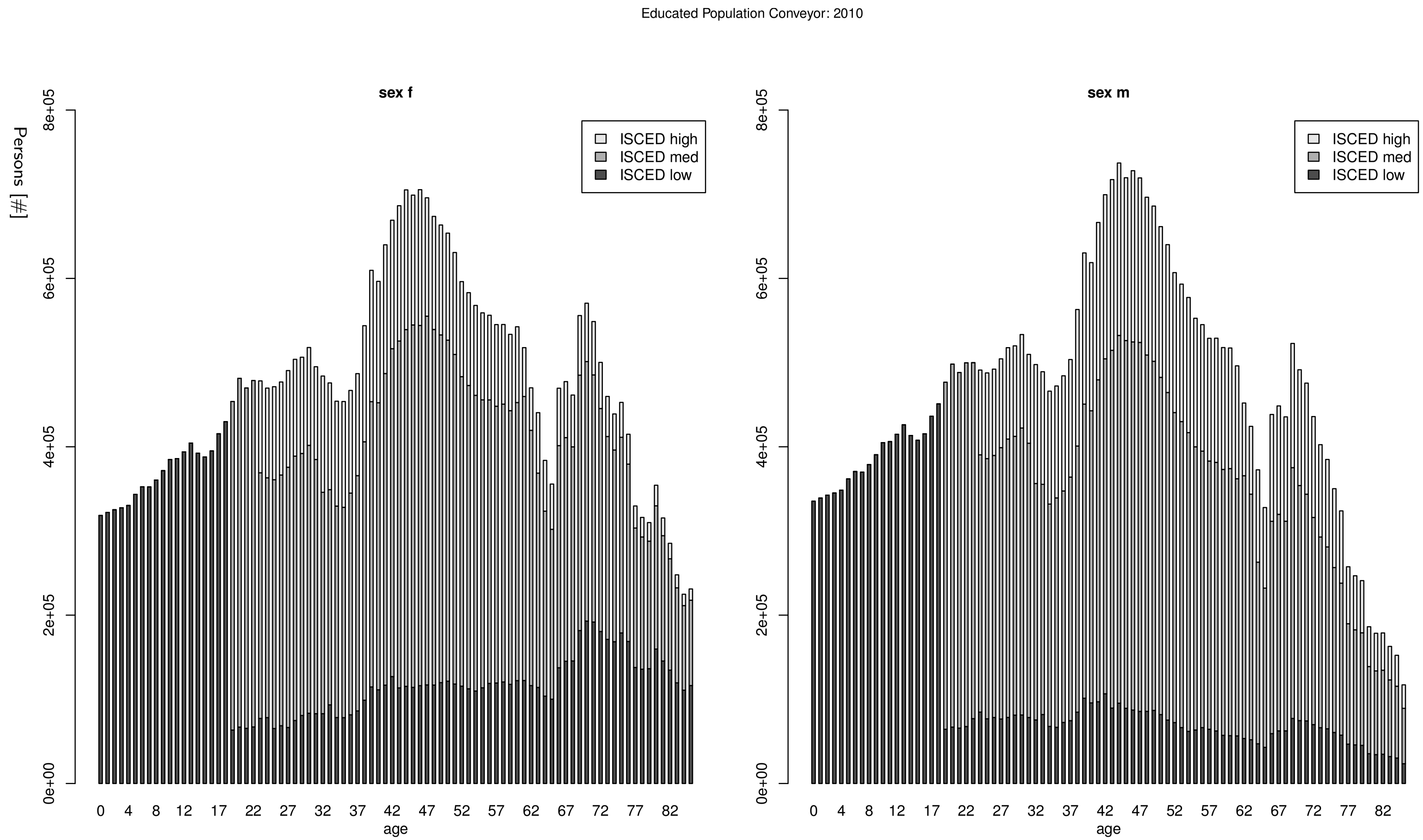

Educated Population Conveyor: 1995
sex f
sex m
Persons [#]
ISCED high
ISCED med
ISCED low
age
0e+00
2e+05
4e+05
6e+05
8e+05
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82



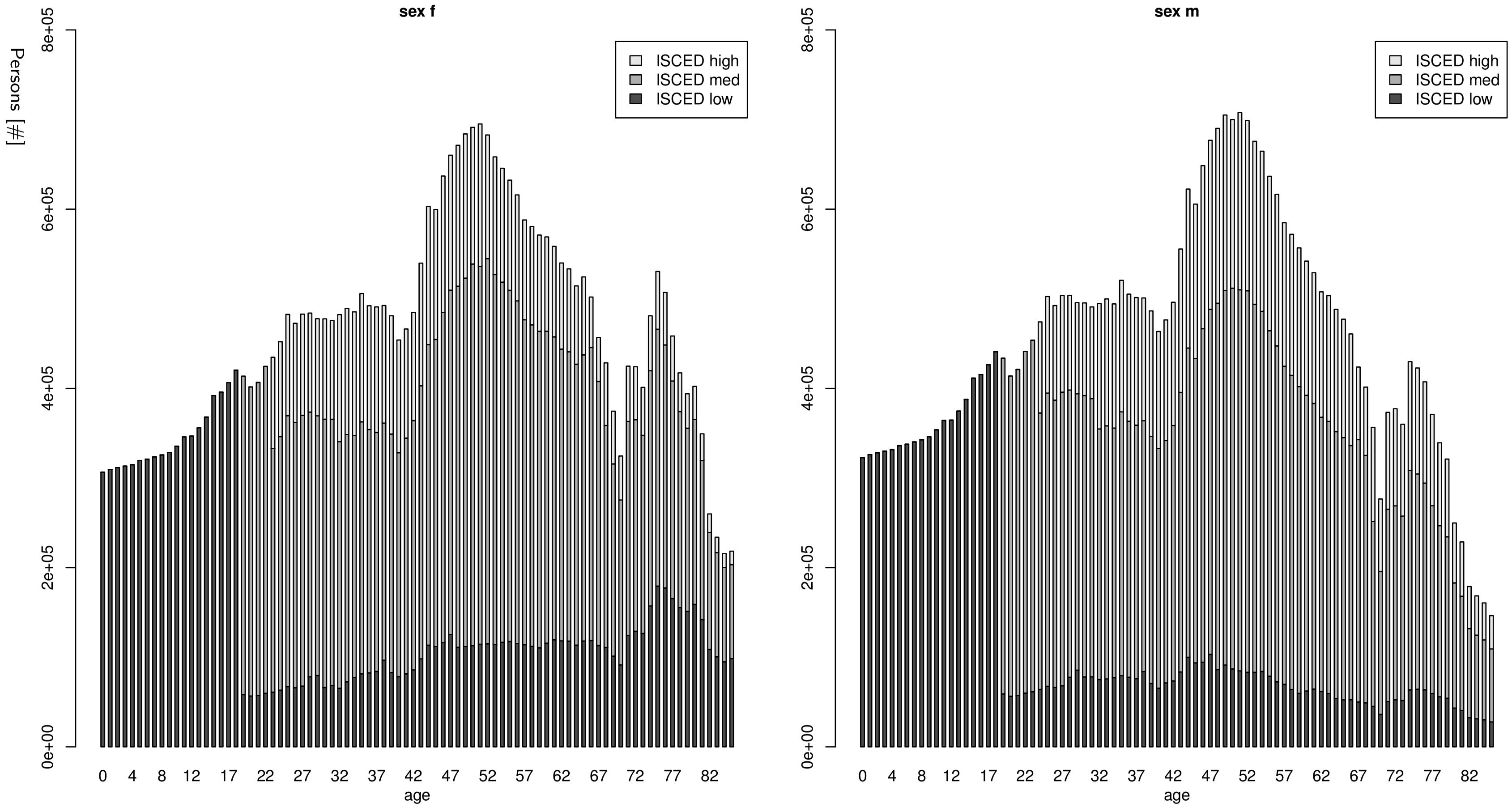
Educated Population Conveyor: 2000
sex f
sex m
ISCED high
ISCED med
ISCED low
Persons [#]
0e+00
2e+05
4e+05
6e+05
8e+05
0 4 8 12 17 22 27 32 37 42 47 52 57 62 67 72 77 82
age

Educated Population Conveyor: 2005

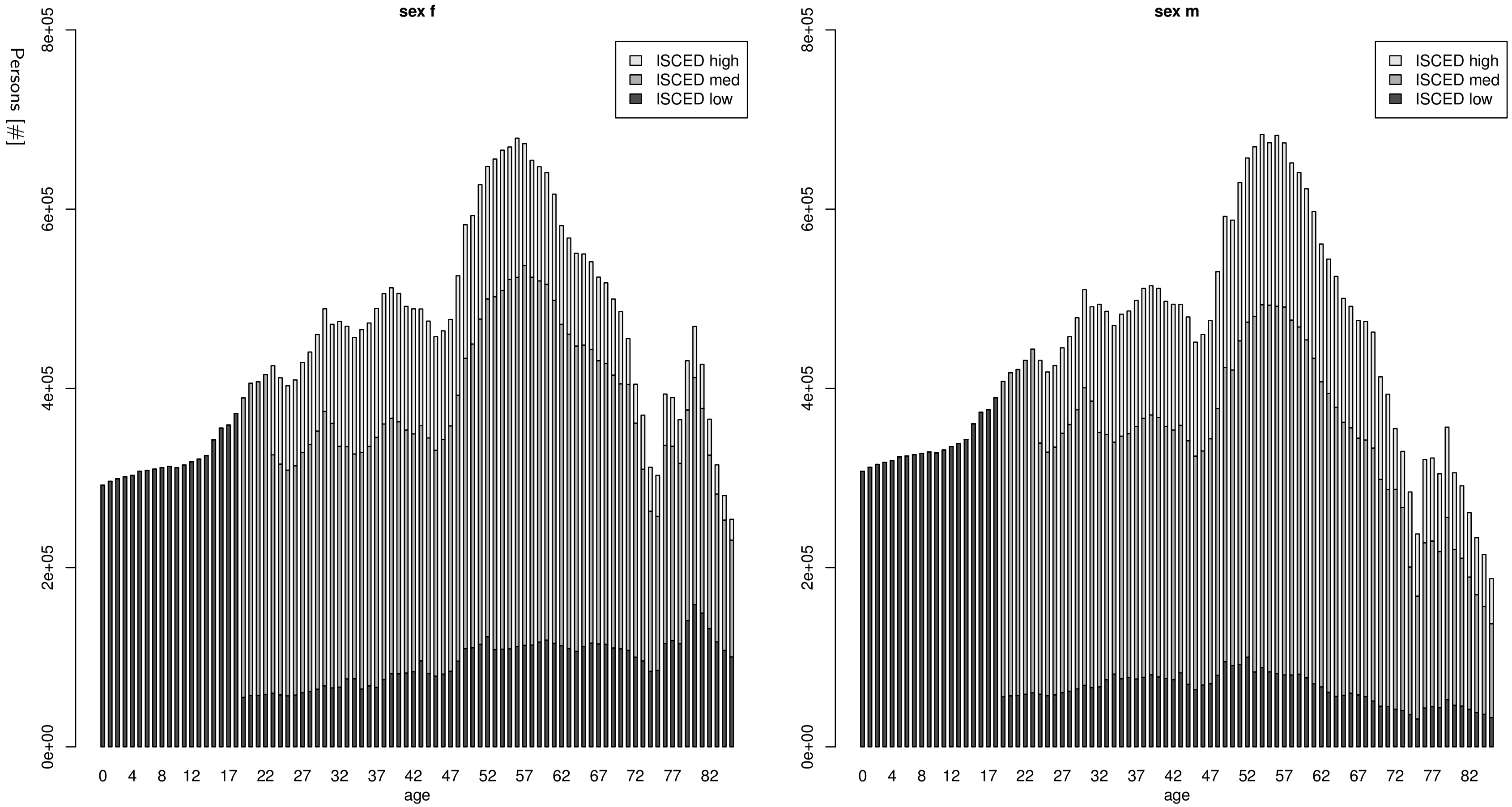


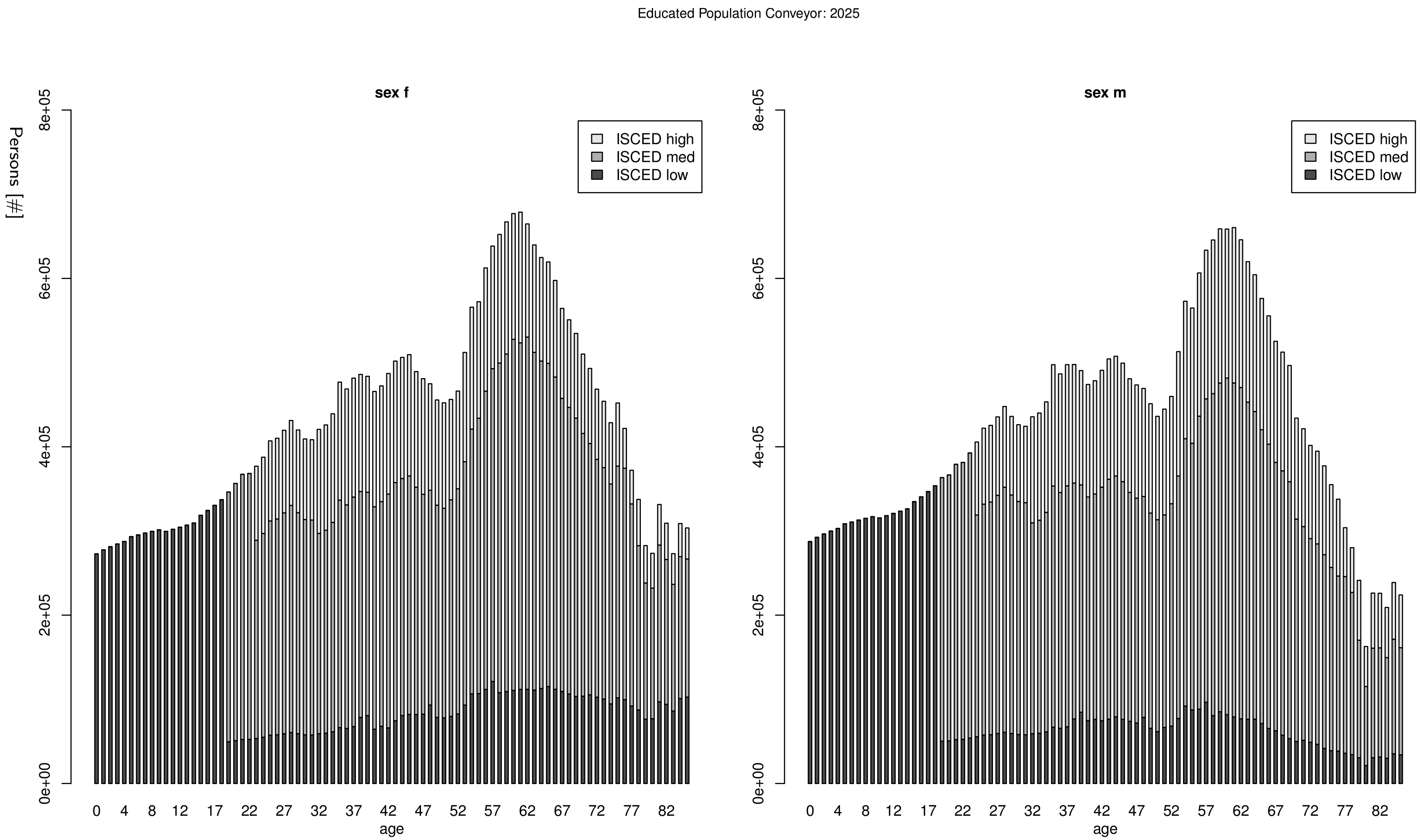

Educated Population Conveyor: 2010
sex f
sex m
Persons [#]
0e+00
2e+05
4e+05
6e+05
8e+05
ISCED high
ISCED med
ISCED low
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82
age

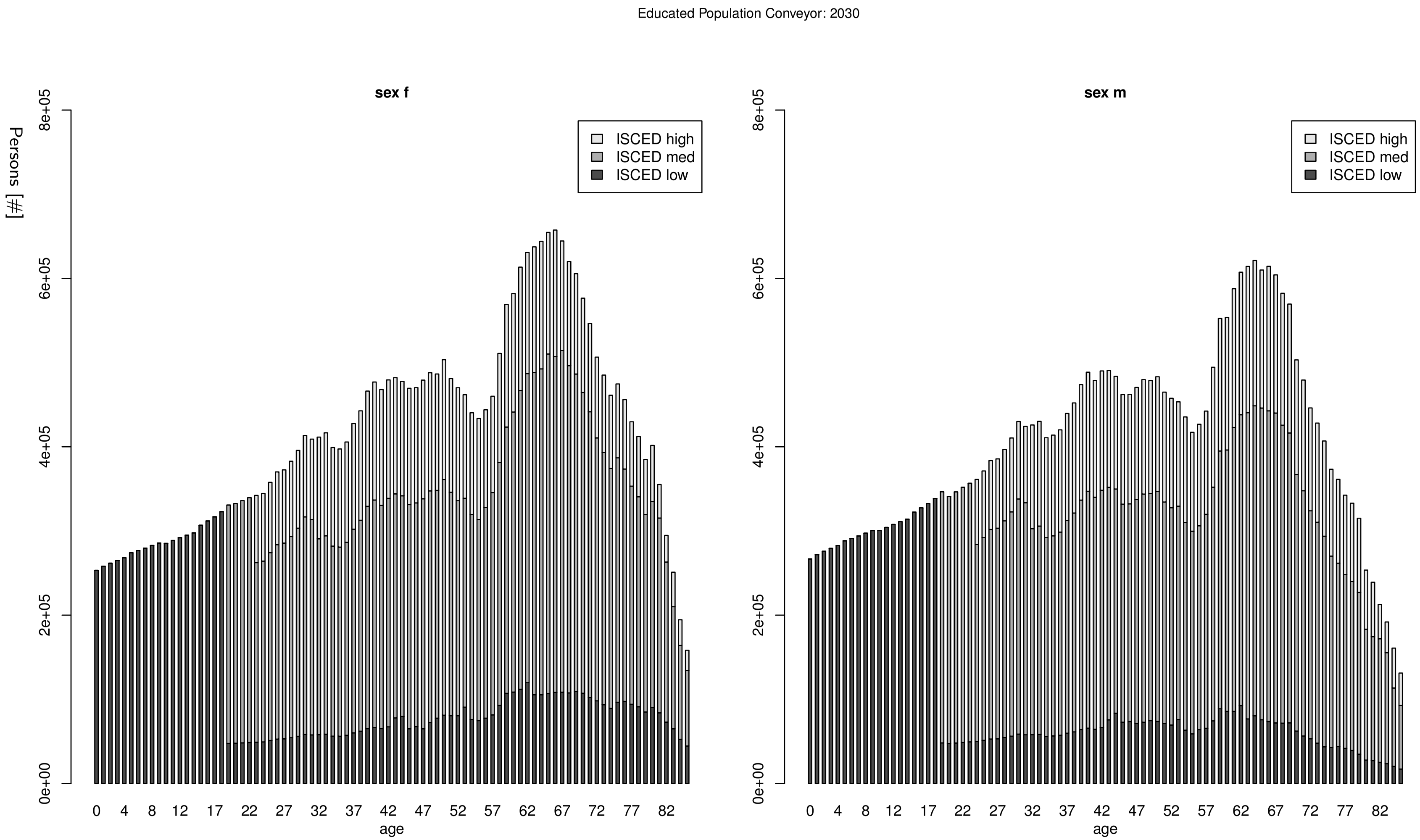
Educated Population Conveyor: 2015



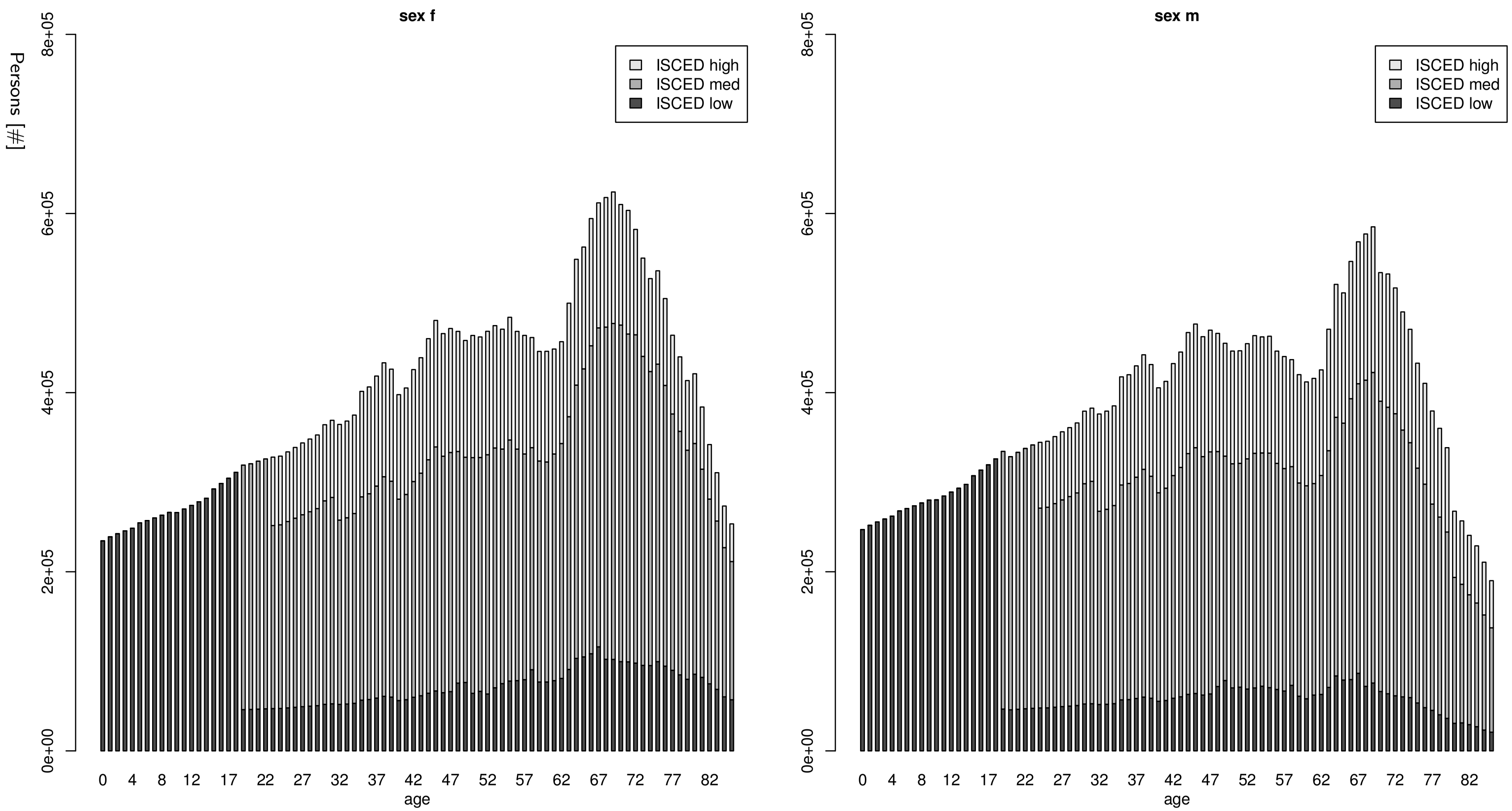
Educated Population Conveyor: 2020

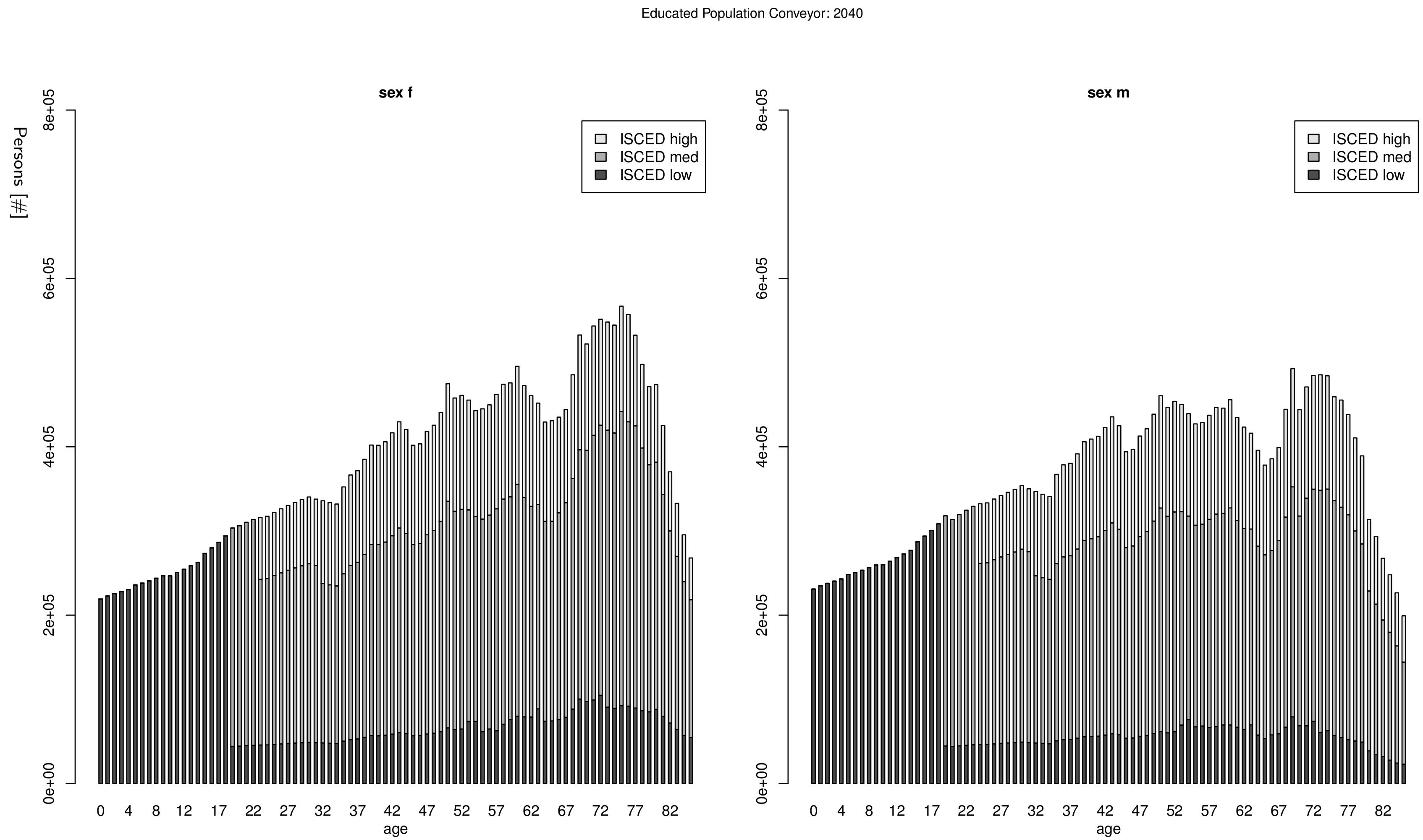


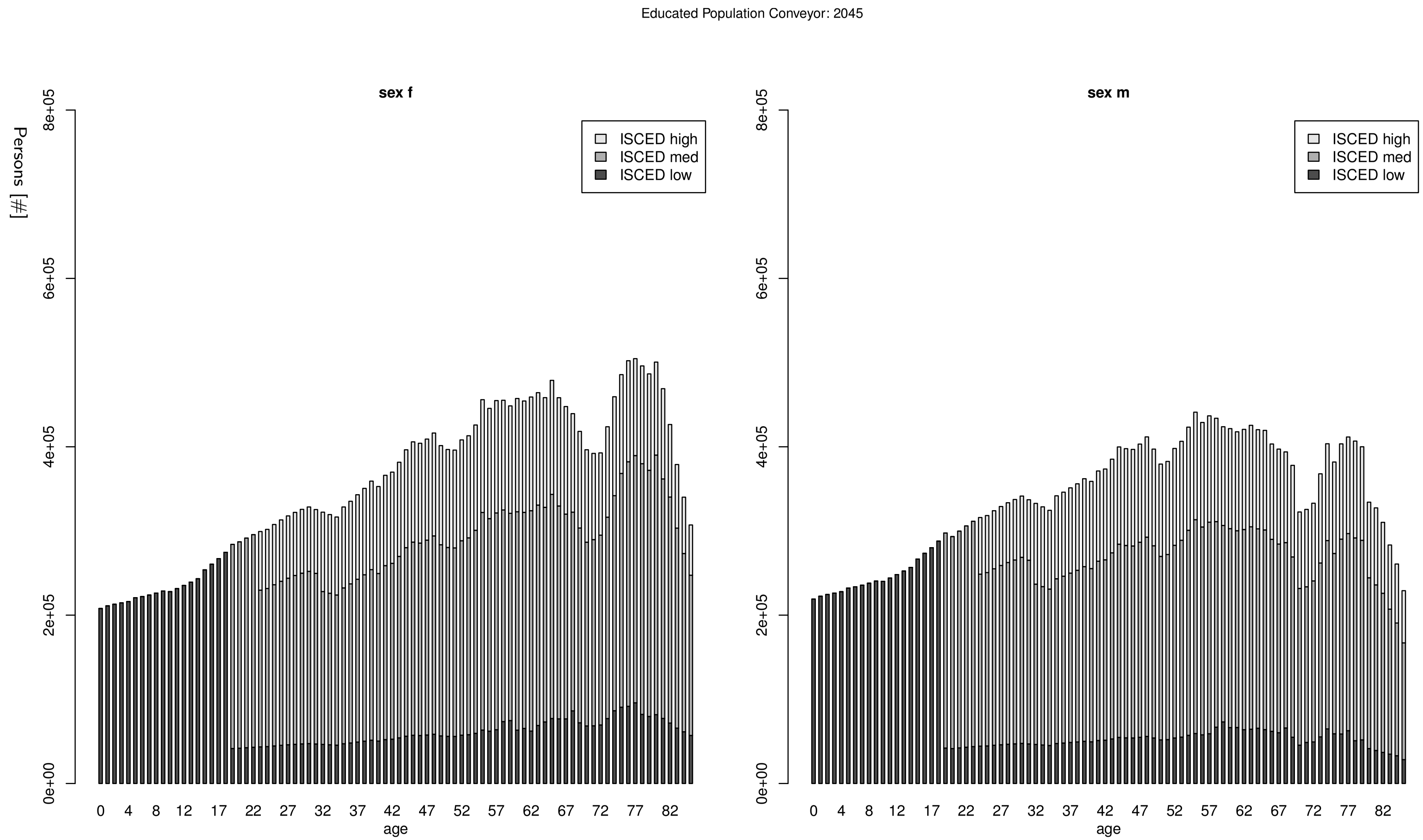

Educated Population Conveyor: 2025
sex f
sex m
Persons [#]
0e+00
2e+05
4e+05
6e+05
8e+05
ISCED high
ISCED med
ISCED low
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82
age

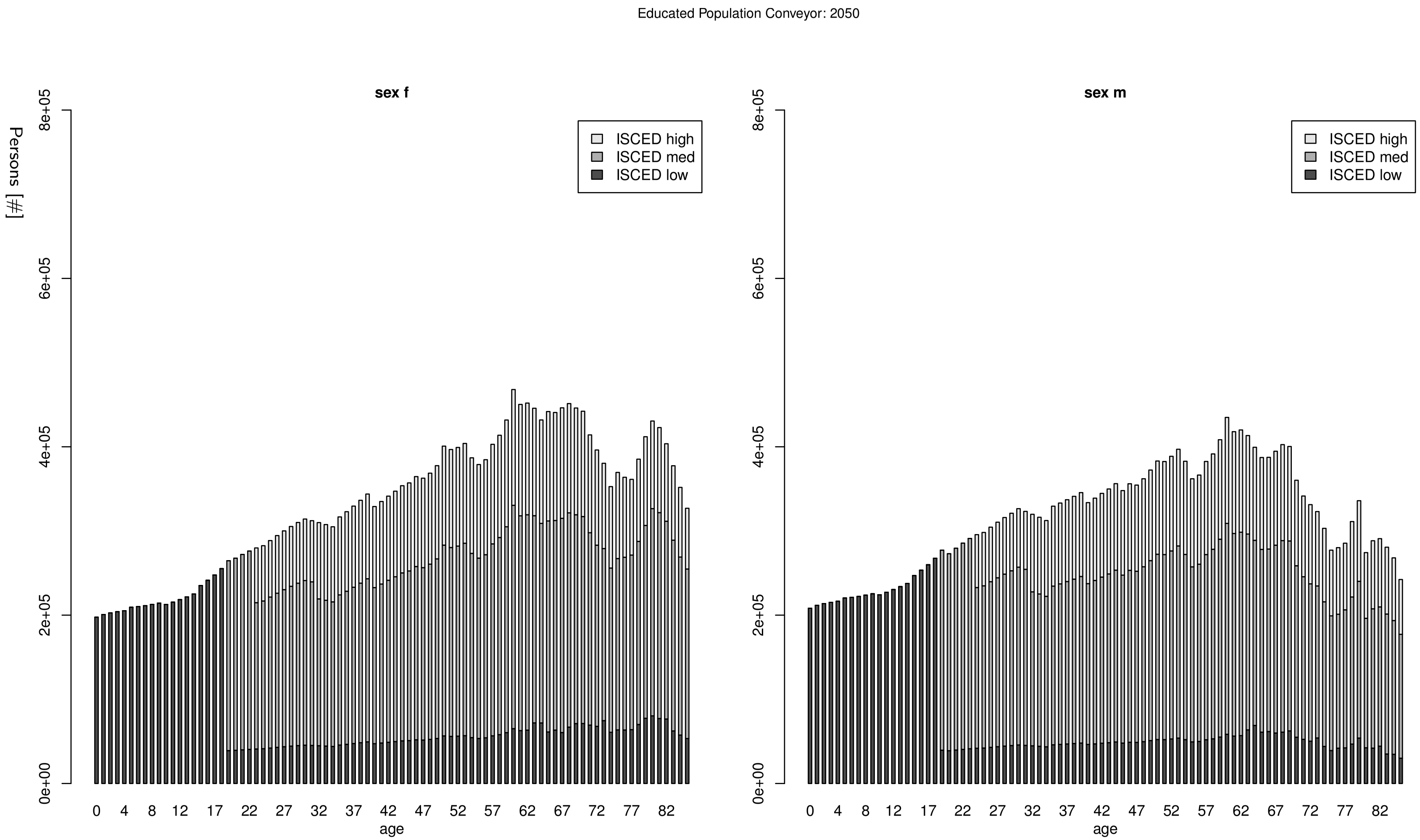

Educated Population Conveyor: 2030
sex f
sex m
Persons [#]
0e+00
2e+05
4e+05
6e+05
8e+05
ISCED high
ISCED med
ISCED low
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82
age

Educated Population Conveyor: 2035




Educated Population Conveyor: 2040
sex f
sex m
Persons [#]
0e+00
2e+05
4e+05
6e+05
8e+05
ISCED high
ISCED med
ISCED low
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82
age

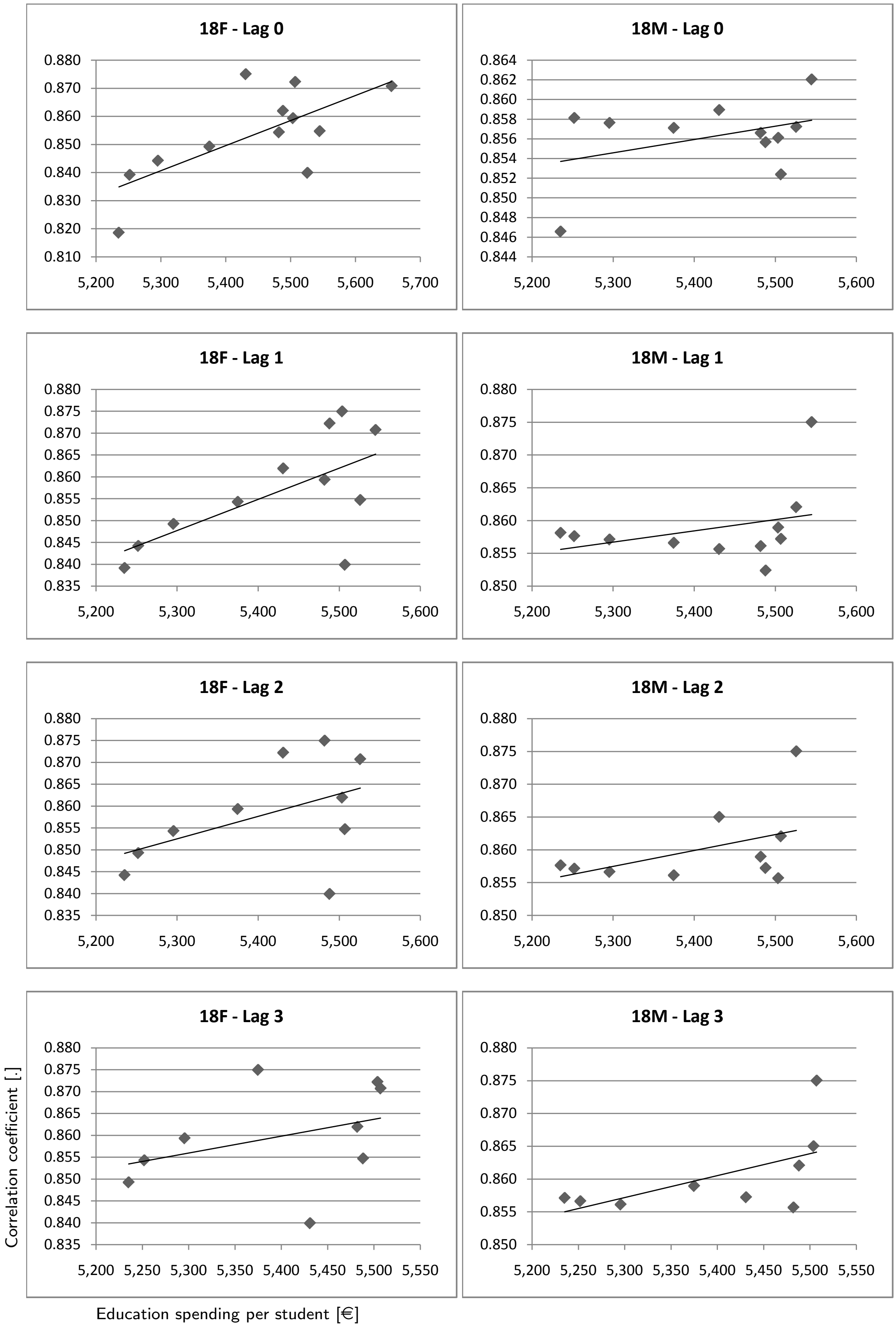

Educated Population Conveyor: 2045
sex f
sex m
Persons [#]
0e+00
2e+05
4e+05
6e+05
8e+05
ISCED high
ISCED med
ISCED low
0 4 8 12 17 22 27 32 37 42 47 52 57 62 67 72 77 82
age

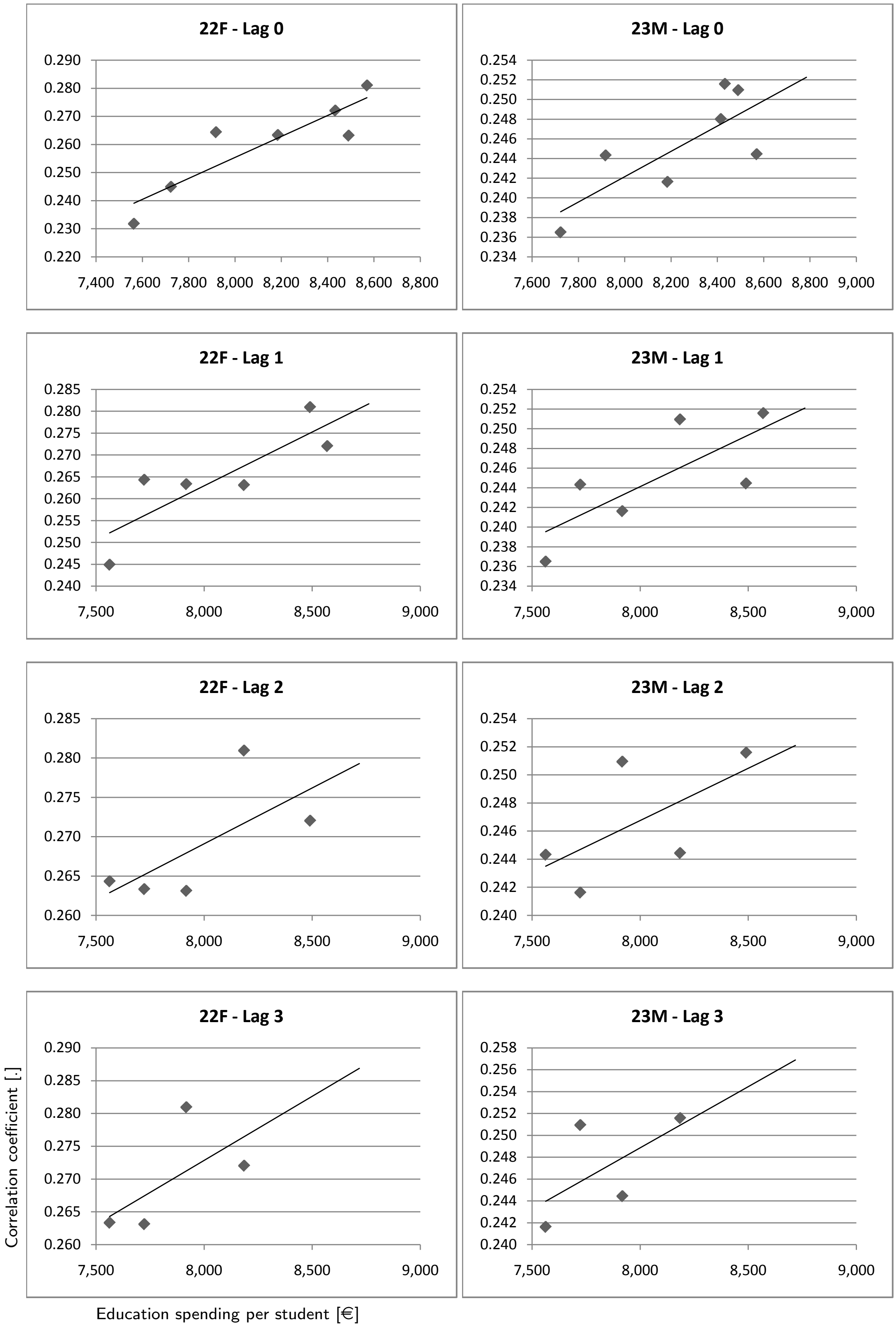


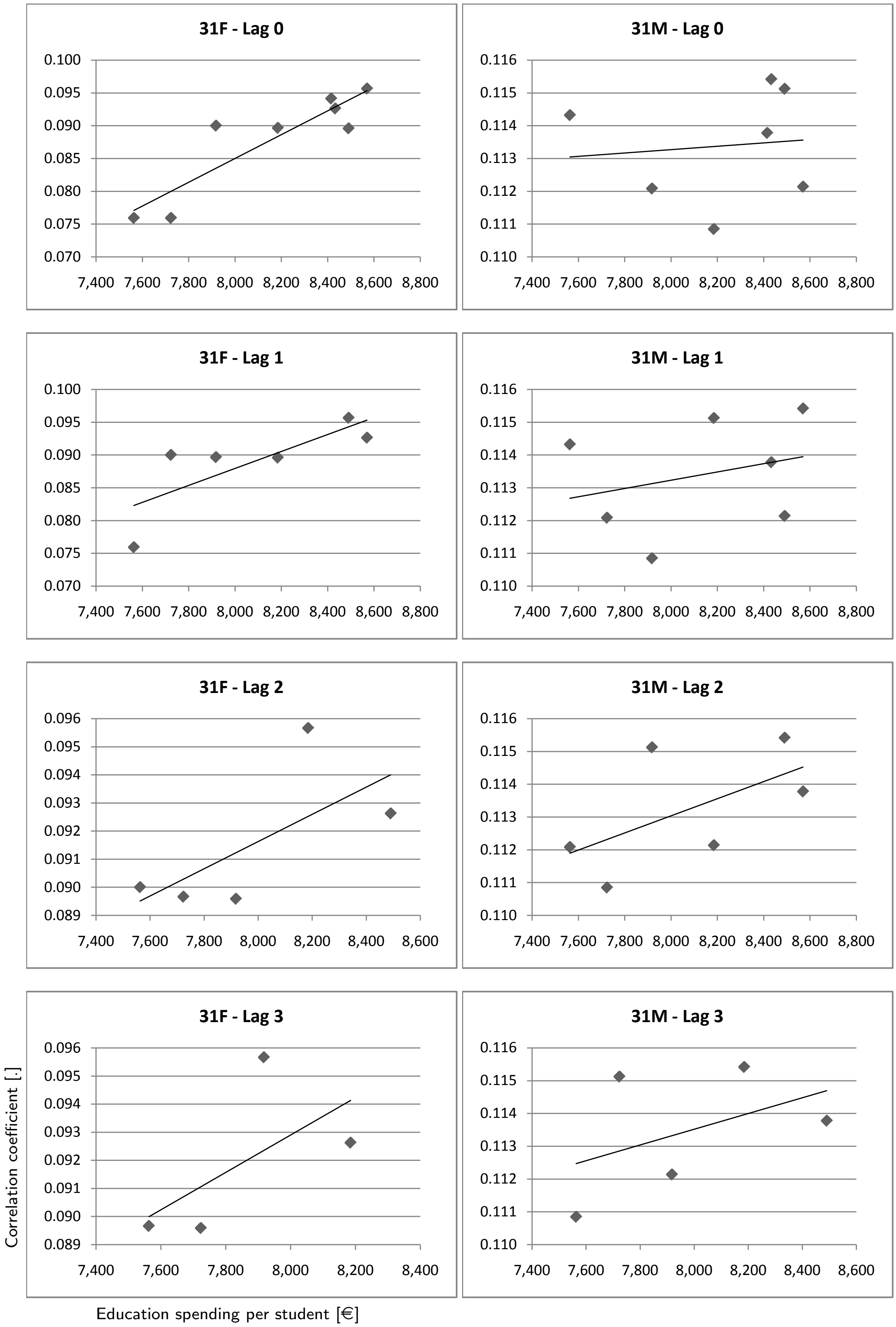
Educated Population Conveyor: 2050
sex f
sex m
ISCED high
ISCED med
ISCED low
Persons [#]
0e+00
2e+05
4e+05
6e+05
8e+05
0
4
8
12
17
22
27
32
37
42
47
52
57
62
67
72
77
82
age

C.3 Education Spending - Graduation Probabilities - Scatter Plots

The following pages contain the full set of scatter plots showing graduation probabilities over education spending, described in detail in section 4.5.1 on page 87. For each graduation point plots of 4 lag levels (0 to 3 years) are included. The according numerical results are compiled in table 4.4 on page 88.


18F - Lag 0
18M - Lag 0
18F - Lag 1
18M - Lag 1
18F - Lag 2
18M - Lag 2
18F - Lag 3
18M - Lag 3
Correlation coefficient [.]
Education spending per student [€]

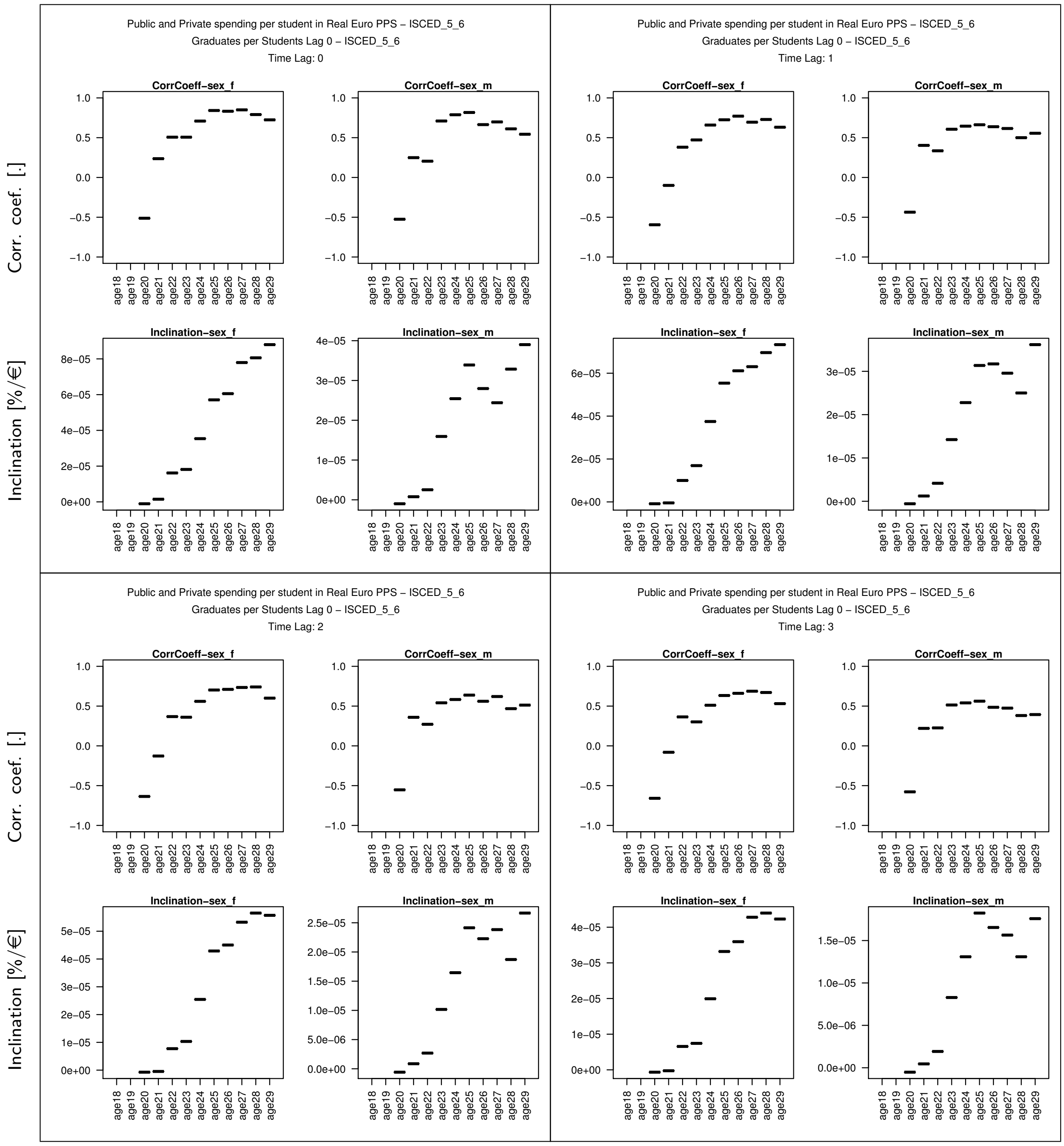

22F - Lag 0
23M - Lag 0
22F - Lag 1
23M - Lag 1
22F - Lag 2
23M - Lag 2
22F - Lag 3
23M - Lag 3
Correlation coefficient [.]
Education spending per student [€]


31F - Lag 0
31M - Lag 0
31F - Lag 1
31M - Lag 1
31F - Lag 2
31M - Lag 2
31F - Lag 3
31M - Lag 3
Correlation coefficient [.]
Education spending per student [€]

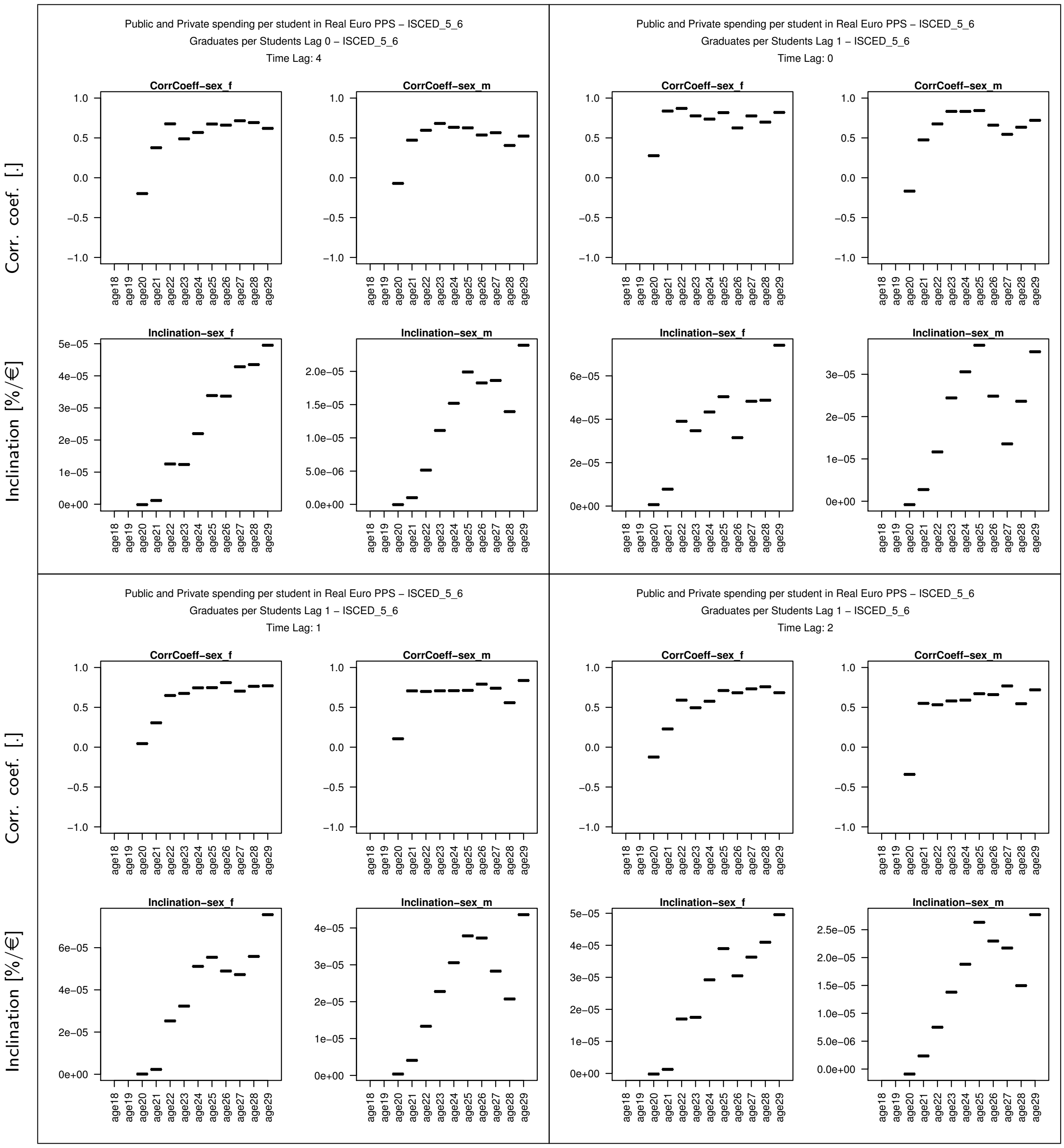
C.4 Education Spending - Graduates per Student - Correlation Analysis

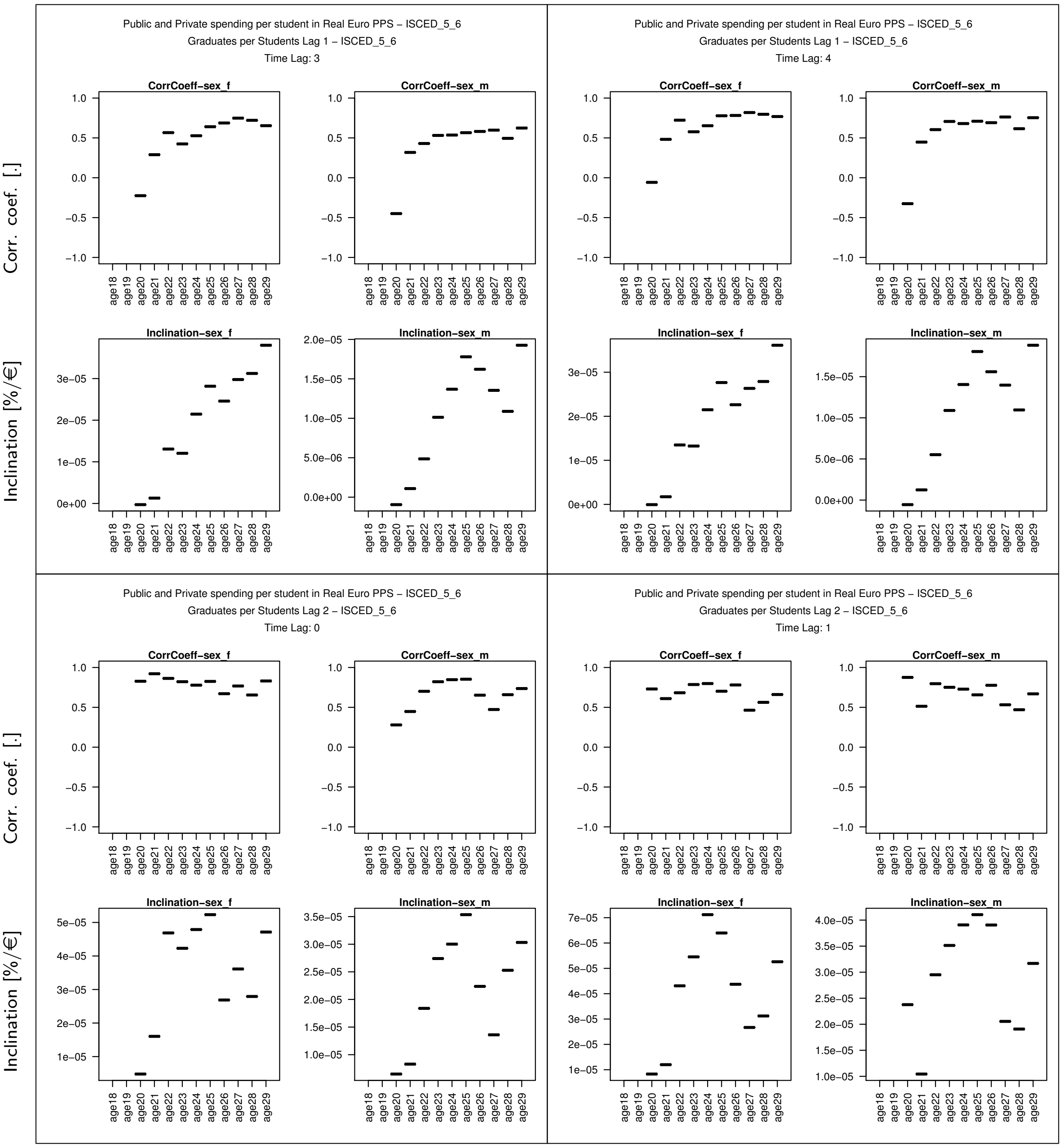
The following pages contain the full results of the analysis of the correlation between education spending per student and the shares of graduates per student. The details of this analysis are described in section 4.5.2 on page 91.

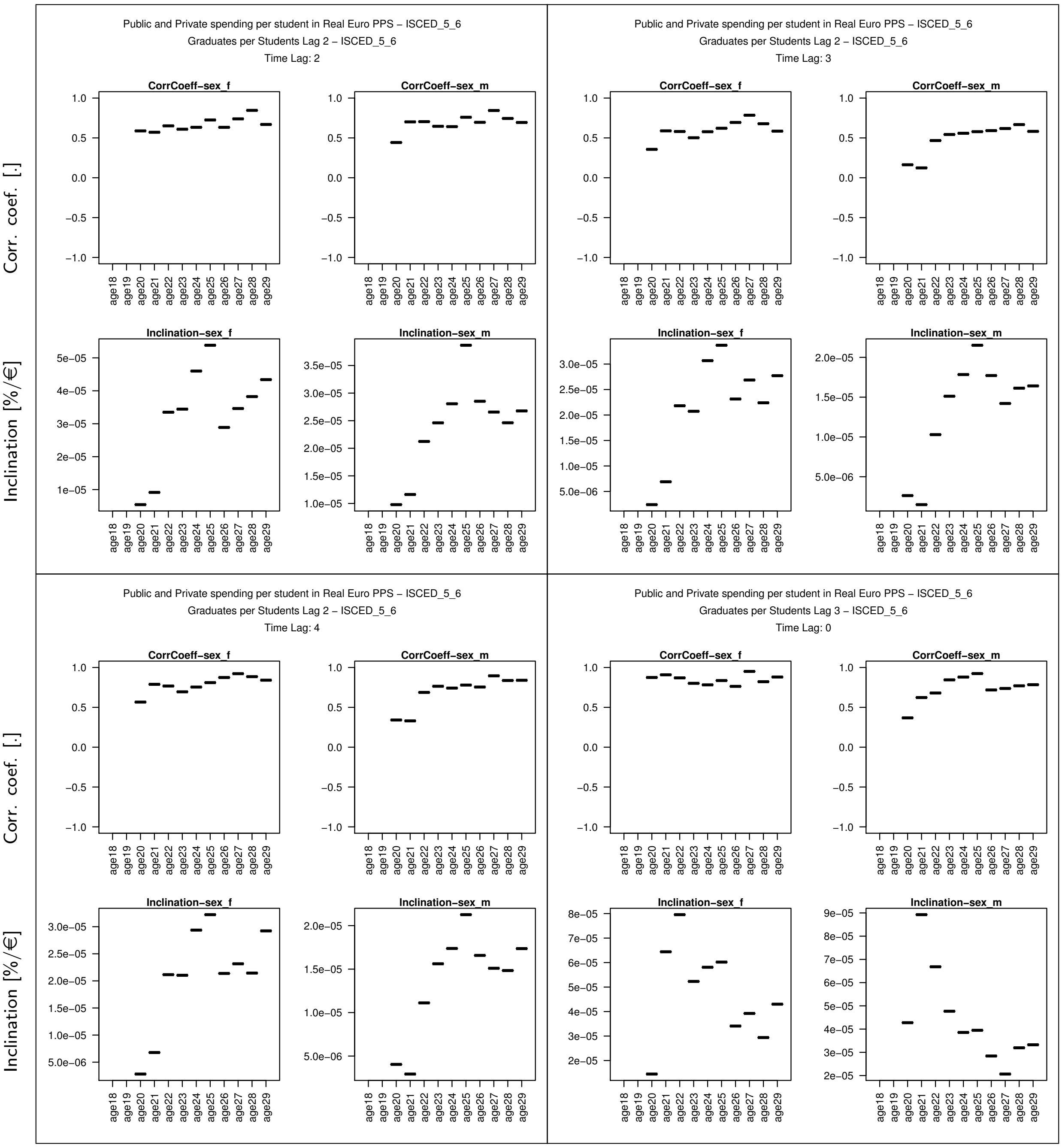
First, the plots are given. Afterwards, the numerical details are listed.

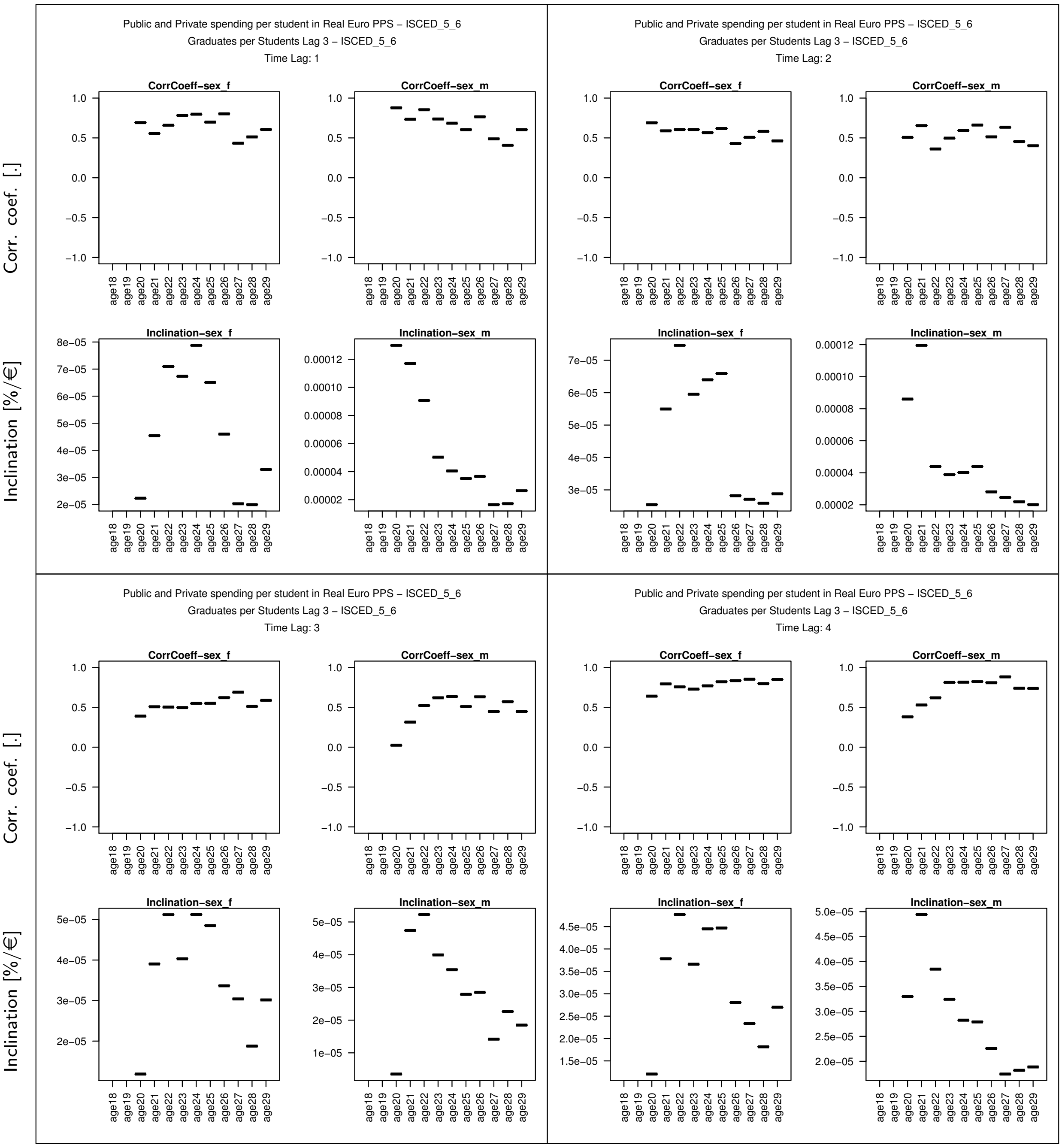


Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 0 – ISCED_5_6
Time Lag: 0
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 0 – ISCED_5_6
Time Lag: 1
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 0 – ISCED_5_6
Time Lag: 2
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 0 – ISCED_5_6
Time Lag: 3
CorrCoeff–sex_f
CorrCoeff–sex_m
Inclination–sex_f
Inclination–sex_m
Corr. coef. [:]
Inclination [%/€]
age18
age19
age20
age21
age22
age23
age24
age25
age26
age27
age28
age29

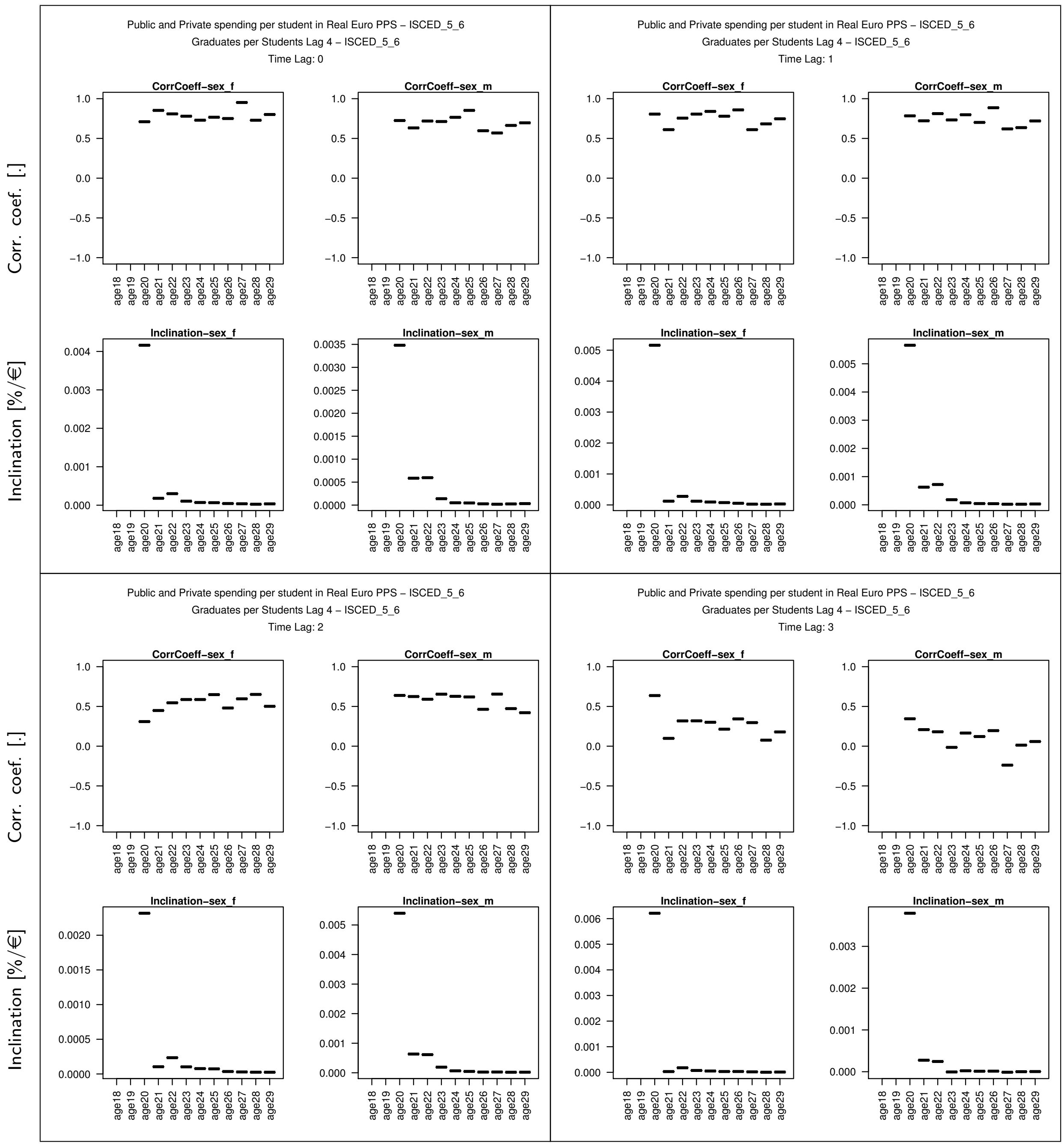

Public and Private spending per student in Real Euro PPS − ISCED_5_6
Graduates per Students Lag 0 − ISCED_5_6
Time Lag: 4
Public and Private spending per student in Real Euro PPS − ISCED_5_6
Graduates per Students Lag 1 − ISCED_5_6
Time Lag: 0
Public and Private spending per student in Real Euro PPS − ISCED_5_6
Graduates per Students Lag 1 − ISCED_5_6
Time Lag: 1
Public and Private spending per student in Real Euro PPS − ISCED_5_6
Graduates per Students Lag 1 − ISCED_5_6
Time Lag: 2
CorrCoeff−sex_f
CorrCoeff−sex_m
Inclination−sex_f
Inclination−sex_m
Corr. coef. [:]
Inclination [%/€]
age18
age19
age20
age21
age22
age23
age24
age25
age26
age27
age28
age29

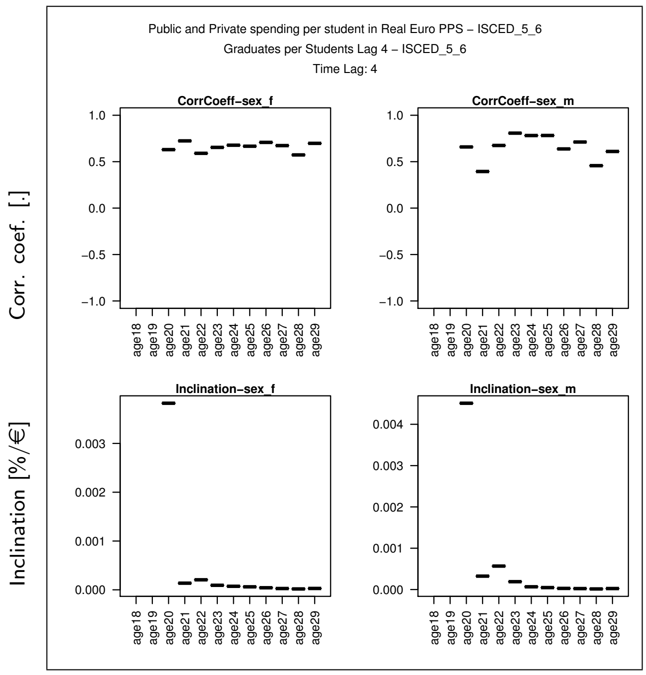

Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 1 – ISCED_5_6
Time Lag: 3
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 1 – ISCED_5_6
Time Lag: 4
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 2 – ISCED_5_6
Time Lag: 0
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 2 – ISCED_5_6
Time Lag: 1
CorrCoeff–sex_f
CorrCoeff–sex_m
Inclination–sex_f
Inclination–sex_m
Corr. coef. [:]
Inclination [%/€]
age18
age19
age20
age21
age22
age23
age24
age25
age26
age27
age28
age29


Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 2 – ISCED_5_6
Time Lag: 2
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 2 – ISCED_5_6
Time Lag: 3
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 2 – ISCED_5_6
Time Lag: 4
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 3 – ISCED_5_6
Time Lag: 0
CorrCoeff–sex_f
CorrCoeff–sex_m
Inclination–sex_f
Inclination–sex_m
Corr. coef. [:]
Inclination [%/€]
age18 age19 age20 age21 age22 age23 age24 age25 age26 age27 age28 age29



Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 3 – ISCED_5_6
Time Lag: 1
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 3 – ISCED_5_6
Time Lag: 2
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 3 – ISCED_5_6
Time Lag: 3
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 3 – ISCED_5_6
Time Lag: 4
CorrCoeff–sex_f
CorrCoeff–sex_m
Inclination–sex_f
Inclination–sex_m
Corr. coef. [:]
Inclination [%/€]
age18 age19 age20 age21 age22 age23 age24 age25 age26 age27 age28 age29


Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 4 – ISCED_5_6
Time Lag: 0
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 4 – ISCED_5_6
Time Lag: 1
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 4 – ISCED_5_6
Time Lag: 2
Public and Private spending per student in Real Euro PPS – ISCED_5_6
Graduates per Students Lag 4 – ISCED_5_6
Time Lag: 3
CorrCoeff–sex_f
CorrCoeff–sex_m
Inclination–sex_f
Inclination–sex_m
Corr. coef. [:]
Inclination [%/€]
age18
age19
age20
age21
age22
age23
age24
age25
age26
age27
age28
age29



Corr. coef. [:]

Inclination [%/€]

The values used for the plots:

Table C.3
Education Spending → Graduates per Student - Full correlation results

Lag Years Studs →Grads	*Spending →Grads*	*Age*	*Sex*	*Data Points*	*Intercept.*	*Inclin.*	*Corr. Coeff.*	*pValue*
0	0	20	f	9	0.010011	-0.0000011	-0.51	0.16
0	1	20	f	10	0.008310	-0.0000009	-0.60	0.07
0	2	20	f	10	0.007166	-0.0000007	-0.64	0.05
0	3	20	f	10	0.006410	-0.0000007	-0.66	0.04
0	4	20	f	9	0.002006	-0.0000001	-0.20	0.61
0	5	20	f	8	-0.000534	0.0000002	0.29	0.48
0	0	20	m	9	0.009219	-0.0000010	-0.53	0.15
0	1	20	m	10	0.005655	-0.0000006	-0.44	0.21
0	2	20	m	10	0.005655	-0.0000006	-0.55	0.10
0	3	20	m	10	0.005092	-0.0000005	-0.58	0.08
0	4	20	m	9	0.001052	0.0000000	-0.07	0.86
0	5	20	m	8	-0.000837	0.0000002	0.30	0.47
1	0	20	f	8	-0.004270	0.0000007	0.28	0.51
1	1	20	f	9	0.000637	0.0000001	0.04	0.91
1	2	20	f	9	0.003101	-0.0000002	-0.12	0.75
1	3	20	f	9	0.003819	-0.0000003	-0.22	0.56
1	4	20	f	9	0.001936	-0.0000001	-0.06	0.88
1	5	20	f	8	-0.001673	0.0000004	0.38	0.35
1	0	20	m	8	0.009094	-0.0000008	-0.17	0.69
1	1	20	m	9	-0.000935	0.0000004	0.11	0.79
1	2	20	m	9	0.009822	-0.0000009	-0.34	0.37
1	3	20	m	9	0.010137	-0.0000009	-0.45	0.22
1	4	20	m	9	0.006808	-0.0000006	-0.33	0.39
1	5	20	m	8	0.000705	0.0000002	0.11	0.80
2	0	20	f	7	-0.037308	0.0000048	0.83	0.02
2	1	20	f	8	-0.066783	0.0000083	0.73	0.04
2	2	20	f	8	-0.041871	0.0000054	0.59	0.13
2	3	20	f	8	-0.015828	0.0000024	0.36	0.39
2	4	20	f	8	-0.018878	0.0000028	0.57	0.14
2	5	20	f	8	-0.013680	0.0000022	0.50	0.20
2	0	20	m	7	-0.043499	0.0000065	0.28	0.54
2	1	20	m	8	-0.190902	0.0000238	0.88	0.00
2	2	20	m	8	-0.070132	0.0000098	0.44	0.27
2	3	20	m	8	-0.008977	0.0000026	0.16	0.70
2	4	20	m	8	-0.020400	0.0000040	0.34	0.41
2	5	20	m	8	-0.022996	0.0000044	0.42	0.30
3	0	20	f	6	-0.111519	0.0000145	0.87	0.02
3	1	20	f	7	-0.176971	0.0000223	0.69	0.08
3	2	20	f	7	-0.203045	0.0000254	0.69	0.09
3	3	20	f	7	-0.085793	0.0000119	0.39	0.39
3	4	20	f	7	-0.086475	0.0000121	0.64	0.12
3	5	20	f	7	-0.052615	0.0000082	0.53	0.23
3	0	20	m	6	-0.309551	0.0000428	0.37	0.47
3	1	20	m	7	-1.054555	0.0001300	0.88	0.01
3	2	20	m	7	-0.672234	0.0000860	0.51	0.25
3	3	20	m	7	0.033923	0.0000035	0.03	0.96
3	4	20	m	7	-0.212754	0.0000330	0.38	0.40
3	5	20	m	7	-0.219050	0.0000343	0.48	0.28
4	0	20	f	5	-33.042000	0.0041614	0.71	0.18
4	1	20	f	6	-41.212746	0.0051589	0.81	0.05
4	2	20	f	6	-16.672222	0.0023169	0.31	0.55
4	3	20	f	6	-49.761667	0.0062107	0.64	0.17

C.4 Education Spending - Graduates per Student - Correlation Analysis

Lag Years Studs →Grads	*Spending →Grads*	*Age*	*Sex*	*Data Points*	*Intercept.*	*Inclin.*	*Corr. Coeff.*	*pValue*
4	4	20	f	6	-29.195531	0.0038237	0.63	0.18
4	5	20	f	6	-15.023876	0.0021846	0.49	0.32
4	0	20	m	5	-28.140845	0.0034811	0.72	0.17
4	1	20	m	6	-46.343416	0.0056574	0.78	0.07
4	2	20	m	6	-43.903016	0.0053964	0.64	0.17
4	3	20	m	6	-29.986243	0.0037925	0.34	0.50
4	4	20	m	6	-35.844658	0.0045097	0.66	0.15
4	5	20	m	6	-18.471015	0.0024974	0.50	0.32
0	0	21	f	9	-0.003457	0.0000015	0.24	0.54
0	1	21	f	10	0.013280	-0.0000005	-0.10	0.78
0	2	21	f	10	0.013307	-0.0000005	-0.13	0.73
0	3	21	f	10	0.011469	-0.0000003	-0.08	0.82
0	4	21	f	9	-0.000321	0.0000012	0.38	0.32
0	5	21	f	8	-0.011891	0.0000026	0.76	0.03
0	0	21	m	9	-0.003618	0.0000008	0.25	0.52
0	1	21	m	10	-0.007135	0.0000012	0.40	0.25
0	2	21	m	10	-0.004076	0.0000009	0.36	0.31
0	3	21	m	10	-0.000587	0.0000005	0.22	0.54
0	4	21	m	9	-0.005098	0.0000010	0.47	0.20
0	5	21	m	8	-0.006913	0.0000012	0.53	0.18
1	0	21	f	8	-0.056804	0.0000078	0.84	0.01
1	1	21	f	9	-0.009413	0.0000023	0.31	0.42
1	2	21	f	9	-0.000543	0.0000013	0.23	0.55
1	3	21	f	9	-0.000561	0.0000013	0.29	0.45
1	4	21	f	9	-0.004081	0.0000017	0.48	0.19
1	5	21	f	8	-0.016386	0.0000032	0.81	0.01
1	0	21	m	8	-0.018926	0.0000028	0.47	0.23
1	1	21	m	9	-0.029934	0.0000041	0.71	0.03
1	2	21	m	9	-0.014861	0.0000023	0.55	0.13
1	3	21	m	9	-0.004099	0.0000011	0.32	0.40
1	4	21	m	9	-0.005223	0.0000012	0.45	0.23
1	5	21	m	8	-0.007771	0.0000016	0.51	0.19
2	0	21	f	7	-0.122596	0.0000160	0.92	0.00
2	1	21	f	8	-0.087169	0.0000120	0.61	0.11
2	2	21	f	8	-0.062125	0.0000092	0.57	0.14
2	3	21	f	8	-0.042136	0.0000069	0.59	0.12
2	4	21	f	8	-0.040471	0.0000068	0.79	0.02
2	5	21	f	8	-0.037060	0.0000065	0.85	0.01
2	0	21	m	7	-0.055108	0.0000083	0.45	0.31
2	1	21	m	8	-0.072910	0.0000104	0.51	0.19
2	2	21	m	8	-0.082213	0.0000116	0.70	0.05
2	3	21	m	8	0.004121	0.0000015	0.12	0.77
2	4	21	m	8	-0.007621	0.0000029	0.33	0.42
2	5	21	m	8	-0.017004	0.0000041	0.52	0.18
3	0	21	f	6	-0.506473	0.0000644	0.91	0.01
3	1	21	f	7	-0.340182	0.0000454	0.56	0.19
3	2	21	f	7	-0.420315	0.0000550	0.59	0.16
3	3	21	f	7	-0.280724	0.0000390	0.51	0.25
3	4	21	f	7	-0.267235	0.0000378	0.79	0.03
3	5	21	f	7	-0.239554	0.0000351	0.89	0.01
3	0	21	m	6	-0.668948	0.0000893	0.62	0.19
3	1	21	m	7	-0.904066	0.0001171	0.73	0.06
3	2	21	m	7	-0.920226	0.0001196	0.65	0.11
3	3	21	m	7	-0.298691	0.0000474	0.31	0.49
3	4	21	m	7	-0.311124	0.0000494	0.53	0.22
3	5	21	m	7	-0.384731	0.0000592	0.77	0.04
4	0	21	f	5	-1.374481	0.0001788	0.85	0.07
4	1	21	f	6	-0.864646	0.0001210	0.61	0.20
4	2	21	f	6	-0.715487	0.0001041	0.45	0.37

Lag Years *Studs* *→Grads*	*Spending* *→Grads*	*Age*	*Sex*	*Data Points*	*Intercept.*	*Inclin.*	*Corr. Coeff.*	*pValue*
4	3	21	f	6	-0.076435	0.0000297	0.10	0.85
4	4	21	f	6	-0.976275	0.0001361	0.72	0.10
4	5	21	f	6	-0.871555	0.0001257	0.91	0.01
4	0	21	m	5	-4.588502	0.0005854	0.63	0.25
4	1	21	m	6	-4.893217	0.0006259	0.72	0.11
4	2	21	m	6	-4.940240	0.0006340	0.62	0.19
4	3	21	m	6	-1.853047	0.0002752	0.21	0.69
4	4	21	m	6	-2.253867	0.0003244	0.39	0.44
4	5	21	m	6	-3.345575	0.0004605	0.76	0.08
0	0	22	f	9	-0.101734	0.0000162	0.51	0.16
0	1	22	f	10	-0.047055	0.0000100	0.38	0.28
0	2	22	f	10	-0.027039	0.0000077	0.37	0.30
0	3	22	f	10	-0.016504	0.0000066	0.36	0.30
0	4	22	f	9	-0.065579	0.0000125	0.68	0.05
0	5	22	f	8	-0.095599	0.0000164	0.80	0.02
0	0	22	m	9	-0.009149	0.0000025	0.20	0.60
0	1	22	m	10	-0.021998	0.0000042	0.34	0.34
0	2	22	m	10	-0.009278	0.0000027	0.27	0.45
0	3	22	m	10	-0.002644	0.0000019	0.23	0.53
0	4	22	m	9	-0.029305	0.0000051	0.60	0.09
0	5	22	m	8	-0.038873	0.0000064	0.66	0.07
1	0	22	f	8	-0.299068	0.0000391	0.87	0.00
1	1	22	f	9	-0.178093	0.0000253	0.65	0.06
1	2	22	f	9	-0.105749	0.0000170	0.59	0.09
1	3	22	f	9	-0.071141	0.0000131	0.57	0.11
1	4	22	f	9	-0.073174	0.0000135	0.72	0.03
1	5	22	f	8	-0.101485	0.0000171	0.84	0.01
1	0	22	m	8	-0.085463	0.0000117	0.68	0.07
1	1	22	m	9	-0.098422	0.0000133	0.70	0.04
1	2	22	m	9	-0.047833	0.0000075	0.53	0.14
1	3	22	m	9	-0.024933	0.0000049	0.43	0.25
1	4	22	m	9	-0.029852	0.0000055	0.60	0.09
1	5	22	m	8	-0.040546	0.0000069	0.68	0.07
2	0	22	f	7	-0.362963	0.0000469	0.86	0.01
2	1	22	f	8	-0.328164	0.0000431	0.68	0.06
2	2	22	f	8	-0.243136	0.0000335	0.65	0.08
2	3	22	f	8	-0.141345	0.0000218	0.58	0.13
2	4	22	f	8	-0.133635	0.0000211	0.77	0.03
2	5	22	f	8	-0.127663	0.0000208	0.85	0.01
2	0	22	m	7	-0.134389	0.0000184	0.70	0.08
2	1	22	m	8	-0.228166	0.0000295	0.80	0.02
2	2	22	m	8	-0.155606	0.0000212	0.70	0.05
2	3	22	m	8	-0.061355	0.0000103	0.47	0.24
2	4	22	m	8	-0.067150	0.0000111	0.69	0.06
2	5	22	m	8	-0.060202	0.0000105	0.73	0.04
3	0	22	f	6	-0.620288	0.0000796	0.87	0.02
3	1	22	f	7	-0.542508	0.0000710	0.66	0.11
3	2	22	f	7	-0.571052	0.0000746	0.60	0.15
3	3	22	f	7	-0.365960	0.0000512	0.50	0.25
3	4	22	f	7	-0.332116	0.0000477	0.76	0.05
3	5	22	f	7	-0.304409	0.0000451	0.87	0.01
3	0	22	m	6	-0.489546	0.0000668	0.68	0.14
3	1	22	m	7	-0.691398	0.0000906	0.85	0.01
3	2	22	m	7	-0.288019	0.0000439	0.36	0.43
3	3	22	m	7	-0.354872	0.0000522	0.52	0.23
3	4	22	m	7	-0.234927	0.0000385	0.62	0.14
3	5	22	m	7	-0.247336	0.0000406	0.79	0.03
4	0	22	f	5	-2.386551	0.0003000	0.81	0.10
4	1	22	f	6	-2.165965	0.0002770	0.76	0.08

C.4 Education Spending - Graduates per Student - Correlation Analysis

Lag Years Studs →Grads	*Spending →Grads*	*Age*	*Sex*	*Data Points*	*Intercept.*	*Inclin.*	*Corr. Coeff.*	*p Value*
4	2	22	f	6	-1.789468	0.0002342	0.55	0.26
4	3	22	f	6	-1.296997	0.0001777	0.32	0.54
4	4	22	f	6	-1.520817	0.0002053	0.59	0.22
4	5	22	f	6	-1.472340	0.0002028	0.79	0.06
4	0	22	m	5	-4.642450	0.0005970	0.72	0.17
4	1	22	m	6	-5.648401	0.0007205	0.81	0.05
4	2	22	m	6	-4.704655	0.0006134	0.59	0.22
4	3	22	m	6	-1.534124	0.0002447	0.18	0.73
4	4	22	m	6	-4.256266	0.0005678	0.67	0.14
4	5	22	m	6	-3.630829	0.0005018	0.81	0.05
0	0	23	f	9	-0.072619	0.0000181	0.51	0.16
0	1	23	f	10	-0.058873	0.0000169	0.47	0.17
0	2	23	f	10	-0.001899	0.0000103	0.36	0.31
0	3	23	f	10	0.023297	0.0000074	0.30	0.40
0	4	23	f	9	-0.016978	0.0000124	0.49	0.18
0	5	23	f	8	-0.051011	0.0000167	0.59	0.13
0	0	23	m	9	-0.102803	0.0000159	0.71	0.03
0	1	23	m	10	-0.086003	0.0000142	0.61	0.06
0	2	23	m	10	-0.050351	0.0000102	0.54	0.11
0	3	23	m	10	-0.033613	0.0000083	0.51	0.13
0	4	23	m	9	-0.056242	0.0000111	0.68	0.04
0	5	23	m	8	-0.067357	0.0000126	0.71	0.05
1	0	23	f	8	-0.217006	0.0000347	0.78	0.02
1	1	23	f	9	-0.192578	0.0000323	0.67	0.05
1	2	23	f	9	-0.064501	0.0000175	0.49	0.18
1	3	23	f	9	-0.016994	0.0000120	0.42	0.25
1	4	23	f	9	-0.025557	0.0000132	0.58	0.10
1	5	23	f	8	-0.050439	0.0000164	0.64	0.08
1	0	23	m	8	-0.172837	0.0000244	0.83	0.01
1	1	23	m	9	-0.156107	0.0000228	0.71	0.03
1	2	23	m	9	-0.078133	0.0000138	0.58	0.10
1	3	23	m	9	-0.046010	0.0000101	0.53	0.14
1	4	23	m	9	-0.051215	0.0000109	0.71	0.03
1	5	23	m	8	-0.060588	0.0000122	0.72	0.04
2	0	23	f	7	-0.281831	0.0000423	0.82	0.02
2	1	23	f	8	-0.383827	0.0000545	0.79	0.02
2	2	23	f	8	-0.208725	0.0000344	0.61	0.11
2	3	23	f	8	-0.089889	0.0000207	0.50	0.20
2	4	23	f	8	-0.090308	0.0000210	0.69	0.06
2	5	23	f	8	-0.075867	0.0000196	0.73	0.04
2	0	23	m	7	-0.190777	0.0000274	0.82	0.02
2	1	23	m	8	-0.254978	0.0000351	0.75	0.03
2	2	23	m	8	-0.162782	0.0000246	0.65	0.08
2	3	23	m	8	-0.080387	0.0000151	0.54	0.16
2	4	23	m	8	-0.082967	0.0000156	0.76	0.03
2	5	23	m	8	-0.067655	0.0000140	0.77	0.02
3	0	23	f	6	-0.360258	0.0000523	0.80	0.06
3	1	23	f	7	-0.486020	0.0000673	0.78	0.04
3	2	23	f	7	-0.416518	0.0000595	0.61	0.15
3	3	23	f	7	-0.248532	0.0000403	0.50	0.26
3	4	23	f	7	-0.214009	0.0000366	0.73	0.06
3	5	23	f	7	-0.172119	0.0000322	0.78	0.04
3	0	23	m	6	-0.335668	0.0000477	0.84	0.03
3	1	23	m	7	-0.355779	0.0000503	0.74	0.06
3	2	23	m	7	-0.255735	0.0000389	0.50	0.26
3	3	23	m	7	-0.261478	0.0000399	0.62	0.14
3	4	23	m	7	-0.195167	0.0000324	0.81	0.03
3	5	23	m	7	-0.154879	0.0000281	0.85	0.01
4	0	23	f	5	-0.761128	0.0001045	0.78	0.12

Lag Years *Studs* *→Grads*	*Spending* *→Grads*	*Age*	*Sex*	*Data Points*	*Intercept.*	*Inclin.*	*Corr. Coeff.*	*pValue*
4	1	23	f	6	-0.887566	0.0001204	0.81	0.05
4	2	23	f	6	-0.730809	0.0001026	0.59	0.22
4	3	23	f	6	-0.469822	0.0000725	0.32	0.54
4	4	23	f	6	-0.635907	0.0000926	0.65	0.16
4	5	23	f	6	-0.477034	0.0000750	0.72	0.11
4	0	23	m	5	-0.935449	0.0001391	0.71	0.18
4	1	23	m	6	-1.285111	0.0001818	0.73	0.10
4	2	23	m	6	-1.348936	0.0001900	0.65	0.16
4	3	23	m	6	0.327613	-0.0000057	-0.02	0.98
4	4	23	m	6	-1.329717	0.0001900	0.81	0.05
4	5	23	m	6	-0.836870	0.0001339	0.77	0.07
0	0	24	f	9	-0.155906	0.0000354	0.71	0.03
0	1	24	f	10	-0.167715	0.0000375	0.66	0.04
0	2	24	f	10	-0.063036	0.0000255	0.56	0.09
0	3	24	f	10	-0.014427	0.0000199	0.51	0.13
0	4	24	f	9	-0.029368	0.0000220	0.57	0.11
0	5	24	f	8	-0.033493	0.0000228	0.53	0.17
0	0	24	m	9	-0.143167	0.0000254	0.79	0.01
0	1	24	m	10	-0.116799	0.0000228	0.64	0.04
0	2	24	m	10	-0.061418	0.0000165	0.58	0.08
0	3	24	m	10	-0.031657	0.0000131	0.54	0.11
0	4	24	m	9	-0.047783	0.0000152	0.63	0.07
0	5	24	m	8	-0.055657	0.0000164	0.62	0.10
1	0	24	f	8	-0.232163	0.0000434	0.74	0.04
1	1	24	f	9	-0.293165	0.0000511	0.74	0.02
1	2	24	f	9	-0.103254	0.0000292	0.58	0.10
1	3	24	f	9	-0.035119	0.0000215	0.53	0.14
1	4	24	f	9	-0.033077	0.0000215	0.65	0.06
1	5	24	f	8	-0.035806	0.0000221	0.62	0.10
1	0	24	m	8	-0.184956	0.0000306	0.83	0.01
1	1	24	m	9	-0.181348	0.0000306	0.71	0.03
1	2	24	m	9	-0.078941	0.0000188	0.59	0.09
1	3	24	m	9	-0.034186	0.0000137	0.54	0.14
1	4	24	m	9	-0.035687	0.0000140	0.68	0.04
1	5	24	m	8	-0.038374	0.0000146	0.65	0.08
2	0	24	f	7	-0.272667	0.0000479	0.78	0.04
2	1	24	f	8	-0.468621	0.0000712	0.80	0.02
2	2	24	f	8	-0.248845	0.0000460	0.63	0.09
2	3	24	f	8	-0.115118	0.0000307	0.58	0.13
2	4	24	f	8	-0.101276	0.0000294	0.75	0.03
2	5	24	f	8	-0.064964	0.0000254	0.74	0.04
2	0	24	m	7	-0.171748	0.0000300	0.85	0.02
2	1	24	m	8	-0.246974	0.0000391	0.73	0.04
2	2	24	m	8	-0.150284	0.0000281	0.64	0.09
2	3	24	m	8	-0.061397	0.0000178	0.56	0.15
2	4	24	m	8	-0.055751	0.0000174	0.74	0.04
2	5	24	m	8	-0.032106	0.0000148	0.71	0.05
3	0	24	f	6	-0.358343	0.0000581	0.78	0.07
3	1	24	f	7	-0.532395	0.0000788	0.80	0.03
3	2	24	f	7	-0.402232	0.0000640	0.57	0.19
3	3	24	f	7	-0.288611	0.0000512	0.55	0.20
3	4	24	f	7	-0.227900	0.0000445	0.77	0.04
3	5	24	f	7	-0.163516	0.0000375	0.78	0.04
3	0	24	m	6	-0.226045	0.0000386	0.88	0.02
3	1	24	m	7	-0.240059	0.0000405	0.68	0.09
3	2	24	m	7	-0.235855	0.0000402	0.59	0.16
3	3	24	m	7	-0.191914	0.0000354	0.63	0.13
3	4	24	m	7	-0.128759	0.0000282	0.82	0.03
3	5	24	m	7	-0.076966	0.0000224	0.79	0.04

C.4 Education Spending - Graduates per Student - Correlation Analysis

Lag Years *Studs* *→Grads*	*Spending* *→Grads*	*Age*	*Sex*	*Data Points*	*Intercept.*	*Inclin.*	*Corr. Coeff.*	*pValue*
4	0	24	f	5	-0.444820	0.0000695	0.73	0.16
4	1	24	f	6	-0.650539	0.0000943	0.84	0.04
4	2	24	f	6	-0.499969	0.0000772	0.59	0.22
4	3	24	f	6	-0.277398	0.0000515	0.30	0.56
4	4	24	f	6	-0.449936	0.0000722	0.68	0.14
4	5	24	f	6	-0.292789	0.0000545	0.70	0.12
4	0	24	m	5	-0.257598	0.0000502	0.77	0.13
4	1	24	m	6	-0.435961	0.0000717	0.80	0.06
4	2	24	m	6	-0.384196	0.0000659	0.63	0.18
4	3	24	m	6	-0.012007	0.0000226	0.17	0.75
4	4	24	m	6	-0.383131	0.0000666	0.78	0.07
4	5	24	m	6	-0.180752	0.0000434	0.69	0.13
0	0	25	f	9	-0.294615	0.0000571	0.84	0.00
0	1	25	f	10	-0.271403	0.0000554	0.72	0.02
0	2	25	f	10	-0.160968	0.0000429	0.70	0.02
0	3	25	f	10	-0.075824	0.0000332	0.63	0.05
0	4	25	f	9	-0.077871	0.0000339	0.67	0.05
0	5	25	f	8	-0.054210	0.0000315	0.59	0.12
0	0	25	m	9	-0.155789	0.0000339	0.82	0.01
0	1	25	m	10	-0.128923	0.0000314	0.66	0.04
0	2	25	m	10	-0.065188	0.0000241	0.64	0.05
0	3	25	m	10	-0.013595	0.0000182	0.56	0.09
0	4	25	m	9	-0.025481	0.0000199	0.63	0.07
0	5	25	m	8	-0.028397	0.0000205	0.59	0.12
1	0	25	f	8	-0.256230	0.0000504	0.82	0.01
1	1	25	f	9	-0.293183	0.0000554	0.75	0.02
1	2	25	f	9	-0.148813	0.0000390	0.71	0.03
1	3	25	f	9	-0.054201	0.0000282	0.64	0.06
1	4	25	f	9	-0.047098	0.0000277	0.78	0.01
1	5	25	f	8	-0.024909	0.0000254	0.68	0.06
1	0	25	m	8	-0.185943	0.0000369	0.84	0.01
1	1	25	m	9	-0.190034	0.0000379	0.71	0.03
1	2	25	m	9	-0.089006	0.0000263	0.67	0.05
1	3	25	m	9	-0.014923	0.0000178	0.57	0.11
1	4	25	m	9	-0.015165	0.0000181	0.71	0.03
1	5	25	m	8	-0.011461	0.0000179	0.66	0.08
2	0	25	f	7	-0.280196	0.0000523	0.83	0.02
2	1	25	f	8	-0.375856	0.0000640	0.70	0.05
2	2	25	f	8	-0.284878	0.0000538	0.73	0.04
2	3	25	f	8	-0.109884	0.0000337	0.62	0.10
2	4	25	f	8	-0.094282	0.0000322	0.81	0.01
2	5	25	f	8	-0.053549	0.0000278	0.79	0.02
2	0	25	m	7	-0.166778	0.0000354	0.85	0.01
2	1	25	m	8	-0.212653	0.0000410	0.66	0.08
2	2	25	m	8	-0.189387	0.0000387	0.76	0.03
2	3	25	m	8	-0.041131	0.0000215	0.58	0.13
2	4	25	m	8	-0.036833	0.0000213	0.78	0.02
2	5	25	m	8	-0.008597	0.0000182	0.75	0.03
3	0	25	f	6	-0.348283	0.0000602	0.84	0.04
3	1	25	f	7	-0.386221	0.0000650	0.70	0.08
3	2	25	f	7	-0.390706	0.0000659	0.62	0.14
3	3	25	f	7	-0.237899	0.0000485	0.55	0.20
3	4	25	f	7	-0.201660	0.0000447	0.82	0.02
3	5	25	f	7	-0.141532	0.0000382	0.85	0.02
3	0	25	m	6	-0.186062	0.0000395	0.92	0.01
3	1	25	m	7	-0.144550	0.0000349	0.60	0.15
3	2	25	m	7	-0.220415	0.0000440	0.66	0.11
3	3	25	m	7	-0.080315	0.0000279	0.51	0.24
3	4	25	m	7	-0.077977	0.0000279	0.82	0.02

Lag Years Studs →Grads	Spending →Grads	Age	Sex	Data Points	Intercept.	Inclin.	Corr. Coeff.	pValue
3	5	25	m	7	-0.031683	0.0000228	0.81	0.03
4	0	25	f	5	-0.388985	0.0000651	0.77	0.13
4	1	25	f	6	-0.471186	0.0000754	0.78	0.07
4	2	25	f	6	-0.451672	0.0000734	0.65	0.16
4	3	25	f	6	-0.091353	0.0000316	0.21	0.68
4	4	25	f	6	-0.340157	0.0000612	0.67	0.15
4	5	25	f	6	-0.241251	0.0000503	0.75	0.09
4	0	25	m	5	-0.210647	0.0000463	0.85	0.07
4	1	25	m	6	-0.192161	0.0000446	0.70	0.12
4	2	25	m	6	-0.203519	0.0000462	0.62	0.19
4	3	25	m	6	0.091879	0.0000118	0.12	0.82
4	4	25	m	6	-0.207882	0.0000472	0.78	0.07
4	5	25	m	6	-0.096716	0.0000346	0.78	0.07
0	0	26	f	9	-0.296591	0.0000605	0.83	0.01
0	1	26	f	10	-0.292336	0.0000611	0.77	0.01
0	2	26	f	10	-0.151195	0.0000450	0.71	0.02
0	3	26	f	10	-0.070791	0.0000359	0.66	0.04
0	4	26	f	9	-0.048238	0.0000337	0.66	0.05
0	5	26	f	8	-0.009061	0.0000294	0.54	0.16
0	0	26	m	9	-0.055544	0.0000280	0.66	0.05
0	1	26	m	10	-0.082114	0.0000317	0.64	0.05
0	2	26	m	10	0.000294	0.0000223	0.56	0.09
0	3	26	m	10	0.050279	0.0000165	0.48	0.16
0	4	26	m	9	0.037694	0.0000183	0.54	0.14
0	5	26	m	8	0.046490	0.0000175	0.47	0.24
1	0	26	f	8	-0.079998	0.0000315	0.63	0.10
1	1	26	f	9	-0.224077	0.0000489	0.81	0.01
1	2	26	f	9	-0.063527	0.0000305	0.68	0.04
1	3	26	f	9	-0.011006	0.0000246	0.69	0.04
1	4	26	f	9	0.007747	0.0000226	0.78	0.01
1	5	26	f	8	0.051672	0.0000176	0.60	0.12
1	0	26	m	8	-0.047440	0.0000248	0.66	0.07
1	1	26	m	9	-0.150111	0.0000373	0.79	0.01
1	2	26	m	9	-0.025668	0.0000230	0.66	0.05
1	3	26	m	9	0.033155	0.0000162	0.58	0.10
1	4	26	m	9	0.039971	0.0000156	0.69	0.04
1	5	26	m	8	0.060614	0.0000133	0.57	0.14
2	0	26	f	7	-0.056307	0.0000269	0.67	0.10
2	1	26	f	8	-0.198529	0.0000437	0.78	0.02
2	2	26	f	8	-0.068860	0.0000289	0.63	0.09
2	3	26	f	8	-0.017601	0.0000231	0.69	0.06
2	4	26	f	8	-0.000607	0.0000214	0.87	0.00
2	5	26	f	8	0.035752	0.0000173	0.80	0.02
2	0	26	m	7	-0.030220	0.0000224	0.65	0.11
2	1	26	m	8	-0.171257	0.0000391	0.78	0.02
2	2	26	m	8	-0.078608	0.0000285	0.70	0.06
2	3	26	m	8	0.015230	0.0000177	0.59	0.12
2	4	26	m	8	0.026440	0.0000166	0.75	0.03
2	5	26	m	8	0.046994	0.0000144	0.74	0.04
3	0	26	f	6	-0.125328	0.0000341	0.76	0.08
3	1	26	f	7	-0.225466	0.0000460	0.80	0.03
3	2	26	f	7	-0.071214	0.0000282	0.43	0.34
3	3	26	f	7	-0.115035	0.0000336	0.62	0.14
3	4	26	f	7	-0.065016	0.0000280	0.83	0.02
3	5	26	f	7	-0.013482	0.0000223	0.80	0.03
3	0	26	m	6	-0.073606	0.0000284	0.72	0.11
3	1	26	m	7	-0.141704	0.0000365	0.76	0.05
3	2	26	m	7	-0.067755	0.0000281	0.51	0.24
3	3	26	m	7	-0.068950	0.0000285	0.63	0.13

C.4 Education Spending - Graduates per Student - Correlation Analysis

Lag Years *Studs* →*Grads*	*Spending* →*Grads*	*Age*	*Sex*	*Data Points*	*Intercept.*	*Inclin.*	*Corr. Coeff.*	*pValue*
3	4	26	m	7	-0.017133	0.0000226	0.81	0.03
3	5	26	m	7	0.010359	0.0000197	0.85	0.01
4	0	26	f	5	-0.204912	0.0000431	0.75	0.14
4	1	26	f	6	-0.292300	0.0000537	0.86	0.03
4	2	26	f	6	-0.131215	0.0000352	0.48	0.34
4	3	26	f	6	-0.108715	0.0000327	0.34	0.51
4	4	26	f	6	-0.185579	0.0000420	0.71	0.12
4	5	26	f	6	-0.102581	0.0000327	0.75	0.09
4	0	26	m	5	-0.045351	0.0000275	0.60	0.29
4	1	26	m	6	-0.153134	0.0000403	0.89	0.02
4	2	26	m	6	-0.017960	0.0000247	0.46	0.35
4	3	26	m	6	0.078132	0.0000135	0.20	0.71
4	4	26	m	6	-0.039217	0.0000275	0.64	0.17
4	5	26	m	6	-0.029379	0.0000267	0.84	0.03
0	0	27	f	9	-0.443902	0.0000779	0.85	0.00
0	1	27	f	10	-0.306999	0.0000630	0.69	0.03
0	2	27	f	10	-0.218313	0.0000532	0.73	0.02
0	3	27	f	10	-0.125618	0.0000428	0.69	0.03
0	4	27	f	9	-0.121851	0.0000428	0.72	0.03
0	5	27	f	8	-0.095972	0.0000403	0.64	0.09
0	0	27	m	9	0.000475	0.0000244	0.70	0.04
0	1	27	m	10	-0.038267	0.0000296	0.62	0.06
0	2	27	m	10	0.012962	0.0000238	0.62	0.06
0	3	27	m	10	0.083383	0.0000156	0.47	0.17
0	4	27	m	9	0.060286	0.0000186	0.57	0.11
0	5	27	m	8	0.077327	0.0000168	0.47	0.24
1	0	27	f	8	-0.234065	0.0000483	0.78	0.02
1	1	27	f	9	-0.219816	0.0000472	0.70	0.03
1	2	27	f	9	-0.122938	0.0000363	0.73	0.02
1	3	27	f	9	-0.064223	0.0000298	0.75	0.02
1	4	27	f	9	-0.032844	0.0000263	0.82	0.01
1	5	27	f	8	0.001402	0.0000226	0.68	0.06
1	0	27	m	8	0.060040	0.0000136	0.54	0.16
1	1	27	m	9	-0.063062	0.0000283	0.74	0.02
1	2	27	m	9	-0.004772	0.0000217	0.77	0.02
1	3	27	m	9	0.065771	0.0000135	0.60	0.09
1	4	27	m	9	0.063684	0.0000140	0.76	0.02
1	5	27	m	8	0.091512	0.0000108	0.58	0.14
2	0	27	f	7	-0.154022	0.0000361	0.77	0.04
2	1	27	f	8	-0.070566	0.0000267	0.46	0.25
2	2	27	f	8	-0.136191	0.0000346	0.74	0.04
2	3	27	f	8	-0.067360	0.0000269	0.78	0.02
2	4	27	f	8	-0.033766	0.0000232	0.92	0.00
2	5	27	f	8	0.005362	0.0000188	0.84	0.01
2	0	27	m	7	0.043417	0.0000136	0.47	0.28
2	1	27	m	8	-0.014685	0.0000205	0.53	0.17
2	2	27	m	8	-0.064330	0.0000266	0.84	0.01
2	3	27	m	8	0.042346	0.0000142	0.62	0.10
2	4	27	m	8	0.036363	0.0000151	0.90	0.00
2	5	27	m	8	0.059305	0.0000126	0.84	0.01
3	0	27	f	6	-0.193146	0.0000392	0.95	0.00
3	1	27	f	7	-0.028362	0.0000203	0.43	0.33
3	2	27	f	7	-0.086173	0.0000271	0.51	0.25
3	3	27	f	7	-0.111830	0.0000304	0.69	0.09
3	4	27	f	7	-0.049683	0.0000233	0.85	0.01
3	5	27	f	7	-0.014874	0.0000195	0.86	0.01
3	0	27	m	6	-0.020290	0.0000206	0.74	0.09
3	1	27	m	7	0.016750	0.0000165	0.49	0.27
3	2	27	m	7	-0.051642	0.0000246	0.63	0.13

Lag Years Studs →Grads	*Spending →Grads*	*Age*	*Sex*	*Data Points*	*Intercept.*	*Inclin.*	*Corr. Coeff.*	*pValue*
3	3	27	m	7	0.038191	0.0000142	0.45	0.32
3	4	27	m	7	0.012195	0.0000174	0.88	0.01
3	5	27	m	7	0.035903	0.0000149	0.91	0.00
4	0	27	f	5	-0.179379	0.0000369	0.95	0.01
4	1	27	f	6	-0.076313	0.0000252	0.61	0.20
4	2	27	f	6	-0.106277	0.0000288	0.60	0.21
4	3	27	f	6	-0.018387	0.0000187	0.30	0.57
4	4	27	f	6	-0.082823	0.0000264	0.67	0.14
4	5	27	f	6	-0.031558	0.0000207	0.72	0.11
4	0	27	m	5	0.004548	0.0000187	0.57	0.32
4	1	27	m	6	-0.014272	0.0000212	0.62	0.19
4	2	27	m	6	-0.056531	0.0000262	0.65	0.16
4	3	27	m	6	0.273535	-0.0000124	-0.24	0.65
4	4	27	m	6	-0.027372	0.0000230	0.71	0.11
4	5	27	m	6	-0.004560	0.0000207	0.87	0.02
0	0	28	f	9	-0.481781	0.0000806	0.79	0.01
0	1	28	f	10	-0.377901	0.0000696	0.73	0.02
0	2	28	f	10	-0.261093	0.0000565	0.74	0.01
0	3	28	f	10	-0.150589	0.0000440	0.67	0.03
0	4	28	f	9	-0.142492	0.0000435	0.69	0.04
0	5	28	f	8	-0.145725	0.0000446	0.67	0.07
0	0	28	m	9	-0.068379	0.0000329	0.61	0.08
0	1	28	m	10	0.003149	0.0000250	0.50	0.14
0	2	28	m	10	0.058526	0.0000187	0.47	0.17
0	3	28	m	10	0.107158	0.0000131	0.38	0.28
0	4	28	m	9	0.101484	0.0000139	0.41	0.28
0	5	28	m	8	0.037230	0.0000219	0.57	0.14
1	0	28	f	8	-0.252715	0.0000488	0.70	0.05
1	1	28	f	9	-0.307574	0.0000558	0.76	0.02
1	2	28	f	9	-0.176430	0.0000410	0.76	0.02
1	3	28	f	9	-0.090631	0.0000312	0.72	0.03
1	4	28	f	9	-0.059904	0.0000279	0.80	0.01
1	5	28	f	8	-0.042444	0.0000262	0.72	0.04
1	0	28	m	8	-0.031906	0.0000236	0.63	0.09
1	1	28	m	9	-0.004547	0.0000207	0.56	0.12
1	2	28	m	9	0.046175	0.0000150	0.55	0.13
1	3	28	m	9	0.081928	0.0000109	0.49	0.18
1	4	28	m	9	0.082467	0.0000110	0.62	0.08
1	5	28	m	8	0.051362	0.0000149	0.74	0.03
2	0	28	f	7	-0.104285	0.0000279	0.65	0.11
2	1	28	f	8	-0.130205	0.0000312	0.56	0.15
2	2	28	f	8	-0.187711	0.0000382	0.85	0.01
2	3	28	f	8	-0.050464	0.0000224	0.68	0.06
2	4	28	f	8	-0.040257	0.0000214	0.88	0.00
2	5	28	f	8	-0.013619	0.0000186	0.86	0.01
2	0	28	m	7	-0.072898	0.0000253	0.66	0.11
2	1	28	m	8	-0.018420	0.0000191	0.47	0.24
2	2	28	m	8	-0.064193	0.0000246	0.74	0.03
2	3	28	m	8	0.009791	0.0000161	0.67	0.07
2	4	28	m	8	0.022161	0.0000148	0.84	0.01
2	5	28	m	8	0.025938	0.0000146	0.93	0.00
3	0	28	f	6	-0.133782	0.0000294	0.82	0.04
3	1	28	f	7	-0.051381	0.0000199	0.51	0.24
3	2	28	f	7	-0.101658	0.0000259	0.58	0.17
3	3	28	f	7	-0.039005	0.0000188	0.51	0.24
3	4	28	f	7	-0.032175	0.0000181	0.80	0.03
3	5	28	f	7	-0.026868	0.0000178	0.95	0.00
3	0	28	m	6	-0.142863	0.0000319	0.77	0.07
3	1	28	m	7	-0.014968	0.0000171	0.41	0.36

C.4 Education Spending - Graduates per Student - Correlation Analysis

Lag Years *Studs →Grads*	*Spending →Grads*	*Age*	*Sex*	*Data Points*	*Intercept.*	*Inclin.*	*Corr. Coeff.*	*p Value*
3	2	28	m	7	-0.054757	0.0000219	0.45	0.31
3	3	28	m	7	-0.059303	0.0000226	0.57	0.18
3	4	28	m	7	-0.020157	0.0000182	0.74	0.06
3	5	28	m	7	-0.028550	0.0000195	0.96	0.00
4	0	28	f	5	-0.103677	0.0000247	0.73	0.16
4	1	28	f	6	-0.084227	0.0000227	0.68	0.13
4	2	28	f	6	-0.105998	0.0000253	0.65	0.16
4	3	28	f	6	0.078235	0.0000038	0.08	0.89
4	4	28	f	6	-0.041839	0.0000180	0.57	0.23
4	5	28	f	6	-0.053043	0.0000197	0.85	0.03
4	0	28	m	5	-0.089942	0.0000255	0.66	0.22
4	1	28	m	6	-0.054416	0.0000215	0.64	0.17
4	2	28	m	6	-0.029643	0.0000187	0.47	0.34
4	3	28	m	6	0.125249	0.0000007	0.01	0.98
4	4	28	m	6	0.006559	0.0000147	0.46	0.36
4	5	28	m	6	-0.052172	0.0000220	0.93	0.01
0	0	29	f	9	-0.570651	0.0000880	0.72	0.03
0	1	29	f	10	-0.433912	0.0000733	0.63	0.05
0	2	29	f	10	-0.278824	0.0000557	0.60	0.07
0	3	29	f	10	-0.161341	0.0000423	0.53	0.11
0	4	29	f	9	-0.217310	0.0000495	0.62	0.08
0	5	29	f	8	-0.253834	0.0000548	0.64	0.09
0	0	29	m	9	-0.126126	0.0000390	0.54	0.13
0	1	29	m	10	-0.095904	0.0000362	0.56	0.10
0	2	29	m	10	-0.012518	0.0000267	0.51	0.13
0	3	29	m	10	0.065615	0.0000176	0.39	0.26
0	4	29	m	9	0.014584	0.0000239	0.52	0.15
0	5	29	m	8	-0.011933	0.0000276	0.56	0.15
1	0	29	f	8	-0.482494	0.0000741	0.82	0.01
1	1	29	f	9	-0.487550	0.0000756	0.77	0.02
1	2	29	f	9	-0.260024	0.0000496	0.68	0.04
1	3	29	f	9	-0.157945	0.0000380	0.65	0.06
1	4	29	f	9	-0.138475	0.0000361	0.77	0.02
1	5	29	f	8	-0.119643	0.0000344	0.70	0.05
1	0	29	m	8	-0.141022	0.0000353	0.72	0.04
1	1	29	m	9	-0.207772	0.0000436	0.84	0.00
1	2	29	m	9	-0.069182	0.0000277	0.72	0.03
1	3	29	m	9	0.004276	0.0000193	0.62	0.07
1	4	29	m	9	0.009978	0.0000188	0.75	0.02
1	5	29	m	8	0.023050	0.0000175	0.69	0.06
2	0	29	f	7	-0.280751	0.0000471	0.83	0.02
2	1	29	f	8	-0.324059	0.0000526	0.66	0.07
2	2	29	f	8	-0.241649	0.0000434	0.67	0.07
2	3	29	f	8	-0.105305	0.0000277	0.58	0.13
2	4	29	f	8	-0.115062	0.0000292	0.84	0.01
2	5	29	f	8	-0.077626	0.0000252	0.82	0.01
2	0	29	m	7	-0.128750	0.0000303	0.74	0.06
2	1	29	m	8	-0.138667	0.0000317	0.67	0.07
2	2	29	m	8	-0.094489	0.0000268	0.69	0.06
2	3	29	m	8	-0.004570	0.0000164	0.58	0.13
2	4	29	m	8	-0.010796	0.0000174	0.84	0.01
2	5	29	m	8	-0.004203	0.0000169	0.92	0.00
3	0	29	f	6	-0.266906	0.0000430	0.88	0.02
3	1	29	f	7	-0.178610	0.0000329	0.61	0.15
3	2	29	f	7	-0.141637	0.0000288	0.46	0.30
3	3	29	f	7	-0.150928	0.0000302	0.59	0.17
3	4	29	f	7	-0.121714	0.0000270	0.85	0.02
3	5	29	f	7	-0.098327	0.0000246	0.94	0.00
3	0	29	m	6	-0.172954	0.0000332	0.78	0.07

Lag Years Studs →Grads	*Spending →Grads*	*Age*	*Sex*	*Data Points*	*Intercept.*	*Inclin.*	*Corr. Coeff.*	*pValue*
3	1	29	m	7	-0.112812	0.0000263	0.60	0.15
3	2	29	m	7	-0.058355	0.0000201	0.40	0.37
3	3	29	m	7	-0.042922	0.0000185	0.45	0.31
3	4	29	m	7	-0.044481	0.0000189	0.74	0.06
3	5	29	m	7	-0.054083	0.0000204	0.96	0.00
4	0	29	f	5	-0.206434	0.0000344	0.80	0.10
4	1	29	f	6	-0.179487	0.0000316	0.75	0.09
4	2	29	f	6	-0.120308	0.0000248	0.50	0.31
4	3	29	f	6	-0.005869	0.0000115	0.18	0.73
4	4	29	f	6	-0.144601	0.0000280	0.70	0.12
4	5	29	f	6	-0.124905	0.0000261	0.88	0.02
4	0	29	m	5	-0.174565	0.0000322	0.70	0.19
4	1	29	m	6	-0.154770	0.0000301	0.72	0.11
4	2	29	m	6	-0.072392	0.0000206	0.42	0.41
4	3	29	m	6	0.072692	0.0000037	0.06	0.91
4	4	29	m	6	-0.100641	0.0000242	0.61	0.20
4	5	29	m	6	-0.128646	0.0000280	0.96	0.00

C.5 Details of partial analyses

This chapter is structured equally to section 5.3 on page 114, containing more detailed information.

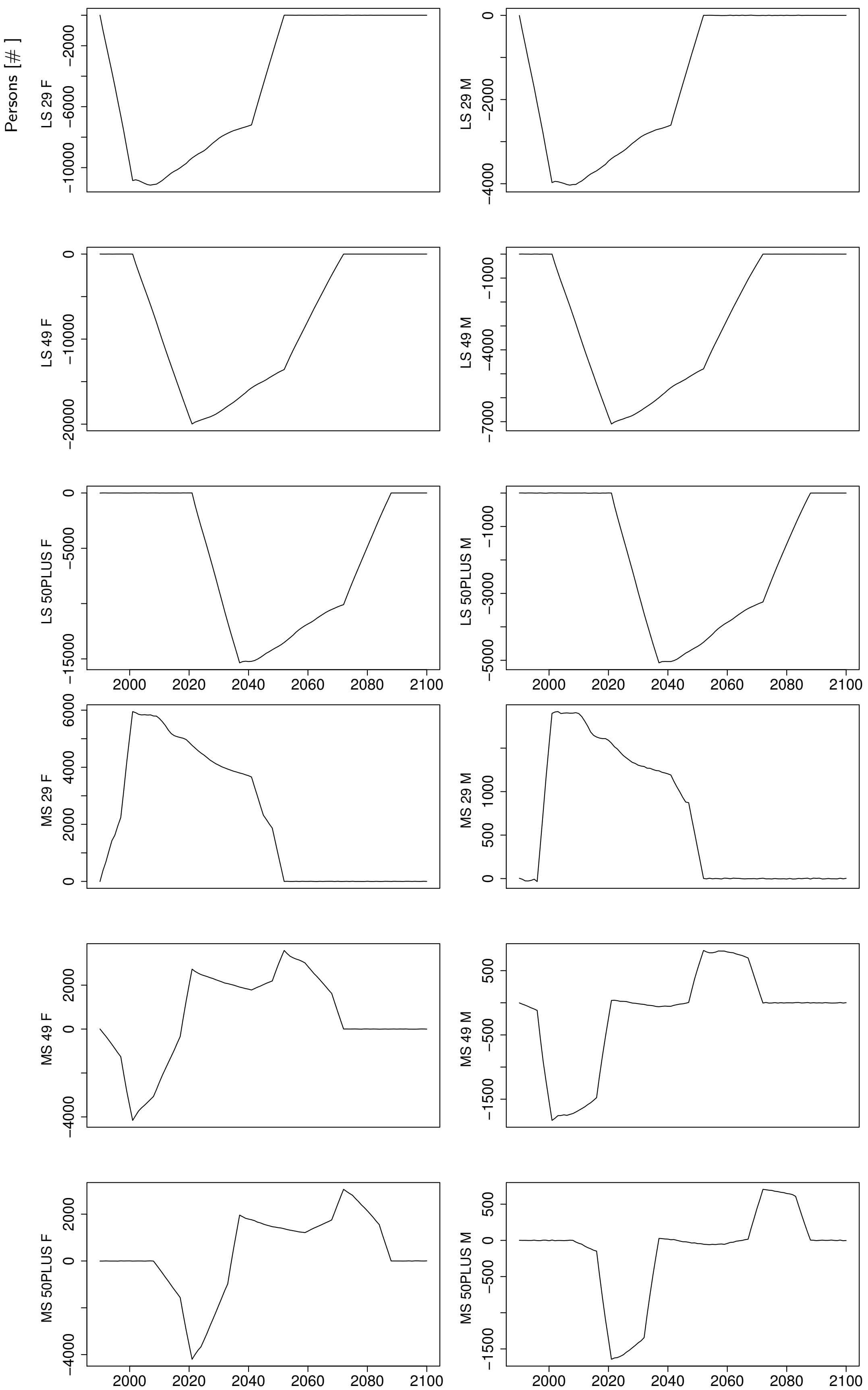
C.5.1 Education Spending → Graduation Probability

Only for consistency in section numbering needed. All relevant information contained in the main part of the thesis.

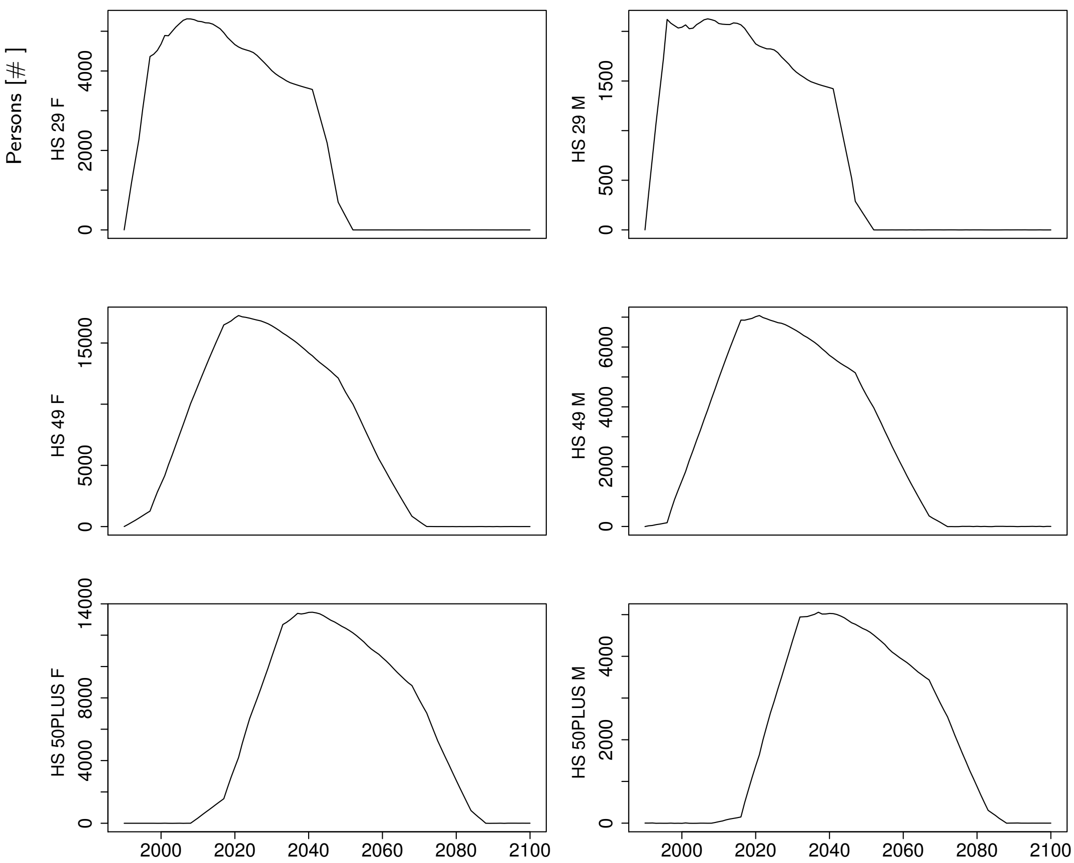
C.5.2 Education Spending → Population Composition

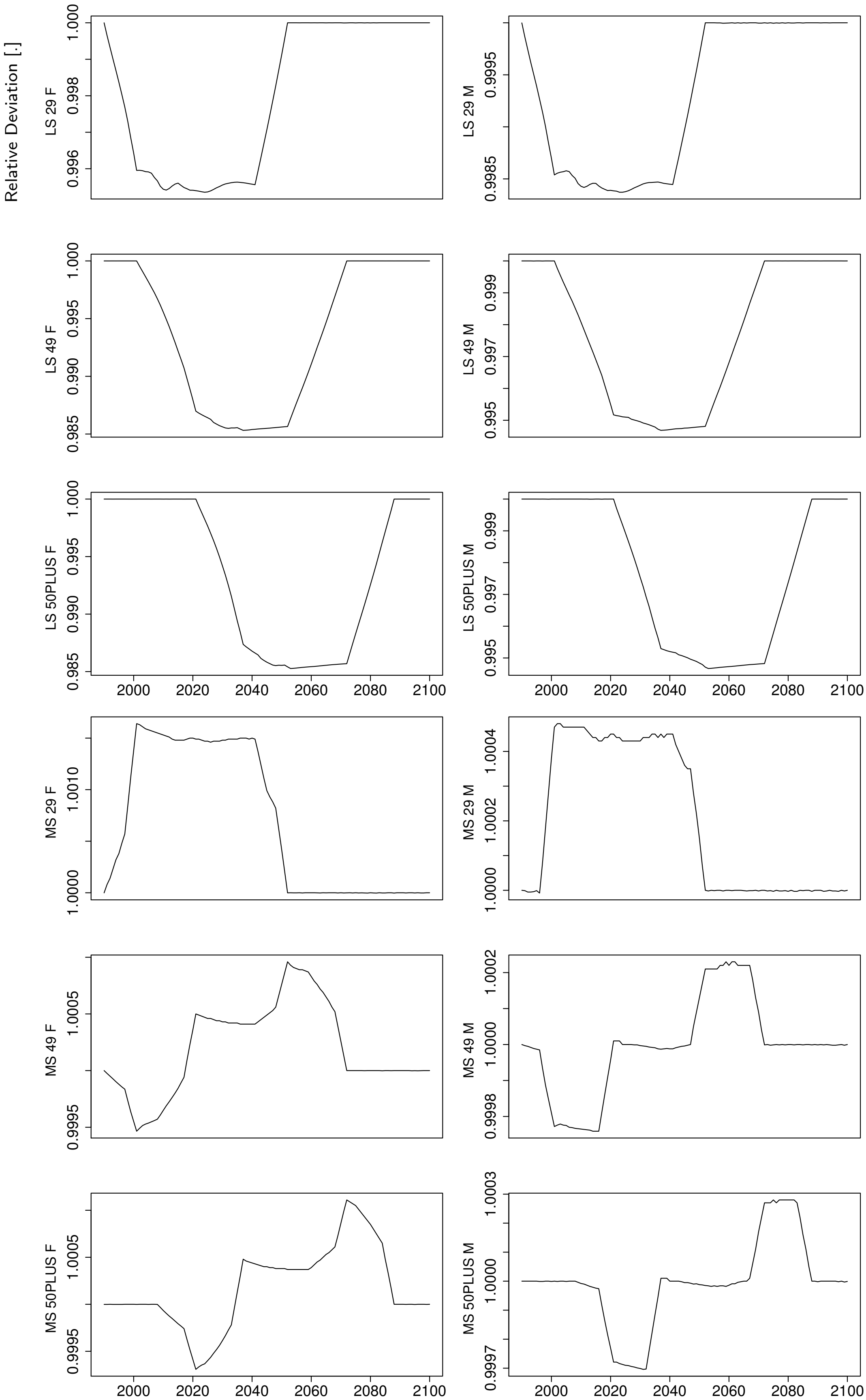
This section contains more detailed data, supplementing the information compiled in section 5.3.2 on page 117. The following graphs show each of the 18 time series combined in figure 5.9 on page 118 as individual plot. For technical reasons the graphs have to start on the next page.

The first two pages contain the absolute deviation from the baseline values. After that, the next two pages show the relative deviation.

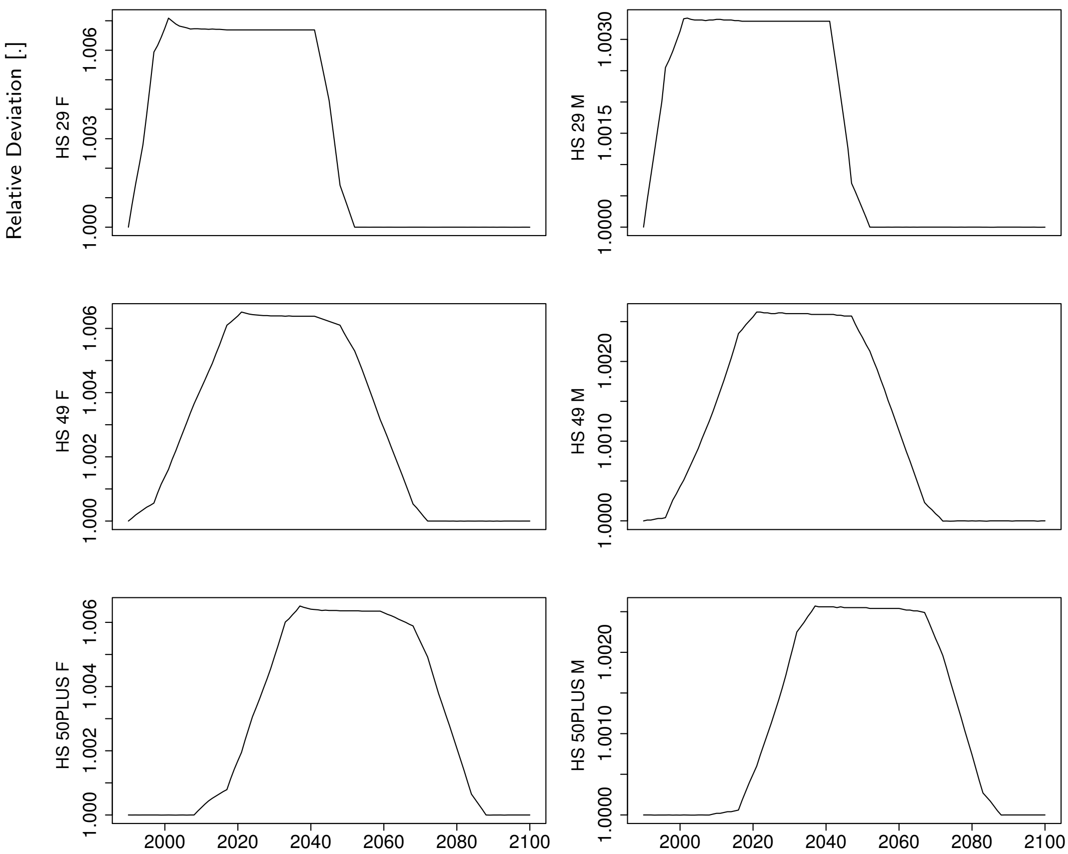


Persons [#]
LS 29 F
−10000
−6000
−2000
LS 29 M
−4000
−2000
0
LS 49 F
−20000
−10000
0
LS 49 M
−7000
−4000
−1000
LS 50PLUS F
−15000
−5000
0
LS 50PLUS M
−5000
−3000
−1000
2000
2020
2040
2060
2080
2100
MS 29 F
0
2000
4000
6000
MS 29 M
0
500
1000
MS 49 F
−4000
0
2000
MS 49 M
−1500
−500
500
MS 50PLUS F
−4000
0
2000
MS 50PLUS M
−1500
−500
0
500
2000
2020
2040
2060
2080
2100


Persons [#]
HS 29 F
HS 29 M
HS 49 F
HS 49 M
HS 50PLUS F
HS 50PLUS M
2000
2020
2040
2060
2080
2100



Relative Deviation [.]
LS 29 F
1.000
0.998
0.996
LS 29 M
0.9995
0.9985
LS 49 F
1.000
0.995
0.990
0.985
LS 49 M
0.999
0.997
0.995
LS 50PLUS F
1.000
0.995
0.990
0.985
LS 50PLUS M
0.999
0.997
0.995
2000
2020
2040
2060
2080
2100
MS 29 F
1.0010
1.0000
MS 29 M
1.0004
1.0002
1.0000
MS 49 F
1.0005
0.9995
MS 49 M
1.0002
1.0000
0.9998
MS 50PLUS F
1.0005
0.9995
MS 50PLUS M
1.0003
1.0000
0.9997
2000
2020
2040
2060
2080
2100



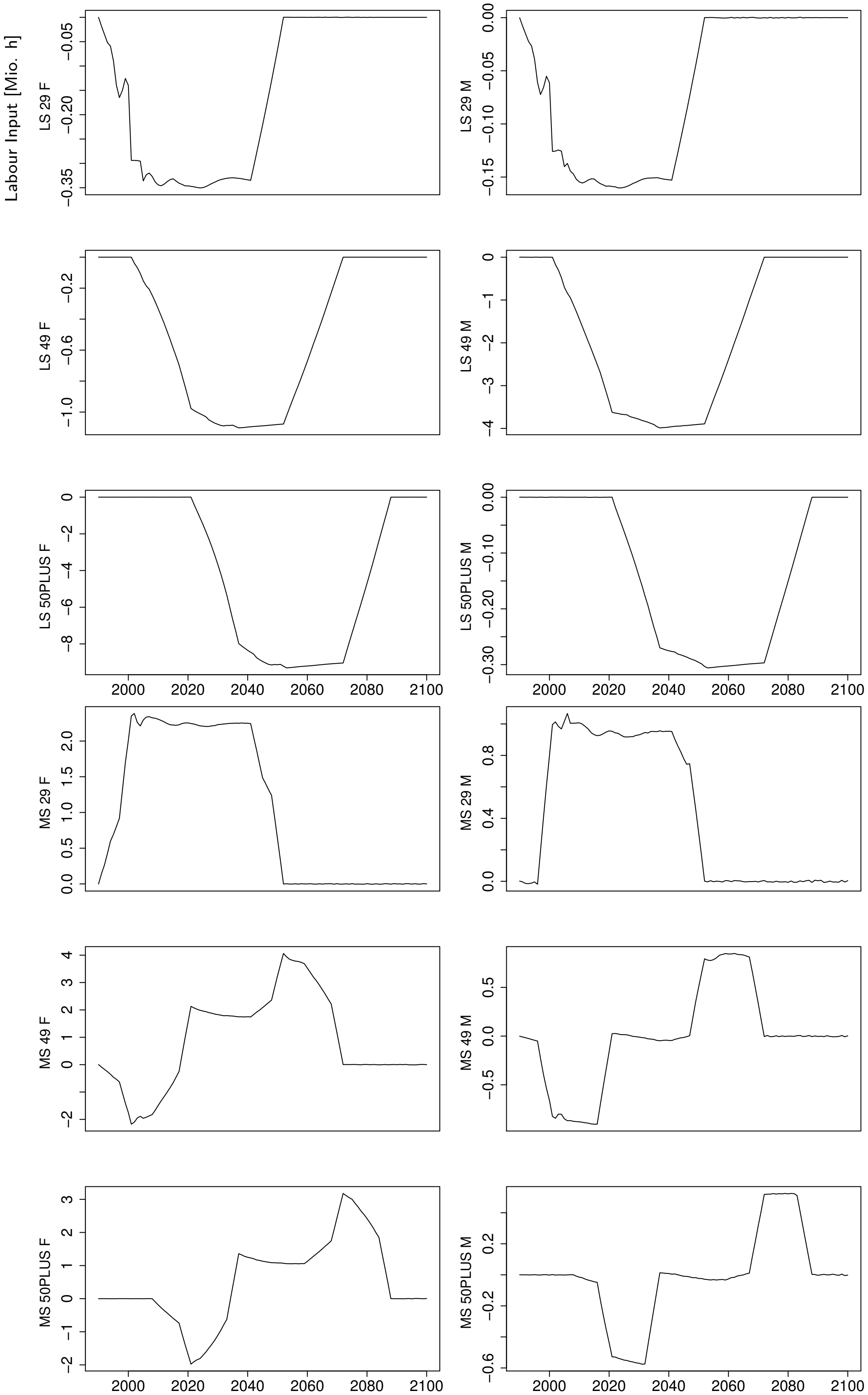
Relative Deviation [.]
HS 29 F
HS 29 M
HS 49 F
HS 49 M
HS 50PLUS F
HS 50PLUS M
1.000
1.003
1.006
1.0000
1.0015
1.0030
1.002
1.004
1.0010
1.0020
2000
2020
2040
2060
2080
2100

C.5.3 Education Spending → Labour Input

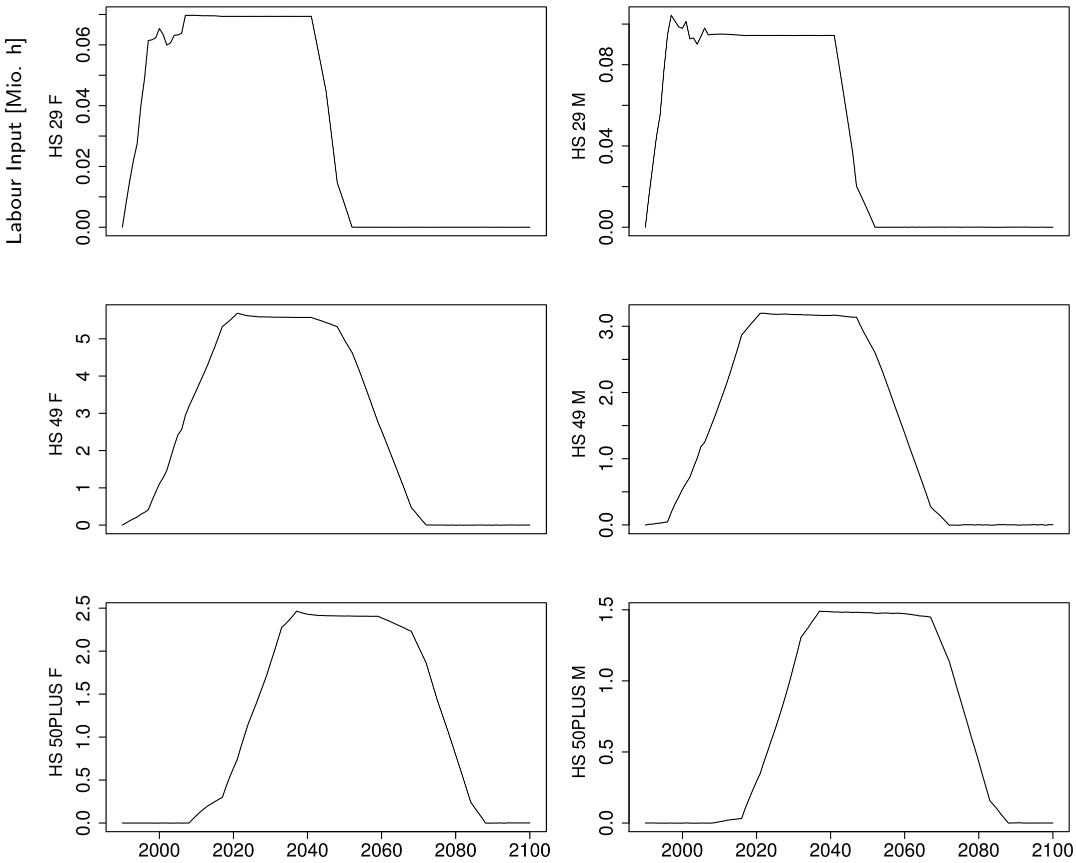
This section contains more detailed data, supplementing the information compiled in section 5.3.3 on page 119 with additional graphs and tables.

- The first two pages contain the absolute deviation [Mio. h] from the baseline values.
- The next two pages show the relative deviation.
- The first table shows detailed results for each sector disaggregated by labour types [h]
- The second table shows the results for each sector disaggregated by ISCED group [Tsd. h]
- After that table, the according graphs are plotted

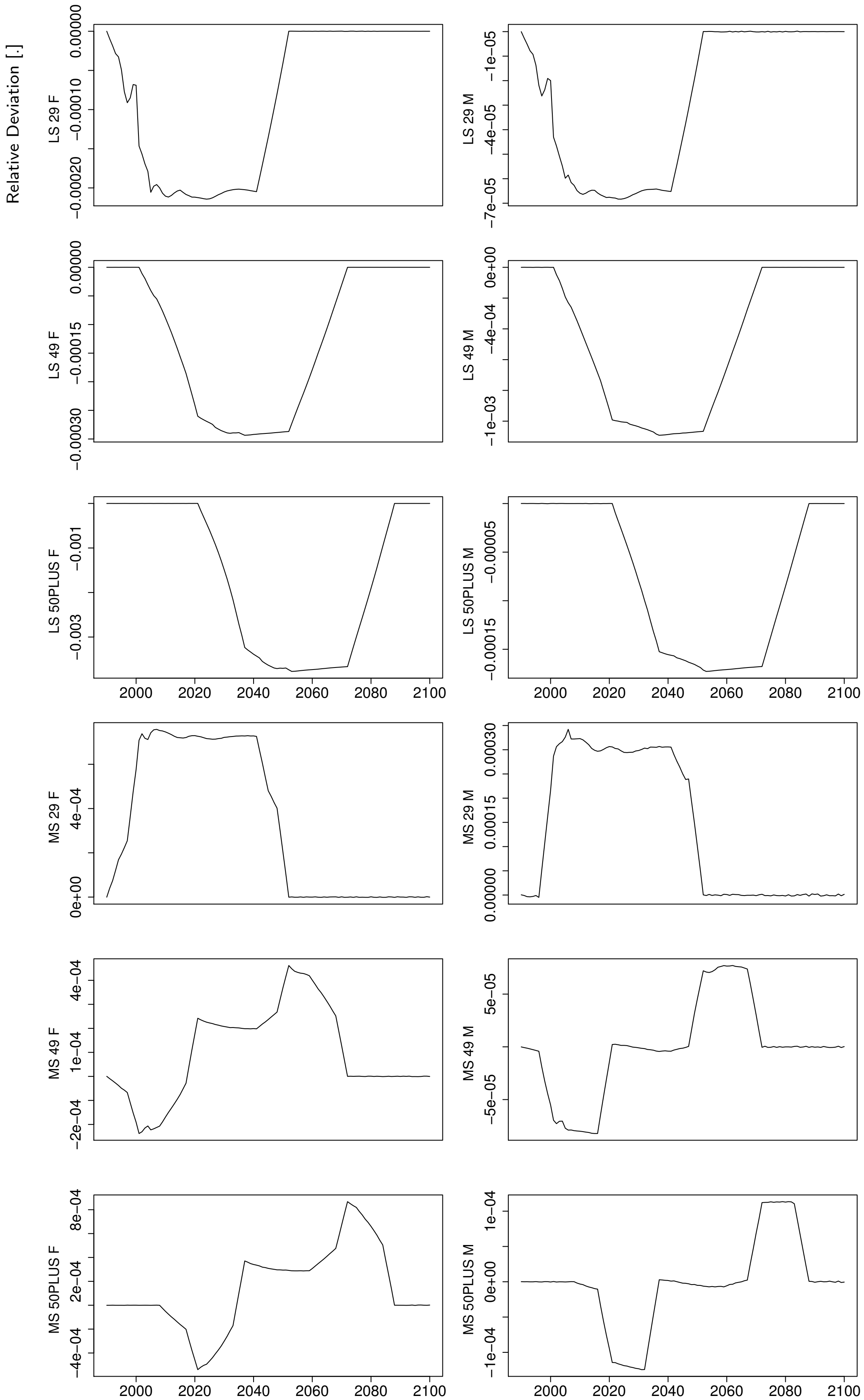
The following graphs show each of the 18 time series combined in figure 5.10 on page 120 as individual plot. For technical reasons the graphs have to start on the next page.

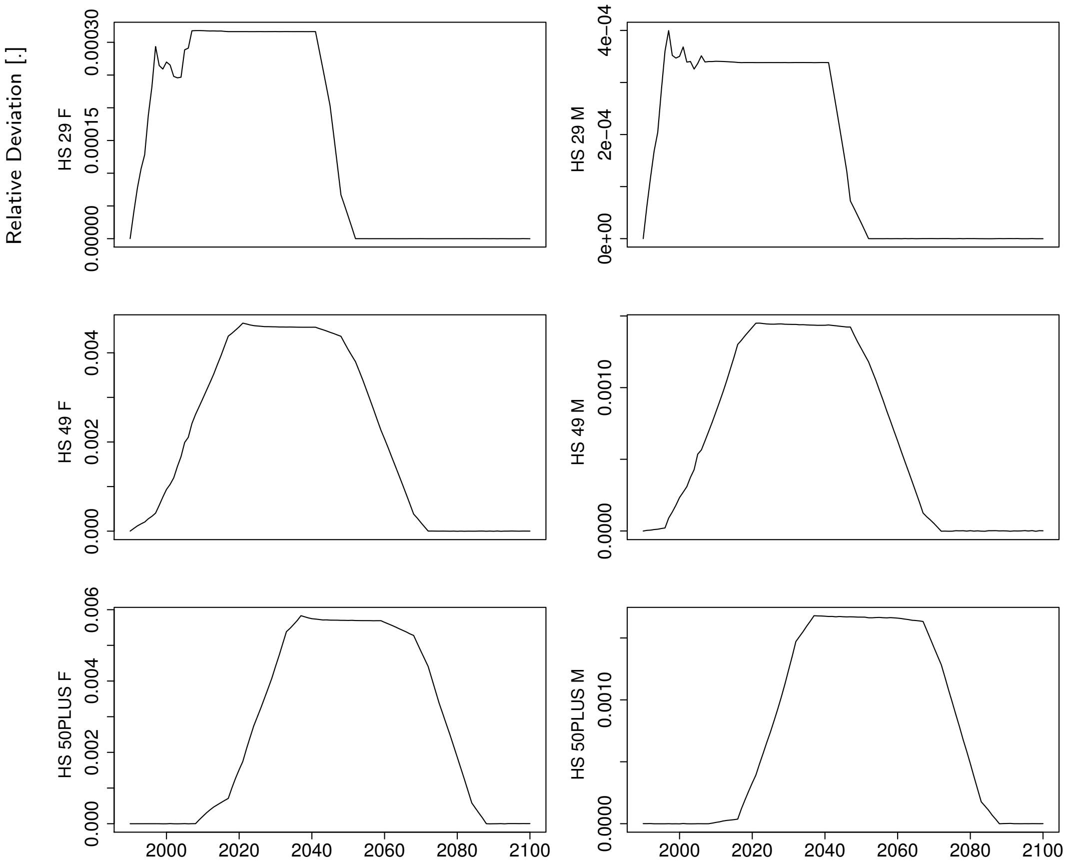


Labour Input [Mio. h]
LS 29 F
LS 29 M
LS 49 F
LS 49 M
LS 50PLUS F
LS 50PLUS M
MS 29 F
MS 29 M
MS 49 F
MS 49 M
MS 50PLUS F
MS 50PLUS M
2000
2020
2040
2060
2080
2100



Labour Input [Mio. h]
HS 29 F
HS 29 M
HS 49 F
HS 49 M
HS 50PLUS F
HS 50PLUS M
0.00
0.02
0.04
0.06
0.08
0
1
2
3
4
5
0.0
1.0
2.0
3.0
0.5
1.5
2.5
2000
2020
2040
2060
2080
2100


Relative Deviation [.]
LS 29 F
LS 29 M
LS 49 F
LS 49 M
LS 50PLUS F
LS 50PLUS M
MS 29 F
MS 29 M
MS 49 F
MS 49 M
MS 50PLUS F
MS 50PLUS M
2000
2020
2040
2060
2080
2100


Relative Deviation [.]
HS 29 F
HS 29 M
HS 49 F
HS 49 M
HS 50PLUS F
HS 50PLUS M
0.00000
0.00015
0.00030
0e+00
2e−04
4e−04
0.000
0.002
0.004
0.0000
0.0010
0.006
2000
2020
2040
2060
2080
2100

The following table contains the complete sectoral results for each labour type of the absolute difference of hours worked [h] disaggregated by labour types.

Sector	*Labour Type*	*2000*	*2010*	*2020*	*2040*	*2050*	*2060*
		2000	2010	2020	2040	2050	2060
AtB	LS 29 F	-501	-1,234	-1,241	-1,196	-239	0
AtB	LS 49 F	0	0	0	0	0	0
AtB	LS 50PLUS F	0	0	0	0	0	0
AtB	LS 29 M	0	0	0	0	0	0
AtB	LS 49 M	0	0	0	0	0	0
AtB	LS 50PLUS M	0	0	0	0	0	0
AtB	MS 29 F	261,088	299,423	292,714	292,202	81,872	-58
AtB	MS 49 F	0	0	0	0	0	0
AtB	MS 50PLUS F	0	0	0	0	0	0
AtB	MS 29 M	114,126	144,145	136,808	136,479	44,495	475
AtB	MS 49 M	0	0	0	0	0	0
AtB	MS 50PLUS M	0	0	0	0	0	0
AtB	HS 29 F	20,168	21,496	21,397	21,400	2,306	-2
AtB	HS 49 F	0	0	0	0	0	0
AtB	HS 50PLUS F	0	0	0	0	0	0
AtB	HS 29 M	0	0	0	0	0	0
AtB	HS 49 M	0	0	0	0	0	0
AtB	HS 50PLUS M	0	0	0	0	0	0
C	LS 29 F	0	0	0	0	0	0
C	LS 49 F	0	-565	-1,533	-1,861	-1,833	-1,140
C	LS 50PLUS F	-30	-38	39	-196,464	-214,831	-216,502
C	LS 29 M	0	0	0	0	0	0
C	LS 49 M	0	0	0	0	0	0
C	LS 50PLUS M	4	0	4	-8,362	-8,991	-9,188
C	MS 29 F	22,553	25,864	25,284	25,240	7,072	-5
C	MS 49 F	0	0	0	0	0	0
C	MS 50PLUS F	0	0	0	0	0	0
C	MS 29 M	17,623	22,258	21,125	21,074	6,871	73
C	MS 49 M	0	0	0	0	0	0
C	MS 50PLUS M	0	0	0	0	0	0
C	HS 29 F	0	0	0	0	0	0
C	HS 49 F	0	0	0	0	0	0
C	HS 50PLUS F	0	0	0	0	0	0
C	HS 29 M	3,667	3,561	3,536	3,536	313	0
C	HS 49 M	0	0	0	0	0	0
C	HS 50PLUS M	0	0	0	0	0	0
15t16	LS 29 F	0	0	0	0	0	0
15t16	LS 49 F	0	0	0	0	0	0
15t16	LS 50PLUS F	-25	-32	32	-163,522	-178,810	-180,200
15t16	LS 29 M	0	0	0	0	0	0
15t16	LS 49 M	0	0	0	0	0	0
15t16	LS 50PLUS M	0	0	0	0	0	0
15t16	MS 29 F	92,045	105,559	103,194	103,014	28,864	-21
15t16	MS 49 F	0	0	0	0	0	0
15t16	MS 50PLUS F	22	-3,130	-27,890	20,788	17,927	18,726
15t16	MS 29 M	12,725	16,072	15,254	15,217	4,961	53
15t16	MS 49 M	0	0	0	0	0	0
15t16	MS 50PLUS M	0	0	0	0	0	0
15t16	HS 29 F	0	0	0	0	0	0
15t16	HS 49 F	17,930	58,749	90,521	90,354	80,427	40,902
15t16	HS 50PLUS F	-4	547	3,997	15,149	15,020	14,882
15t16	HS 29 M	0	0	0	0	0	0
15t16	HS 49 M	3,971	13,558	23,197	23,436	20,780	10,258
15t16	HS 50PLUS M	-10	90	2,898	14,756	14,692	14,619
17t19	LS 29 F	0	0	0	0	0	0

Sector	*Labour Type*	*2000*	*2010*	*2020*	*2040*	*2050*	*2060*
17t19	LS 49 F	0	-955	-2,590	-3,144	-3,097	-1,926
17t19	LS 50PLUS F	-95	-122	125	-629,571	-688,431	-693,784
17t19	LS 29 M	0	0	0	0	0	0
17t19	LS 49 M	0	0	0	0	0	0
17t19	LS 50PLUS M	5	1	5	-11,369	-12,224	-12,492
17t19	MS 29 F	134,396	154,128	150,675	150,412	42,144	-30
17t19	MS 49 F	0	0	0	0	0	0
17t19	MS 50PLUS F	0	0	0	0	0	0
17t19	MS 29 M	24,470	30,907	29,334	29,263	9,541	102
17t19	MS 49 M	0	0	0	0	0	0
17t19	MS 50PLUS M	0	0	0	0	0	0
17t19	HS 29 F	14,685	15,652	15,580	15,581	1,679	-2
17t19	HS 49 F	0	0	0	0	0	0
17t19	HS 50PLUS F	0	0	0	0	0	0
17t19	HS 29 M	1,823	1,771	1,758	1,758	155	0
17t19	HS 49 M	0	0	0	0	0	0
17t19	HS 50PLUS M	0	0	0	0	0	0
20	LS 29 F	0	0	0	0	0	0
20	LS 49 F	6	-16,767	-45,476	-55,197	-54,376	-33,810
20	LS 50PLUS F	-23	-29	30	-150,881	-164,987	-166,269
20	LS 29 M	0	0	0	0	0	0
20	LS 49 M	0	0	0	0	0	0
20	LS 50PLUS M	8	1	8	-16,575	-17,822	-18,213
20	MS 29 F	13,880	15,918	15,561	15,534	4,352	-3
20	MS 49 F	0	0	0	0	0	0
20	MS 50PLUS F	0	0	0	0	0	0
20	MS 29 M	7,694	9,717	9,223	9,200	3,000	32
20	MS 49 M	0	0	0	0	0	0
20	MS 50PLUS M	0	0	0	0	0	0
20	HS 29 F	1,593	1,698	1,690	1,691	182	0
20	HS 49 F	1,948	6,384	9,837	9,819	8,740	4,445
20	HS 50PLUS F	-1	116	846	3,205	3,177	3,148
20	HS 29 M	1,631	1,584	1,573	1,573	139	0
20	HS 49 M	0	0	0	0	0	0
20	HS 50PLUS M	0	0	0	0	0	0
21t22	LS 29 F	0	0	0	0	0	0
21t22	LS 49 F	0	-1,254	-3,402	-4,129	-4,067	-2,529
21t22	LS 50PLUS F	-39	-50	51	-255,372	-279,247	-281,418
21t22	LS 29 M	0	0	0	0	0	0
21t22	LS 49 M	0	0	0	0	0	0
21t22	LS 50PLUS M	0	0	0	-700	-752	-769
21t22	MS 29 F	44,767	51,340	50,190	50,102	14,038	-10
21t22	MS 49 F	0	0	0	0	0	0
21t22	MS 50PLUS F	0	-61	-540	402	347	362
21t22	MS 29 M	28,113	35,507	33,700	33,619	10,961	117
21t22	MS 49 M	0	0	0	0	0	0
21t22	MS 50PLUS M	0	0	0	0	0	0
21t22	HS 29 F	641	683	680	680	73	0
21t22	HS 49 F	7,111	23,301	35,902	35,836	31,899	16,222
21t22	HS 50PLUS F	-3	382	2,795	10,594	10,503	10,407
21t22	HS 29 M	1,568	1,523	1,512	1,512	134	0
21t22	HS 49 M	0	0	0	0	0	0
21t22	HS 50PLUS M	0	0	0	0	0	0
23	LS 29 F	0	0	0	0	0	0
23	LS 49 F	0	0	0	0	0	0
23	LS 50PLUS F	-3	-4	5	-22,680	-24,800	-24,993
23	LS 29 M	0	0	0	0	0	0
23	LS 49 M	0	0	0	0	0	0
23	LS 50PLUS M	0	0	0	-137	-147	-150
23	MS 29 F	4,404	5,051	4,937	4,929	1,381	-1
23	MS 49 F	0	0	0	0	0	0

Sector	*Labour Type*	*2000*	*2010*	*2020*	*2040*	*2050*	*2060*
23	MS 50PLUS F	0	0	0	0	0	0
23	MS 29 M	2,943	3,717	3,528	3,519	1,147	12
23	MS 49 M	0	0	0	0	0	0
23	MS 50PLUS M	0	0	0	0	0	0
23	HS 29 F	712	759	756	756	81	0
23	HS 49 F	0	0	0	0	0	0
23	HS 50PLUS F	0	3	19	72	71	70
23	HS 29 M	263	255	253	253	22	0
23	HS 49 M	0	0	0	0	0	0
23	HS 50PLUS M	0	0	0	0	0	0
24	LS 29 F	0	0	0	0	0	0
24	LS 49 F	1	-2,352	-6,379	-7,743	-7,628	-4,743
24	LS 50PLUS F	-41	-53	54	-272,831	-298,339	-300,658
24	LS 29 M	0	0	0	0	0	0
24	LS 49 M	0	0	0	0	0	0
24	LS 50PLUS M	2	0	2	-4,460	-4,795	-4,900
24	MS 29 F	42,330	48,546	47,458	47,375	13,274	-9
24	MS 49 F	0	0	0	0	0	0
24	MS 50PLUS F	0	0	0	0	0	0
24	MS 29 M	27,022	34,130	32,392	32,315	10,535	112
24	MS 49 M	0	0	0	0	0	0
24	MS 50PLUS M	0	0	0	0	0	0
24	HS 29 F	2,817	3,003	2,989	2,989	322	0
24	HS 49 F	2,991	9,800	15,099	15,071	13,415	6,822
24	HS 50PLUS F	-2	260	1,899	7,198	7,136	7,071
24	HS 29 M	2,529	2,456	2,439	2,439	216	0
24	HS 49 M	0	0	0	0	0	0
24	HS 50PLUS M	0	0	0	0	0	0
25	LS 29 F	0	0	0	0	0	0
25	LS 49 F	1	-2,813	-7,629	-9,259	-9,122	-5,672
25	LS 50PLUS F	-7	-8	9	-43,685	-47,769	-48,140
25	LS 29 M	0	0	0	0	0	0
25	LS 49 M	0	0	0	0	0	0
25	LS 50PLUS M	0	0	0	0	0	0
25	MS 29 F	5,217	5,984	5,849	5,839	1,636	-1
25	MS 49 F	-1,248	-1,062	1,104	1,248	2,313	2,514
25	MS 50PLUS F	10	-1,489	-13,262	9,885	8,524	8,904
25	MS 29 M	2,683	3,388	3,216	3,208	1,046	11
25	MS 49 M	-2,124	-2,830	-514	-144	1,615	2,709
25	MS 50PLUS M	-34	-334	-9,853	188	-530	-593
25	HS 29 F	0	0	0	0	0	0
25	HS 49 F	12,253	40,150	61,863	61,749	54,965	27,953
25	HS 50PLUS F	-2	359	2,623	9,941	9,856	9,766
25	HS 29 M	0	0	0	0	0	0
25	HS 49 M	8,087	27,608	47,233	47,721	42,312	20,888
25	HS 50PLUS M	-13	116	3,732	19,005	18,923	18,829
26	LS 29 F	0	0	0	0	0	0
26	LS 49 F	3	-8,677	-23,533	-28,564	-28,139	-17,497
26	LS 50PLUS F	-31	-39	40	-201,509	-220,348	-222,061
26	LS 29 M	0	0	0	0	0	0
26	LS 49 M	0	0	0	0	0	0
26	LS 50PLUS M	5	0	5	-9,734	-10,467	-10,696
26	MS 29 F	26,799	30,734	30,045	29,993	8,404	-6
26	MS 49 F	0	0	0	0	0	0
26	MS 50PLUS F	0	0	0	0	0	0
26	MS 29 M	15,849	20,018	18,999	18,953	6,179	66
26	MS 49 M	0	0	0	0	0	0
26	MS 50PLUS M	0	0	0	0	0	0
26	HS 29 F	2,987	3,184	3,170	3,170	342	0
26	HS 49 F	1,647	5,395	8,313	8,298	7,386	3,756
26	HS 50PLUS F	-1	142	1,042	3,950	3,916	3,880

Sector	*Labour Type*	*2000*	*2010*	*2020*	*2040*	*2050*	*2060*
26	HS 29 M	2,635	2,559	2,541	2,541	225	0
26	HS 49 M	0	0	0	0	0	0
26	HS 50PLUS M	0	0	0	0	0	0
27t28	LS 29 F	0	0	0	0	0	0
27t28	LS 49 F	2	-4,457	-12,088	-14,672	-14,454	-8,987
27t28	LS 50PLUS F	-42	-54	55	-276,056	-301,865	-304,212
27t28	LS 29 M	0	0	0	0	0	0
27t28	LS 49 M	0	0	0	0	0	0
27t28	LS 50PLUS M	0	0	0	0	0	0
27t28	MS 29 F	41,064	47,093	46,038	45,957	12,877	-9
27t28	MS 49 F	0	0	0	0	0	0
27t28	MS 50PLUS F	14	-2,051	-18,273	13,620	11,745	12,269
27t28	MS 29 M	25,367	32,039	30,409	30,336	9,890	105
27t28	MS 49 M	0	0	0	0	0	0
27t28	MS 50PLUS M	-5	-45	-1,314	25	-71	-79
27t28	HS 29 F	0	0	0	0	0	0
27t28	HS 49 F	25,391	83,197	128,189	127,953	113,895	57,922
27t28	HS 50PLUS F	-6	865	6,329	23,988	23,783	23,565
27t28	HS 29 M	0	0	0	0	0	0
27t28	HS 49 M	4,649	15,873	27,157	27,437	24,327	12,010
27t28	HS 50PLUS M	-18	161	5,183	26,389	26,274	26,144
29	LS 29 F	0	0	0	0	0	0
29	LS 49 F	0	-347	-940	-1,141	-1,124	-699
29	LS 50PLUS F	-61	-78	80	-400,914	-438,396	-441,805
29	LS 29 M	0	0	0	0	0	0
29	LS 49 M	0	0	0	0	0	0
29	LS 50PLUS M	0	0	0	-538	-578	-591
29	MS 29 F	67,463	77,368	75,635	75,502	21,155	-15
29	MS 49 F	0	0	0	0	0	0
29	MS 50PLUS F	3	-425	-3,783	2,820	2,432	2,540
29	MS 29 M	44,327	55,986	53,137	53,009	17,282	184
29	MS 49 M	0	0	0	0	0	0
29	MS 50PLUS M	0	0	0	0	0	0
29	HS 29 F	471	502	499	499	54	0
29	HS 49 F	14,636	47,958	73,893	73,757	65,653	33,388
29	HS 50PLUS F	-5	729	5,334	20,215	20,042	19,858
29	HS 29 M	1,202	1,167	1,159	1,159	102	0
29	HS 49 M	0	0	0	0	0	0
29	HS 50PLUS M	-1	9	285	1,449	1,442	1,435
30t33	LS 29 F	0	0	0	0	0	0
30t33	LS 49 F	2	-6,541	-17,740	-21,533	-21,212	-13,190
30t33	LS 50PLUS F	-63	-80	82	-414,612	-453,374	-456,899
30t33	LS 29 M	0	0	0	0	0	0
30t33	LS 49 M	0	0	0	0	0	0
30t33	LS 50PLUS M	0	0	0	0	0	0
30t33	MS 29 F	100,611	115,383	112,798	112,600	31,550	-22
30t33	MS 49 F	0	0	0	0	0	0
30t33	MS 50PLUS F	0	0	-2	1	1	1
30t33	MS 29 M	44,201	55,828	52,986	52,859	17,233	184
30t33	MS 49 M	0	0	0	0	0	0
30t33	MS 50PLUS M	0	0	0	0	0	0
30t33	HS 29 F	12,696	13,532	13,470	13,471	1,452	-2
30t33	HS 49 F	612	2,006	3,091	3,086	2,747	1,397
30t33	HS 50PLUS F	-2	345	2,524	9,566	9,484	9,397
30t33	HS 29 M	41,311	40,120	39,833	39,838	3,521	3
30t33	HS 49 M	0	0	0	0	0	0
30t33	HS 50PLUS M	0	0	0	0	0	0
34t35	LS 29 F	0	0	0	0	0	0
34t35	LS 49 F	7	-19,051	-51,672	-62,718	-61,784	-38,417
34t35	LS 50PLUS F	-16	-21	21	-107,320	-117,354	-118,266
34t35	LS 29 M	0	0	0	0	0	0

Sector	*Labour Type*	*2000*	*2010*	*2020*	*2040*	*2050*	*2060*
34t35	LS 49 M	0	0	0	0	0	0
34t35	LS 50PLUS M	0	0	0	0	0	0
34t35	MS 29 F	22,979	26,353	25,762	25,717	7,206	-5
34t35	MS 49 F	0	0	0	0	0	0
34t35	MS 50PLUS F	13	-1,799	-16,032	11,949	10,305	10,764
34t35	MS 29 M	783	989	939	937	305	3
34t35	MS 49 M	-5,652	-7,529	-1,366	-384	4,296	7,208
34t35	MS 50PLUS M	-103	-1,012	-29,876	571	-1,606	-1,799
34t35	HS 29 F	0	0	0	0	0	0
34t35	HS 49 F	17,702	58,003	89,370	89,205	79,405	40,382
34t35	HS 50PLUS F	-4	598	4,374	16,576	16,434	16,283
34t35	HS 29 M	8,469	8,225	8,166	8,167	722	1
34t35	HS 49 M	18,244	62,285	106,562	107,661	95,459	47,125
34t35	HS 50PLUS M	-33	300	9,640	49,084	48,871	48,629
36t37	LS 29 F	0	0	0	0	0	0
36t37	LS 49 F	1	-1,409	-3,820	-4,637	-4,568	-2,840
36t37	LS 50PLUS F	-31	-40	41	-206,858	-226,198	-227,956
36t37	LS 29 M	0	0	0	0	0	0
36t37	LS 49 M	0	0	0	0	0	0
36t37	LS 50PLUS M	3	0	3	-5,343	-5,746	-5,871
36t37	MS 29 F	17,944	20,578	20,117	20,082	5,627	-4
36t37	MS 49 F	0	0	0	0	0	0
36t37	MS 50PLUS F	1	-82	-733	546	471	492
36t37	MS 29 M	16,676	21,063	19,991	19,943	6,502	69
36t37	MS 49 M	0	0	0	0	0	0
36t37	MS 50PLUS M	0	0	0	0	0	0
36t37	HS 29 F	0	0	0	0	0	0
36t37	HS 49 F	0	0	0	0	0	0
36t37	HS 50PLUS F	-2	306	2,239	8,487	8,414	8,337
36t37	HS 29 M	3,129	3,039	3,017	3,017	267	0
36t37	HS 49 M	0	0	0	0	0	0
36t37	HS 50PLUS M	0	0	0	0	0	0
E	LS 29 F	0	0	0	0	0	0
E	LS 49 F	0	-964	-2,614	-3,173	-3,126	-1,944
E	LS 50PLUS F	-29	-37	38	-191,503	-209,407	-211,035
E	LS 29 M	0	0	0	0	0	0
E	LS 49 M	0	0	0	0	0	0
E	LS 50PLUS M	2	0	2	-4,036	-4,340	-4,435
E	MS 29 F	17,414	19,971	19,524	19,490	5,461	-4
E	MS 49 F	0	0	0	0	0	0
E	MS 50PLUS F	2	-235	-2,095	1,562	1,347	1,407
E	MS 29 M	16,433	20,755	19,699	19,651	6,407	68
E	MS 49 M	0	0	0	0	0	0
E	MS 50PLUS M	0	0	0	0	0	0
E	HS 29 F	0	0	0	0	0	0
E	HS 49 F	136	447	689	688	612	311
E	HS 50PLUS F	-2	344	2,513	9,526	9,444	9,358
E	HS 29 M	2,652	2,575	2,557	2,557	226	0
E	HS 49 M	0	0	0	0	0	0
E	HS 50PLUS M	0	0	1	5	5	5
F	LS 29 F	0	0	0	0	0	0
F	LS 49 F	11	-29,449	-79,873	-96,948	-95,505	-59,384
F	LS 50PLUS F	0	0	0	-852	-932	-939
F	LS 29 M	0	0	0	0	0	0
F	LS 49 M	0	0	0	0	0	0
F	LS 50PLUS M	20	2	20	-42,617	-45,824	-46,828
F	MS 29 F	65,599	75,230	73,545	73,416	20,571	-15
F	MS 49 F	0	0	0	0	0	0
F	MS 50PLUS F	0	0	0	0	0	0
F	MS 29 M	177,645	224,371	212,951	212,440	69,260	739
F	MS 49 M	0	0	0	0	0	0

Sector	*Labour Type*	*2000*	*2010*	*2020*	*2040*	*2050*	*2060*
F	MS 50PLUS M	0	0	0	0	0	0
F	HS 29 F	4,934	5,259	5,235	5,236	564	-1
F	HS 49 F	0	0	0	0	0	0
F	HS 50PLUS F	0	0	0	0	0	0
F	HS 29 M	17,193	16,698	16,578	16,580	1,465	1
F	HS 49 M	0	0	0	0	0	0
F	HS 50PLUS M	0	0	0	0	0	0
50	LS 29 F	-220	-542	-545	-525	-105	0
50	LS 49 F	0	0	0	0	0	0
50	LS 50PLUS F	0	0	0	0	0	0
50	LS 29 M	-212	-534	-548	-528	-105	-1
50	LS 49 M	-48	-67,907	-159,045	-186,901	-183,889	-112,683
50	LS 50PLUS M	0	0	0	0	0	0
50	MS 29 F	8,454	9,695	9,478	9,461	2,651	-2
50	MS 49 F	-19,182	-16,321	16,967	19,190	35,552	38,645
50	MS 50PLUS F	30	-4,339	-38,658	28,814	24,848	25,955
50	MS 29 M	186	235	223	222	73	1
50	MS 49 M	-15,148	-20,180	-3,662	-1,029	11,514	19,320
50	MS 50PLUS M	-64	-632	-18,678	357	-1,004	-1,125
50	HS 29 F	0	0	0	0	0	0
50	HS 49 F	10,648	34,890	53,758	53,659	47,763	24,290
50	HS 50PLUS F	-5	775	5,668	21,481	21,297	21,102
50	HS 29 M	0	0	0	0	0	0
50	HS 49 M	13,395	45,730	78,238	79,046	70,087	34,600
50	HS 50PLUS M	-17	154	4,966	25,285	25,175	25,050
51	LS 29 F	0	0	0	0	0	0
51	LS 49 F	4	-10,355	-28,086	-34,090	-33,582	-20,881
51	LS 50PLUS F	0	0	0	0	0	0
51	LS 29 M	0	0	0	0	0	0
51	LS 49 M	-30	-42,534	-99,618	-117,066	-115,179	-70,579
51	LS 50PLUS M	0	0	0	0	0	0
51	MS 29 F	235,892	270,527	264,466	264,003	73,971	-53
51	MS 49 F	0	0	0	0	0	0
51	MS 50PLUS F	0	0	0	0	0	0
51	MS 29 M	47,863	60,452	57,375	57,238	18,661	199
51	MS 49 M	0	0	0	0	0	0
51	MS 50PLUS M	0	0	0	0	0	0
51	HS 29 F	124	132	131	131	14	0
51	HS 49 F	189	620	956	954	849	432
51	HS 50PLUS F	-6	935	6,838	25,918	25,695	25,460
51	HS 29 M	1,037	1,007	1,000	1,000	88	0
51	HS 49 M	930	3,174	5,431	5,487	4,865	2,402
51	HS 50PLUS M	-11	103	3,326	16,934	16,860	16,777
52	LS 29 F	0	0	0	0	0	0
52	LS 49 F	0	0	0	0	0	0
52	LS 50PLUS F	0	0	0	0	0	0
52	LS 29 M	0	0	0	0	0	0
52	LS 49 M	-123	-174,095	-407,748	-479,161	-471,439	-288,887
52	LS 50PLUS M	0	0	0	0	0	0
52	MS 29 F	172,415	197,730	193,300	192,962	54,066	-39
52	MS 49 F	0	0	0	0	0	0
52	MS 50PLUS F	2	-224	-2,000	1,490	1,285	1,343
52	MS 29 M	28,914	36,519	34,660	34,577	11,273	120
52	MS 49 M	0	0	0	0	0	0
52	MS 50PLUS M	0	0	0	0	0	0
52	HS 29 F	0	0	0	0	0	0
52	HS 49 F	15,573	51,027	78,623	78,478	69,856	35,525
52	HS 50PLUS F	-13	1,960	14,332	54,320	53,854	53,361
52	HS 29 M	0	0	0	0	0	0
52	HS 49 M	24,565	83,866	143,484	144,965	128,534	63,453
52	HS 50PLUS M	-36	325	10,470	53,309	53,078	52,815

Sector	*Labour Type*	*2000*	*2010*	*2020*	*2040*	*2050*	*2060*
H	LS 29 F	-1,267	-3,121	-3,140	-3,026	-605	-1
H	LS 49 F	0	0	0	0	0	0
H	LS 50PLUS F	0	0	0	0	0	0
H	LS 29 M	-830	-2,094	-2,146	-2,067	-413	-3
H	LS 49 M	-109	-153,828	-360,281	-423,381	-416,558	-255,257
H	LS 50PLUS M	0	0	0	0	0	0
H	MS 29 F	0	0	0	0	0	0
H	MS 49 F	-90,044	-76,613	79,644	90,078	166,885	181,404
H	MS 50PLUS F	49	-6,992	-62,292	46,430	40,039	41,824
H	MS 29 M	0	0	0	0	0	0
H	MS 49 M	-57,375	-76,434	-13,871	-3,899	43,610	73,175
H	MS 50PLUS M	-104	-1,028	-30,361	581	-1,632	-1,828
H	HS 29 F	0	0	0	0	0	0
H	HS 49 F	21,238	69,588	107,222	107,024	95,265	48,448
H	HS 50PLUS F	-9	1,325	9,694	36,739	36,425	36,091
H	HS 29 M	0	0	0	0	0	0
H	HS 49 M	27,641	94,366	161,447	163,113	144,626	71,397
H	HS 50PLUS M	-29	268	8,612	43,853	43,663	43,446
60t63	LS 29 F	0	0	0	0	0	0
60t63	LS 49 F	0	0	0	0	0	0
60t63	LS 50PLUS F	0	0	0	0	0	0
60t63	LS 29 M	0	0	0	0	0	0
60t63	LS 49 M	-5	-7,296	-17,088	-20,081	-19,757	-12,107
60t63	LS 50PLUS M	0	0	0	0	0	0
60t63	MS 29 F	178,222	204,389	199,810	199,460	55,887	-40
60t63	MS 49 F	0	0	0	0	0	0
60t63	MS 50PLUS F	0	0	0	0	0	0
60t63	MS 29 M	71,093	89,793	85,223	85,018	27,718	296
60t63	MS 49 M	0	0	0	0	0	0
60t63	MS 50PLUS M	-56	-551	-16,262	311	-874	-979
60t63	HS 29 F	0	0	0	0	0	0
60t63	HS 49 F	6,460	21,169	32,617	32,557	28,980	14,738
60t63	HS 50PLUS F	-6	927	6,779	25,694	25,473	25,240
60t63	HS 29 M	12	11	11	11	1	0
60t63	HS 49 M	0	0	0	0	0	0
60t63	HS 50PLUS M	0	0	0	0	0	0
64	LS 29 F	0	0	0	0	0	0
64	LS 49 F	0	0	0	0	0	0
64	LS 50PLUS F	-14	-17	18	-89,727	-98,116	-98,878
64	LS 29 M	0	0	0	0	0	0
64	LS 49 M	0	0	0	0	0	0
64	LS 50PLUS M	0	0	0	0	0	0
64	MS 29 F	106,519	122,159	119,422	119,213	33,403	-24
64	MS 49 F	0	0	0	0	0	0
64	MS 50PLUS F	0	0	0	0	0	0
64	MS 29 M	41,531	52,455	49,785	49,665	16,192	173
64	MS 49 M	0	0	0	0	0	0
64	MS 50PLUS M	0	0	0	0	0	0
64	HS 29 F	0	0	0	0	0	0
64	HS 49 F	0	0	0	0	0	0
64	HS 50PLUS F	0	35	259	981	973	964
64	HS 29 M	2,185	2,122	2,107	2,107	186	0
64	HS 49 M	0	0	0	0	0	0
64	HS 50PLUS M	0	0	0	0	0	0
J	LS 29 F	0	0	0	0	0	0
J	LS 49 F	9	-23,642	-64,123	-77,831	-76,673	-47,674
J	LS 50PLUS F	-113	-145	148	-748,637	-818,629	-824,994
J	LS 29 M	-30	-74	-76	-73	-15	0
J	LS 49 M	-4	-5,410	-12,672	-14,891	-14,651	-8,978
J	LS 50PLUS M	0	0	0	0	-1	-1
J	MS 29 F	115,518	132,478	129,510	129,284	36,224	-26

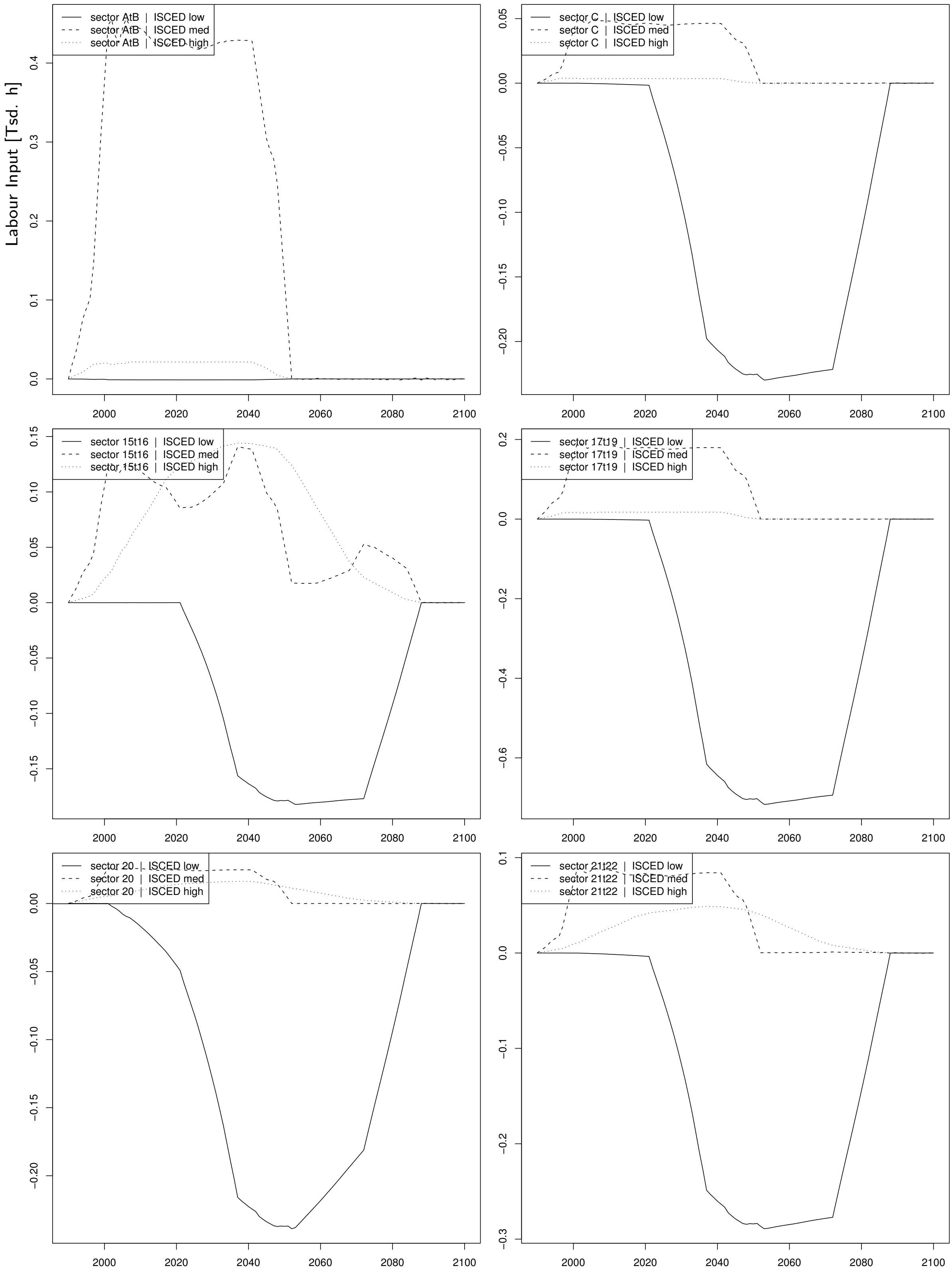
Sector	*Labour Type*	*2000*	*2010*	*2020*	*2040*	*2050*	*2060*
J	MS 49 F	-2,189	-1,863	1,936	2,190	4,057	4,410
J	MS 50PLUS F	86	-12,219	-108,861	81,140	69,972	73,090
J	MS 29 M	9,968	12,590	11,949	11,921	3,886	41
J	MS 49 M	0	0	0	0	0	0
J	MS 50PLUS M	-59	-576	-17,015	325	-915	-1,025
J	HS 29 F	0	0	0	0	0	0
J	HS 49 F	82,150	269,177	414,747	413,981	368,498	187,402
J	HS 50PLUS F	-18	2,682	19,616	74,345	73,708	73,033
J	HS 29 M	5,645	5,482	5,443	5,444	481	0
J	HS 49 M	41,517	141,739	242,496	244,999	217,231	107,240
J	HS 50PLUS M	-70	642	20,668	105,239	104,783	104,263
70	LS 29 F	0	0	0	0	0	0
70	LS 49 F	0	-325	-883	-1,071	-1,055	-656
70	LS 50PLUS F	0	0	0	0	0	0
70	LS 29 M	-948	-2,392	-2,452	-2,361	-472	-3
70	LS 49 M	-42	-58,830	-137,785	-161,917	-159,307	-97,620
70	LS 50PLUS M	0	0	0	0	0	0
70	MS 29 F	0	0	0	0	0	0
70	MS 49 F	-35,486	-30,193	31,387	35,499	65,768	71,490
70	MS 50PLUS F	16	-2,336	-20,815	15,515	13,379	13,975
70	MS 29 M	0	0	0	0	0	0
70	MS 49 M	-28,140	-37,488	-6,803	-1,912	21,389	35,889
70	MS 50PLUS M	-32	-311	-9,187	176	-494	-553
70	HS 29 F	0	0	0	0	0	0
70	HS 49 F	34,482	112,986	174,089	173,767	154,676	78,661
70	HS 50PLUS F	-7	1,037	7,582	28,736	28,489	28,228
70	HS 29 M	0	0	0	0	0	0
70	HS 49 M	29,059	99,207	169,730	171,482	152,046	75,060
70	HS 50PLUS M	-27	248	7,981	40,635	40,459	40,259
71t74	LS 29 F	-28,540	-70,288	-70,708	-68,157	-13,622	-21
71t74	LS 49 F	0	0	0	0	0	0
71t74	LS 50PLUS F	0	0	0	0	0	0
71t74	LS 29 M	-33,751	-85,171	-87,297	-84,085	-16,814	-110
71t74	LS 49 M	-385	-544,908	-1,276,230	-1,499,750	-1,475,580	-904,199
71t74	LS 50PLUS M	0	0	0	0	0	0
71t74	MS 29 F	0	0	0	0	0	0
71t74	MS 49 F	-705,761	-600,485	624,243	706,021	1,308,040	1,421,830
71t74	MS 50PLUS F	284	-40,475	-360,612	268,783	231,788	242,117
71t74	MS 29 M	0	0	0	0	0	0
71t74	MS 49 M	-415,469	-553,478	-100,441	-28,236	315,791	529,877
71t74	MS 50PLUS M	-642	-6,325	-186,799	3,573	-10,042	-11,250
71t74	HS 29 F	0	0	0	0	0	0
71t74	HS 49 F	409,955	1,343,280	2,069,730	2,065,910	1,838,930	935,198
71t74	HS 50PLUS F	-80	11,833	86,544	328,007	325,197	322,216
71t74	HS 29 M	0	0	0	0	0	0
71t74	HS 49 M	364,020	1,242,780	2,126,230	2,148,170	1,904,700	940,288
71t74	HS 50PLUS M	-399	3,661	117,833	599,979	597,380	594,417
L	LS 29 F	0	0	0	0	0	0
L	LS 49 F	77	-203,155	-551,001	-668,794	-658,838	-409,659
L	LS 50PLUS F	-546	-698	714	-3,599,250	-3,935,750	-3,966,350
L	LS 29 M	0	0	0	0	0	0
L	LS 49 M	0	0	0	0	0	0
L	LS 50PLUS M	80	8	80	-169,755	-182,528	-186,529
L	MS 29 F	175,202	200,926	196,425	196,081	54,940	-39
L	MS 49 F	0	0	0	0	0	0
L	MS 50PLUS F	71	-10,055	-89,586	66,773	57,582	60,148
L	MS 29 M	18,971	23,961	22,741	22,687	7,396	79
L	MS 49 M	0	0	0	0	0	0
L	MS 50PLUS M	0	0	0	0	0	0
L	HS 29 F	3,553	3,787	3,770	3,770	406	0
L	HS 49 F	0	0	0	0	0	0

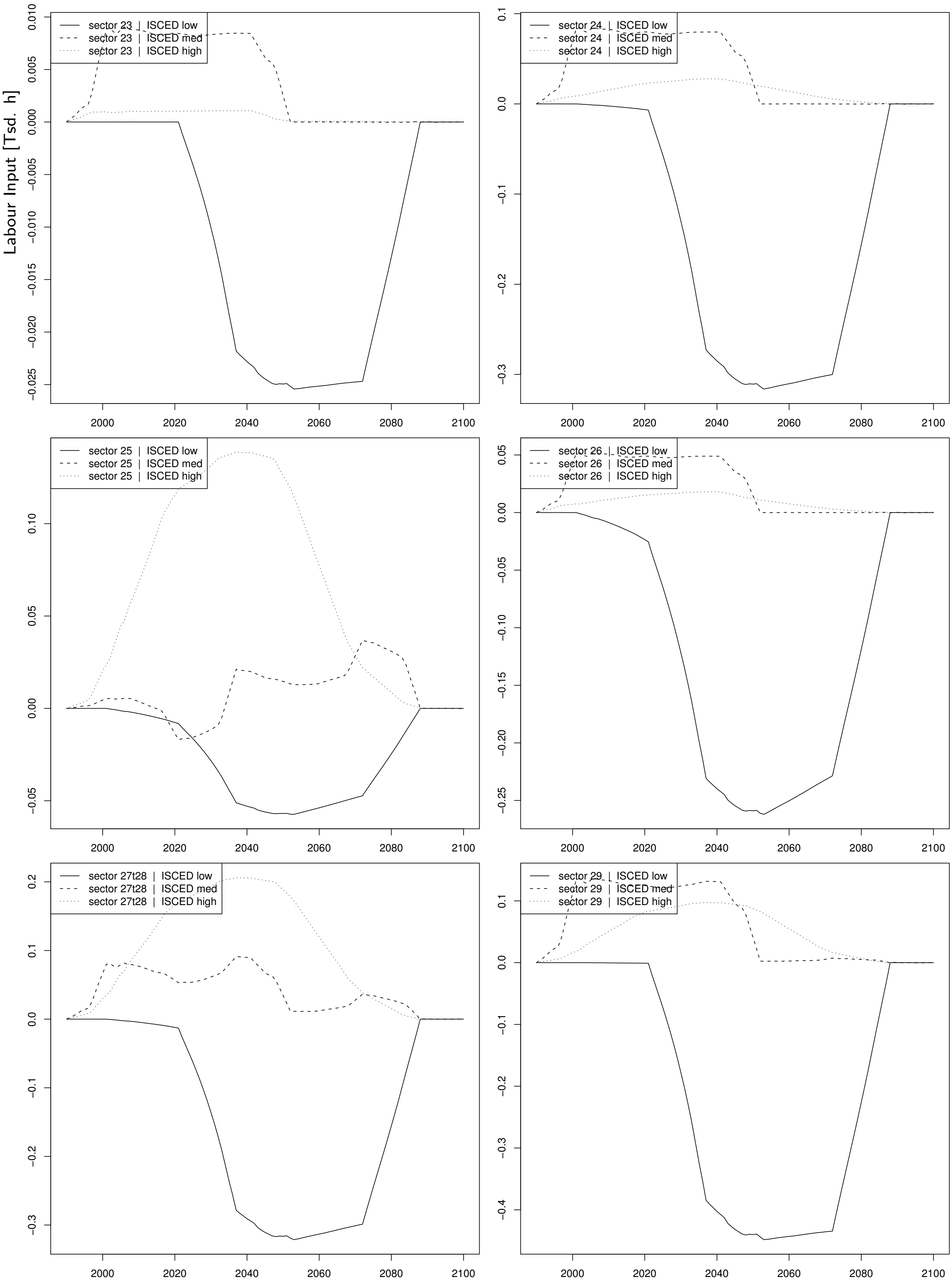
Sector	*Labour Type*	*2000*	*2010*	*2020*	*2040*	*2050*	*2060*
L	HS 50PLUS F	-50	7,385	54,010	204,703	202,949	201,089
L	HS 29 M	0	0	0	0	0	0
L	HS 49 M	0	0	0	0	0	0
L	HS 50PLUS M	-31	281	9,044	46,050	45,850	45,623
M	LS 29 F	0	0	0	0	0	0
M	LS 49 F	0	0	0	0	0	0
M	LS 50PLUS F	-58	-74	75	-379,707	-415,206	-418,434
M	LS 29 M	-3,159	-7,972	-8,171	-7,870	-1,574	-10
M	LS 49 M	-55	-77,008	-180,360	-211,948	-208,532	-127,784
M	LS 50PLUS M	0	0	0	0	0	0
M	MS 29 F	0	0	0	0	0	0
M	MS 49 F	-138,179	-117,568	122,219	138,230	256,097	278,377
M	MS 50PLUS F	181	-25,826	-230,099	171,505	147,899	154,490
M	MS 29 M	0	0	0	0	0	0
M	MS 49 M	-7,845	-10,451	-1,897	-533	5,963	10,005
M	MS 50PLUS M	-163	-1,607	-47,449	908	-2,551	-2,857
M	HS 29 F	0	0	0	0	0	0
M	HS 49 F	179,995	589,783	908,737	907,059	807,402	410,609
M	HS 50PLUS F	-269	40,051	292,921	1,110,200	1,100,680	1,090,590
M	HS 29 M	0	0	0	0	0	0
M	HS 49 M	0	0	0	0	0	0
M	HS 50PLUS M	-186	1,710	55,032	280,211	278,998	277,614
N	LS 29 F	-79,417	-195,590	-196,758	-189,659	-37,906	-59
N	LS 49 F	0	0	0	0	0	0
N	LS 50PLUS F	0	0	0	0	0	0
N	LS 29 M	-5,557	-14,023	-14,373	-13,845	-2,768	-18
N	LS 49 M	-53	-74,606	-174,734	-205,337	-202,028	-123,798
N	LS 50PLUS M	1	0	1	-1,543	-1,659	-1,695
N	MS 29 F	0	0	0	0	0	0
N	MS 49 F	-758,664	-645,496	671,035	758,943	1,406,080	1,528,410
N	MS 50PLUS F	459	-65,501	-583,584	434,976	375,106	391,822
N	MS 29 M	0	0	0	0	0	0
N	MS 49 M	-128,751	-171,519	-31,126	-8,750	97,861	164,205
N	MS 50PLUS M	-148	-1,460	-43,132	825	-2,319	-2,598
N	HS 29 F	0	0	0	0	0	0
N	HS 49 F	190,475	624,121	961,645	959,869	854,411	434,515
N	HS 50PLUS F	-57	8,429	61,645	233,641	231,639	229,515
N	HS 29 M	0	0	0	0	0	0
N	HS 49 M	0	0	0	0	0	0
N	HS 50PLUS M	-82	752	24,195	123,194	122,661	122,052
O	LS 29 F	-29,810	-73,416	-73,854	-71,190	-14,228	-22
O	LS 49 F	0	0	0	0	0	0
O	LS 50PLUS F	0	0	0	0	0	0
O	LS 29 M	-16,763	-42,300	-43,356	-41,761	-8,351	-55
O	LS 49 M	-167	-235,570	-551,727	-648,357	-637,907	-390,895
O	LS 50PLUS M	0	0	0	0	0	0
O	MS 29 F	37,467	42,968	42,005	41,932	11,749	-8
O	MS 49 F	0	0	0	0	0	0
O	MS 50PLUS F	78	-11,070	-98,631	73,515	63,396	66,221
O	MS 29 M	0	0	0	0	0	0
O	MS 49 M	0	0	0	0	0	0
O	MS 50PLUS M	-93	-915	-27,023	517	-1,453	-1,627
O	HS 29 F	0	0	0	0	0	0
O	HS 49 F	52,430	171,794	264,700	264,211	235,183	119,603
O	HS 50PLUS F	-35	5,263	38,496	145,901	144,651	143,325
O	HS 29 M	948	921	914	914	81	0
O	HS 49 M	0	0	0	0	0	0
O	HS 50PLUS M	-27	250	8,053	41,004	40,826	40,623

The following table contains the complete sectoral results for each labour type of the absolute difference of hours worked [Tsd h] disaggregated by ISCED group. After the table, the same figures are given as plots per sector.

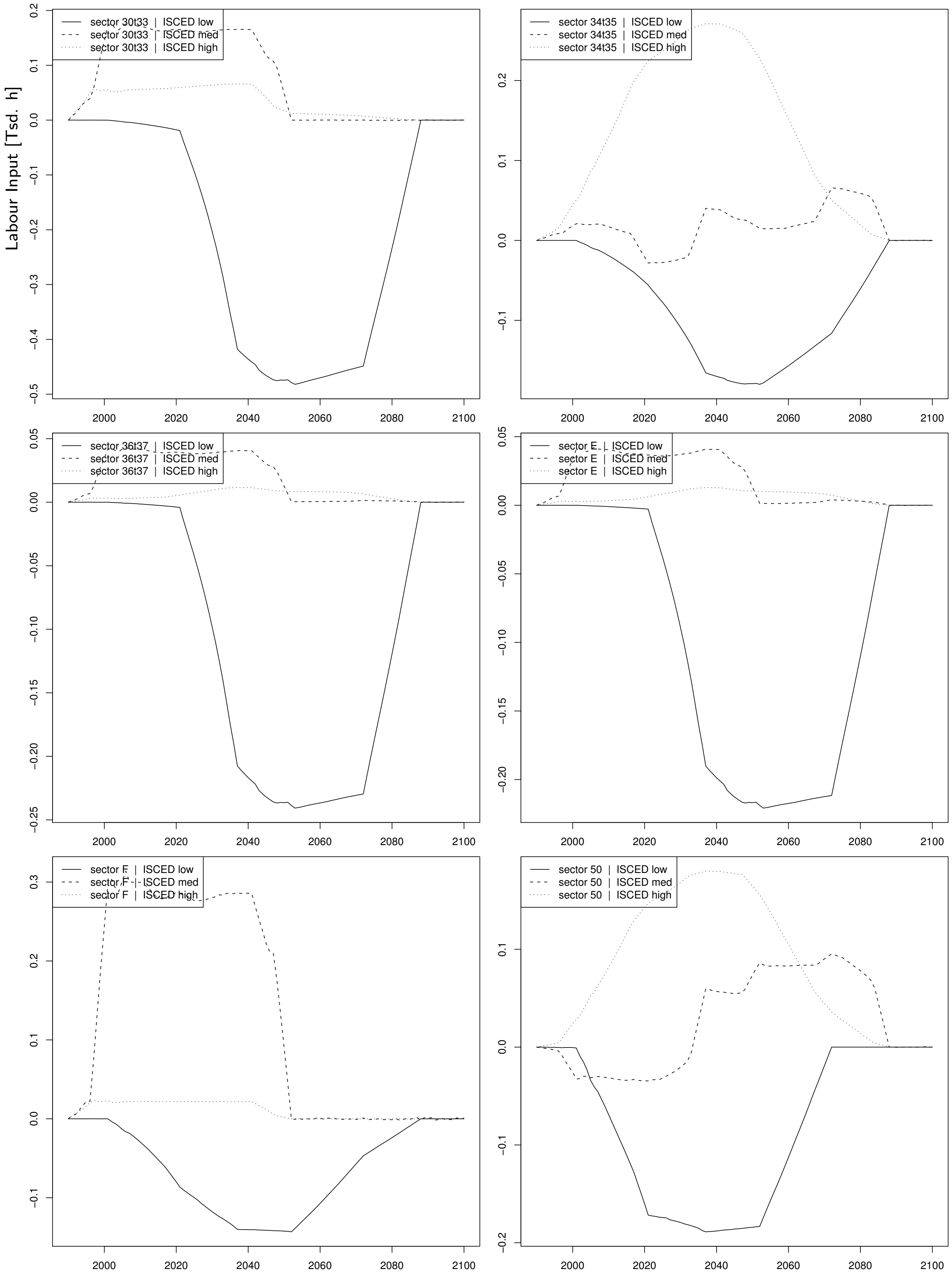
Sector	*ISCED*	*1995*	*2000*	*2010*	*2020*	*2040*	*2060*	*2080*	*2100*
AtB	low	-0.3	-0.5	-1.2	-1.2	-1.2	0.0	0.0	0.0
AtB	med	89.3	375.2	443.6	429.5	428.7	0.4	-0.4	0.6
AtB	high	12.4	20.2	21.5	21.4	21.4	0.0	0.0	0.0
C	low	0.0	0.0	-0.6	-1.5	-206.7	-226.8	-115.2	0.0
C	med	7.7	40.2	48.1	46.4	46.3	0.1	-0.1	0.1
C	high	2.9	3.7	3.6	3.5	3.5	0.0	0.0	0.0
15t16	low	0.0	0.0	0.0	0.0	-163.5	-180.2	-92.0	0.0
15t16	med	31.6	104.8	118.5	90.6	139.0	18.8	40.3	0.1
15t16	high	5.0	21.9	72.9	120.6	143.7	80.7	9.2	0.0
17t19	low	0.0	-0.1	-1.1	-2.5	-644.1	-708.2	-360.6	0.0
17t19	med	46.1	158.9	185.0	180.0	179.7	0.1	0.1	0.1
17t19	high	10.4	16.5	17.4	17.3	17.3	0.0	0.0	0.0
20	low	0.0	0.0	-16.8	-45.4	-222.7	-218.3	-94.0	0.0
20	med	4.7	21.6	25.6	24.8	24.7	0.0	0.0	0.0
20	high	2.8	5.2	9.8	13.9	16.3	7.6	1.0	0.0
21t22	low	0.0	0.0	-1.3	-3.4	-260.2	-284.7	-144.1	0.0
21t22	med	15.3	72.9	86.8	83.4	84.1	0.5	0.6	0.2
21t22	high	3.5	9.3	25.9	40.9	48.6	26.6	3.4	0.0
23	low	0.0	0.0	0.0	0.0	-22.8	-25.1	-12.8	0.0
23	med	1.5	7.3	8.8	8.5	8.4	0.0	0.0	0.0
23	high	0.6	1.0	1.0	1.0	1.1	0.1	0.0	0.0
24	low	0.0	0.0	-2.4	-6.3	-285.0	-310.3	-156.0	0.0
24	med	14.4	69.4	82.7	79.9	79.7	0.1	-0.1	0.1
24	high	4.5	8.3	15.5	22.4	27.7	13.9	2.3	0.0
25	low	0.0	0.0	-2.8	-7.6	-52.9	-53.8	-24.6	0.0
25	med	1.3	4.5	3.7	-13.5	20.2	13.5	30.9	0.0
25	high	3.8	20.3	68.2	115.5	138.4	77.4	8.8	0.1
26	low	0.0	0.0	-8.7	-23.5	-239.8	-250.3	-118.8	0.0
26	med	9.1	42.6	50.8	49.0	48.9	0.1	-0.1	0.1
26	high	4.3	7.3	11.3	15.1	18.0	7.6	1.3	0.0
27t28	low	0.0	0.0	-4.5	-12.0	-290.7	-313.2	-155.4	0.0
27t28	med	14.0	66.4	77.0	56.9	89.9	12.3	27.8	0.2
27t28	high	7.0	30.0	100.1	166.9	205.8	119.6	15.4	0.1
29	low	0.0	-0.1	-0.4	-0.9	-402.6	-443.1	-226.0	0.0
29	med	23.0	111.8	132.9	125.0	131.3	2.7	5.2	0.2
29	high	5.1	16.3	50.4	81.2	97.1	54.7	6.9	0.0
30t33	low	0.0	-0.1	-6.6	-17.7	-436.1	-470.1	-233.4	0.0
30t33	med	34.4	144.8	171.2	165.8	165.5	0.2	-0.1	0.2
30t33	high	40.4	54.6	56.0	58.9	66.0	10.8	3.1	0.0
34t35	low	0.0	0.0	-19.1	-51.7	-170.0	-156.7	-60.4	0.0
34t35	med	7.6	18.0	17.0	-20.6	38.8	16.2	58.8	-0.1
34t35	high	12.6	44.4	129.4	218.1	270.7	152.4	19.7	0.1
36t37	low	0.0	0.0	-1.4	-3.8	-216.8	-236.7	-119.4	0.0
36t37	med	6.1	34.6	41.6	39.4	40.6	0.6	1.0	0.1
36t37	high	2.5	3.1	3.3	5.3	11.5	8.3	2.8	0.0
E	low	0.0	0.0	-1.0	-2.6	-198.7	-217.4	-110.0	0.0
E	med	5.9	33.8	40.5	37.1	40.7	1.5	2.9	0.1
E	high	2.1	2.8	3.4	5.8	12.8	9.7	3.1	0.0
F	low	0.0	0.0	-29.4	-79.9	-140.4	-107.2	-23.8	0.0
F	med	21.7	243.2	299.6	286.5	285.9	0.7	-1.3	1.0
F	high	16.5	22.1	22.0	21.8	21.8	0.0	0.0	0.0
50	low	-0.2	-0.5	-69.0	-160.1	-188.0	-112.7	0.0	0.0
50	med	-3.1	-25.7	-31.5	-34.3	57.0	82.8	78.2	0.1
50	high	3.7	24.0	81.5	142.6	179.5	105.0	14.4	0.1
51	low	0.0	0.0	-52.9	-127.7	-151.2	-91.5	0.0	0.0
51	med	81.0	283.8	331.0	321.8	321.2	0.1	0.1	0.2

Sector	*ISCED*	*1995*	*2000*	*2010*	*2020*	*2040*	*2060*	*2080*	*2100*
51	high	1.0	2.3	6.0	17.7	50.4	45.1	13.3	0.0
52	low	0.1	-0.1	-174.1	-407.7	-479.2	-288.9	-0.1	0.1
52	med	59.2	201.3	234.0	226.0	229.0	1.4	3.0	0.1
52	high	5.8	40.1	137.2	246.9	331.1	205.2	33.2	0.2
H	low	-1.2	-2.2	-159.0	-365.6	-428.5	-255.3	-0.1	0.1
H	med	-27.2	-147.5	-161.1	-26.9	133.2	294.6	126.4	0.2
H	high	7.5	48.8	165.5	287.0	350.7	199.4	24.8	0.2
60t63	low	0.0	0.0	-7.3	-17.1	-20.1	-12.1	0.0	0.0
60t63	med	61.0	249.3	293.6	268.8	284.8	-0.7	19.2	0.3
60t63	high	1.7	6.5	22.1	39.4	58.3	40.0	8.3	0.0
64	low	0.0	0.0	0.0	0.0	-89.7	-98.9	-50.5	0.0
64	med	36.5	148.1	174.6	169.2	168.9	0.1	-0.1	0.2
64	high	1.7	2.2	2.2	2.4	3.1	1.0	0.3	0.0
J	low	0.0	-0.1	-29.3	-76.7	-841.4	-881.6	-421.4	0.1
J	med	39.1	123.3	130.4	17.5	224.9	76.5	177.5	0.3
J	high	28.8	129.2	419.7	703.0	844.0	471.9	54.7	0.3
70	low	-0.6	-1.0	-61.5	-141.1	-165.3	-98.3	0.0	0.0
70	med	-11.1	-63.6	-70.3	-5.4	49.3	120.8	41.1	0.1
70	high	11.1	63.5	213.5	359.4	414.6	222.2	21.2	0.2
71t74	low	-39.3	-62.7	-700.4	-1,434.2	-1,652.0	-904.3	-0.1	0.2
71t74	med	-211.1	-1,121.6	-1,200.8	-23.6	950.1	2,182.6	745.8	1.0
71t74	high	132.9	773.5	2,601.6	4,400.3	5,142.1	2,792.1	281.8	2.5
L	low	0.0	-0.4	-203.8	-550.2	-4,437.8	-4,562.5	-2,118.9	0.3
L	med	60.1	194.2	214.8	129.6	285.5	60.2	129.4	0.3
L	high	2.2	3.5	11.5	66.8	254.5	246.7	79.7	0.1
M	low	-2.0	-3.3	-85.1	-188.5	-599.5	-546.2	-213.7	0.1
M	med	-36.7	-146.0	-155.5	-157.2	310.1	440.0	389.2	0.3
M	high	47.0	179.5	631.5	1,256.7	2,297.5	1,778.8	440.8	0.8
N	low	-54.1	-85.0	-284.2	-385.9	-410.4	-125.6	-1.0	0.0
N	med	-206.9	-887.1	-884.0	13.2	1,186.0	2,081.8	896.4	1.1
N	high	49.8	190.3	633.3	1,047.5	1,316.7	786.1	110.9	0.3
O	low	-29.5	-46.7	-351.3	-668.9	-761.3	-391.0	-0.1	0.1
O	med	12.9	37.5	31.0	-83.6	116.0	64.6	174.6	0.2
O	high	14.5	53.3	178.2	312.2	452.0	303.6	59.1	0.1

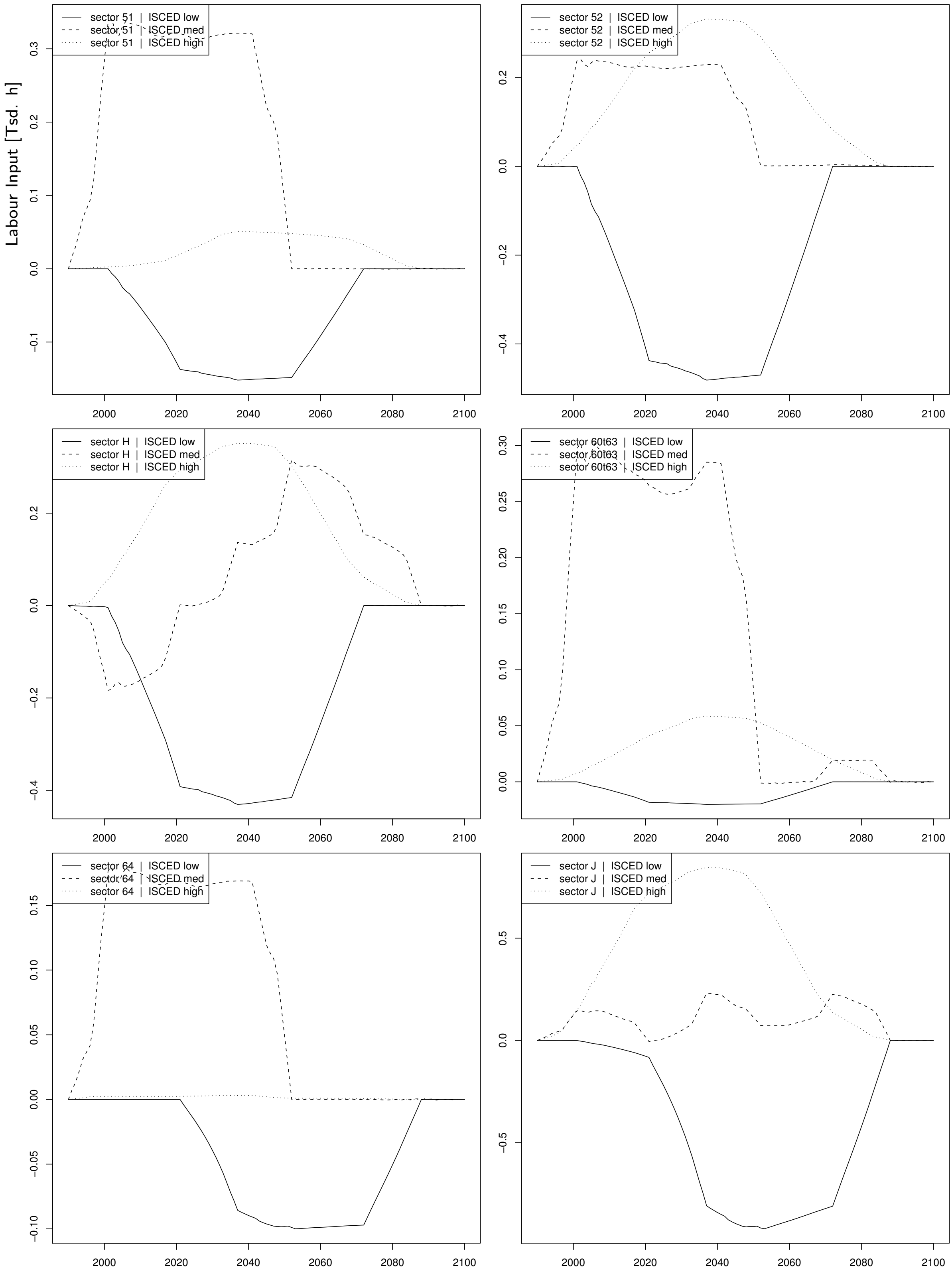

Labour Input [Tsd. h]
sector AtB | ISCED low
sector AtB | ISCED med
sector AtB | ISCED high
sector C | ISCED low
sector C | ISCED med
sector C | ISCED high
sector 15t16 | ISCED low
sector 15t16 | ISCED med
sector 15t16 | ISCED high
sector 17t19 | ISCED low
sector 17t19 | ISCED med
sector 17t19 | ISCED high
sector 20 | ISCED low
sector 20 | ISCED med
sector 20 | ISCED high
sector 21t22 | ISCED low
sector 21t22 | ISCED med
sector 21t22 | ISCED high
2000
2020
2040
2060
2080
2100



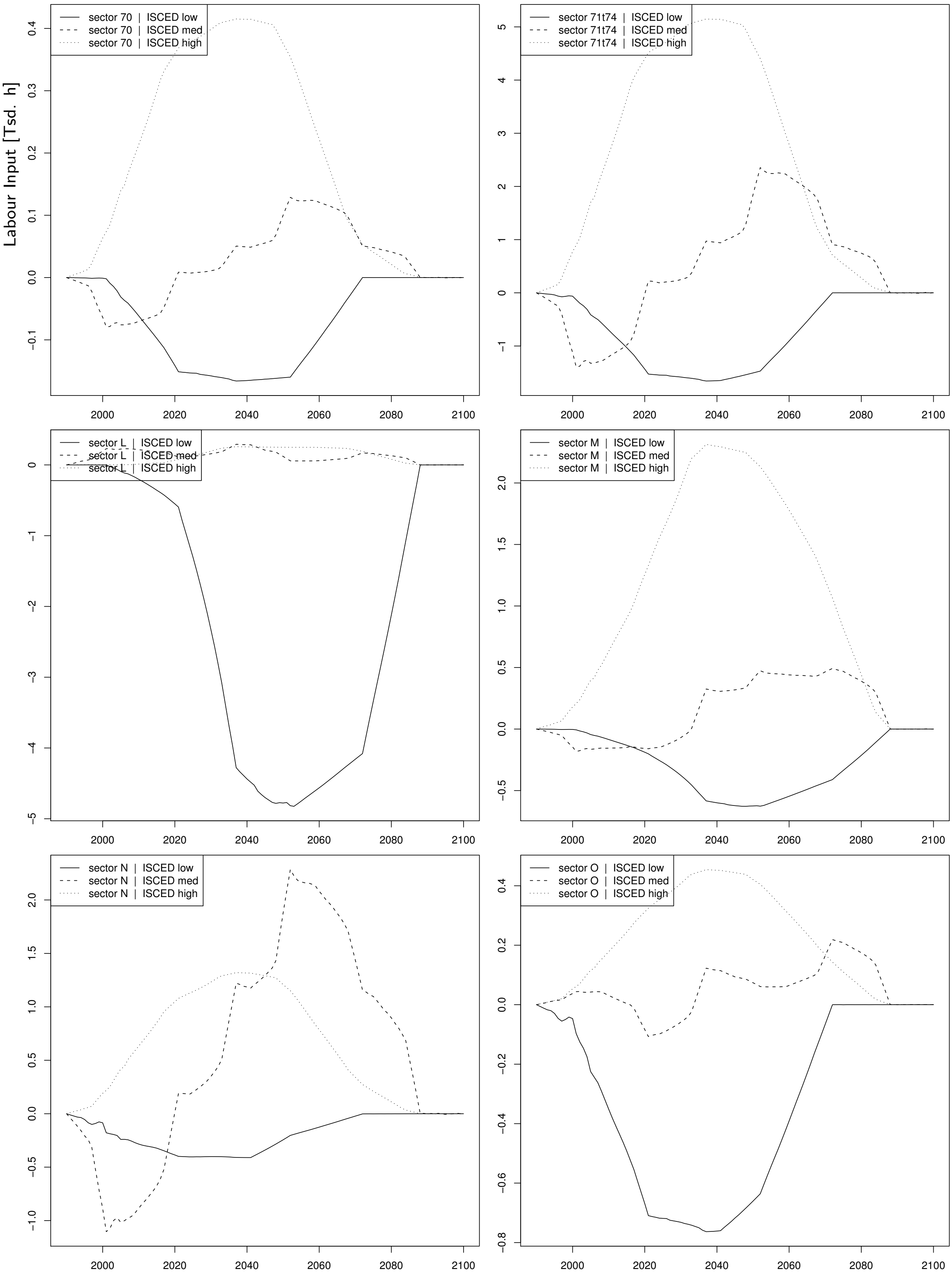
Labour Input [Tsd. h]
sector 23 | ISCED low
sector 23 | ISCED med
sector 23 | ISCED high
sector 24 | ISCED low
sector 24 | ISCED med
sector 24 | ISCED high
sector 25 | ISCED low
sector 25 | ISCED med
sector 25 | ISCED high
sector 26 | ISCED low
sector 26 | ISCED med
sector 26 | ISCED high
sector 27t28 | ISCED low
sector 27t28 | ISCED med
sector 27t28 | ISCED high
sector 29 | ISCED low
sector 29 | ISCED med
sector 29 | ISCED high
2000 2020 2040 2060 2080 2100



Labour Input [Tsd. h]
sector 30t33 | ISCED low
sector 30t33 | ISCED med
sector 30t33 | ISCED high
sector 34t35 | ISCED low
sector 34t35 | ISCED med
sector 34t35 | ISCED high
sector 36t37 | ISCED low
sector 36t37 | ISCED med
sector 36t37 | ISCED high
sector E | ISCED low
sector E | ISCED med
sector E | ISCED high
sector F | ISCED low
sector F | ISCED med
sector F | ISCED high
sector 50 | ISCED low
sector 50 | ISCED med
sector 50 | ISCED high
2000
2020
2040
2060
2080
2100



Labour Input [Tsd. h]
sector 51 | ISCED low
sector 51 | ISCED med
sector 51 | ISCED high
sector 52 | ISCED low
sector 52 | ISCED med
sector 52 | ISCED high
sector H | ISCED low
sector H | ISCED med
sector H | ISCED high
sector 60t63 | ISCED low
sector 60t63 | ISCED med
sector 60t63 | ISCED high
sector 64 | ISCED low
sector 64 | ISCED med
sector 64 | ISCED high
sector J | ISCED low
sector J | ISCED med
sector J | ISCED high
2000 2020 2040 2060 2080 2100

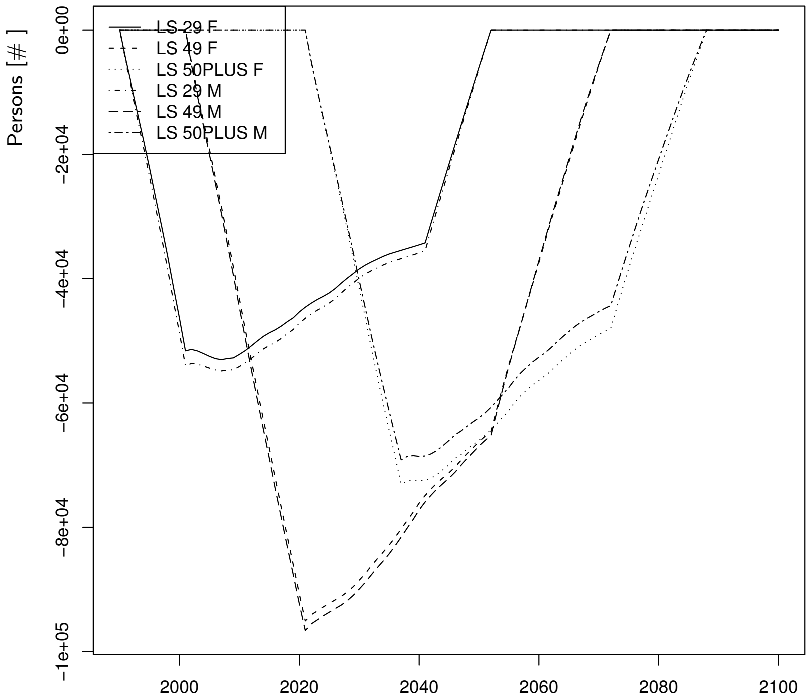

Labour Input [Tsd. h]
sector 70 | ISCED low
sector 70 | ISCED med
sector 70 | ISCED high
sector 71t74 | ISCED low
sector 71t74 | ISCED med
sector 71t74 | ISCED high
sector L | ISCED low
sector L | ISCED med
sector L | ISCED high
sector M | ISCED low
sector M | ISCED med
sector M | ISCED high
sector N | ISCED low
sector N | ISCED med
sector N | ISCED high
sector O | ISCED low
sector O | ISCED med
sector O | ISCED high
2000
2020
2040
2060
2080
2100

C.5.4 Graduation Probability → Population

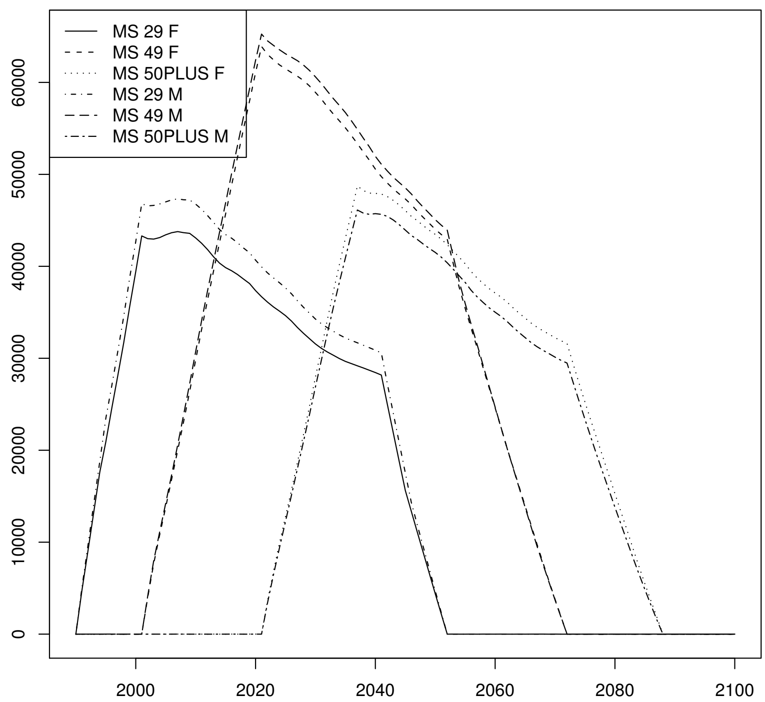
This section contains more detailed data, supplementing the information compiled in section 5.3.4 on page 122. The following graphs show the 18 time series of each one of the three plots combined in figure 5.12 on page 123 groups of 6 time series.

The first three graphs show the reaction to a 1% point increase of the graduation probability at the graduation points 18F and 18M. The next two show the reaction to the same change at graduation point 22F and 23M. The last two graphs show the similar reaction to a change a graduation points 31F and 31M. There is no reaction in low qualified labour types in the last two cases, since at these graduation points people shift from medium to high qualification level. For technical reasons the graphs have to start on the next page.

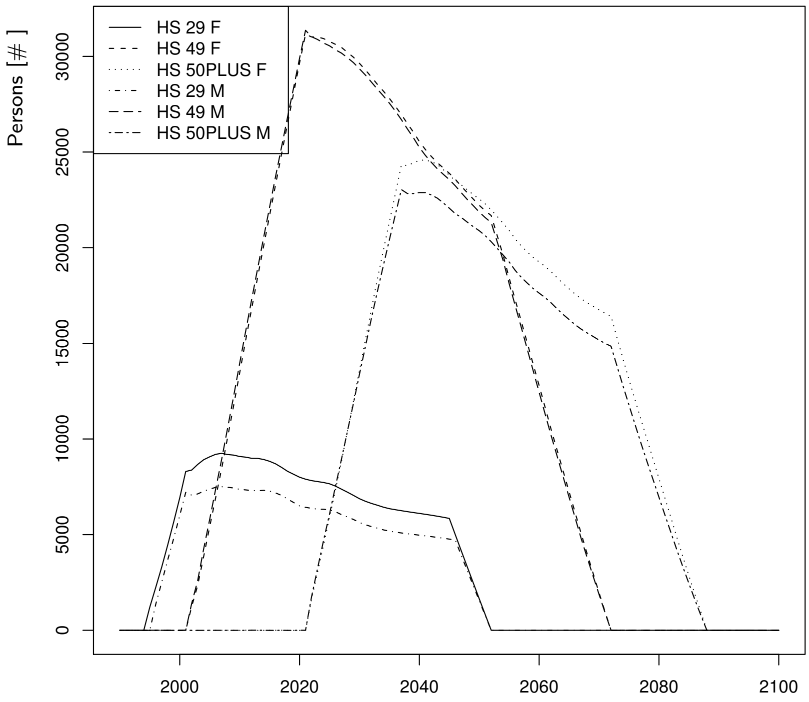
Population by Labour type BaseDifAbs | 18_1990_2040



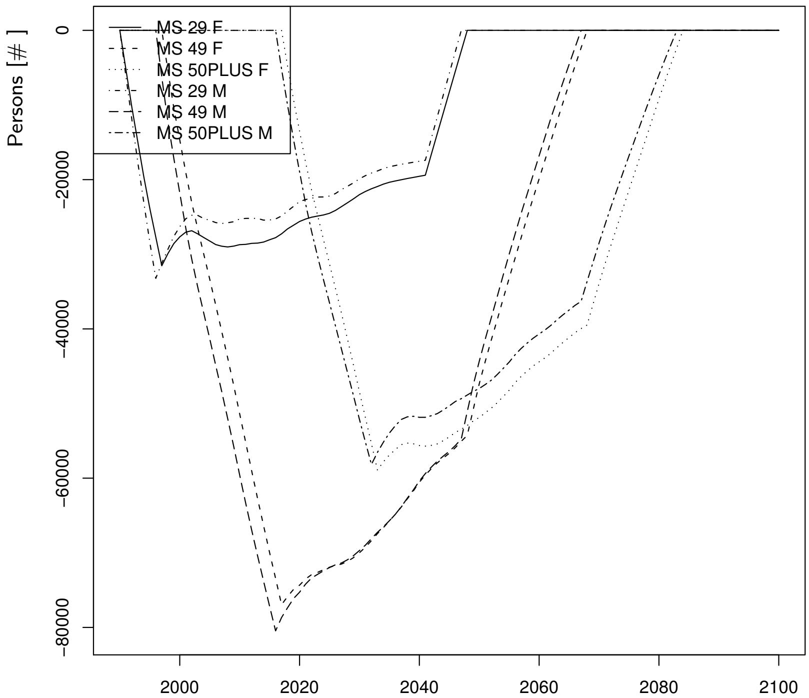
Population by Labour type BaseDifAbs | 18_1990_2040



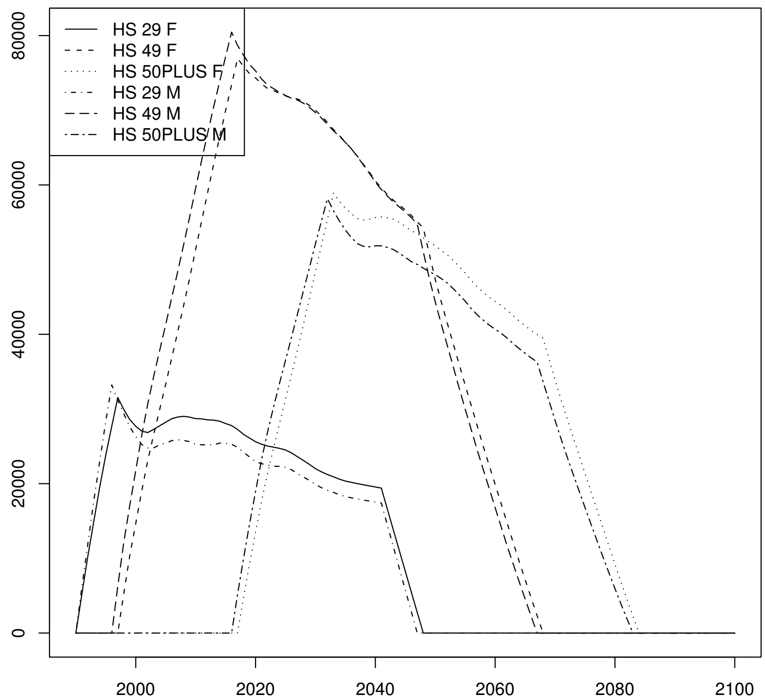
Population by Labour type BaseDifAbs | 18_1990_2040

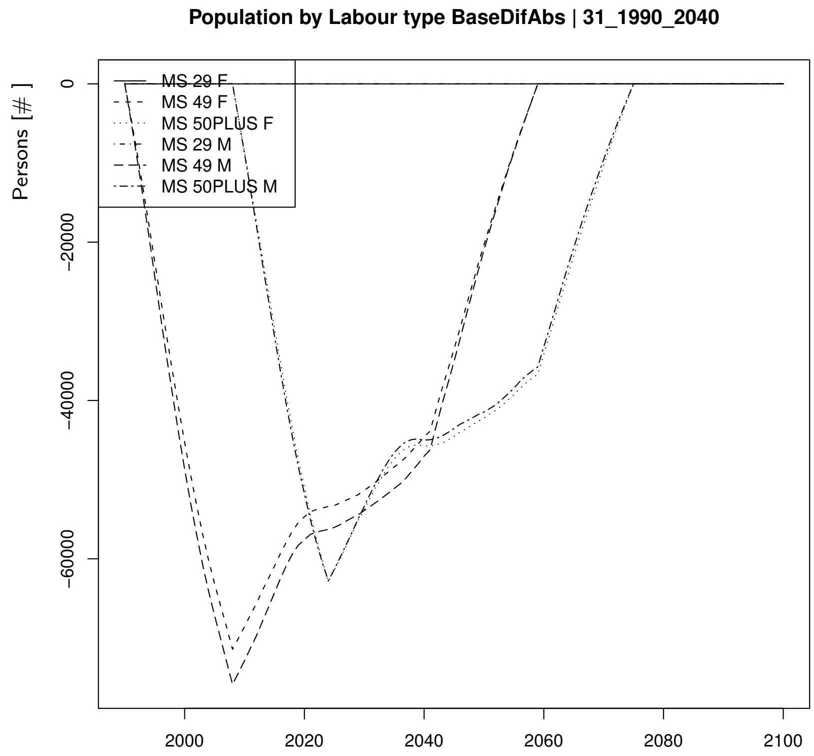


Population by Labour type BaseDifAbs | 22_1990_2040



Population by Labour type BaseDifAbs | 22_1990_2040




Population by Labour type BaseDifAbs | 31_1990_2040
MS 29 F
MS 49 F
MS 50PLUS F
MS 29 M
MS 49 M
MS 50PLUS M
Persons [#]
0
−20000
−40000
−60000
2000
2020
2040
2060
2080
2100

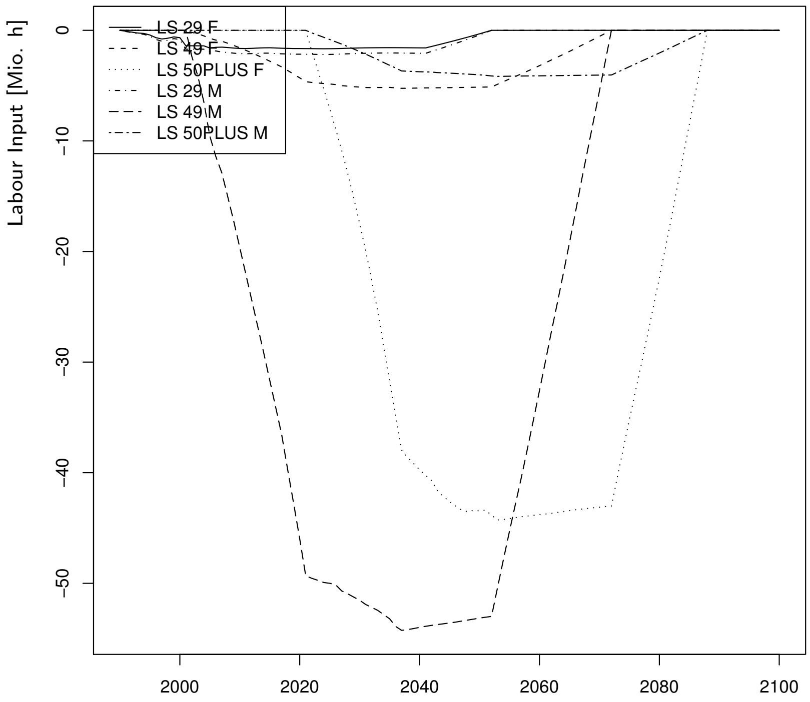

Population by Labour type BaseDifAbs | 31_1990_2040
HS 29 F
HS 49 F
HS 50PLUS F
HS 29 M
HS 49 M
HS 50PLUS M
60000
40000
20000
0
2000
2020
2040
2060
2080
2100

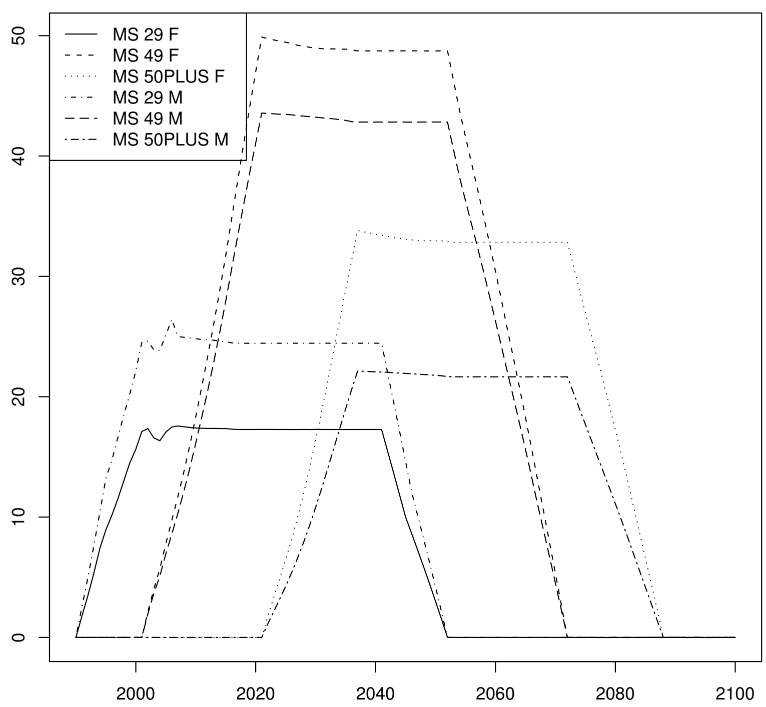
C.5.5 Graduation Probability → Labour Input

This section contains more detailed data, supplementing the information compiled in section 5.3.5 on page 125. The following graphs show the 18 time series of each one of the three plots combined in figure 5.13 on page 126 groups of 6 time series.

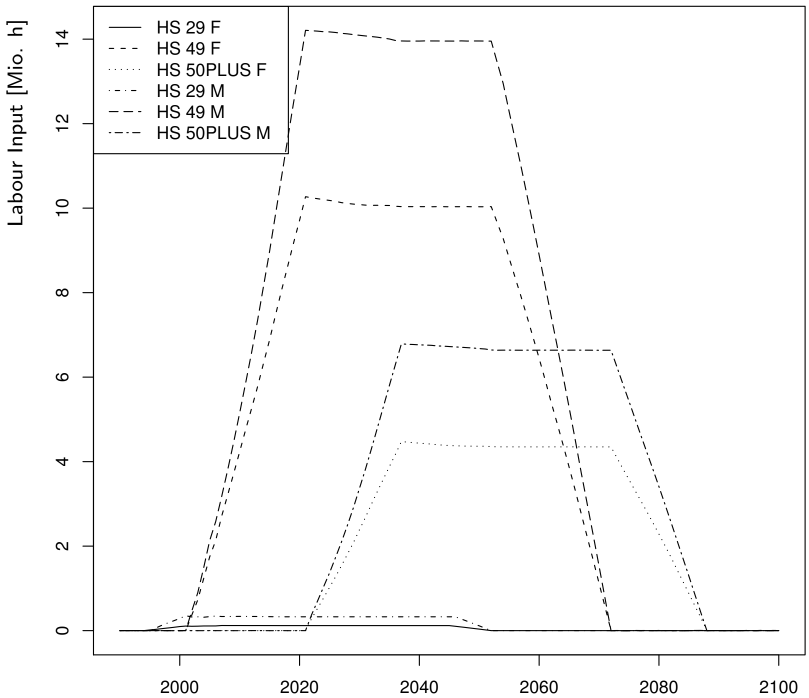
The first three graphs show the reaction to a 1% point increase of the graduation probability at the graduation points 18F and 18M. The next two show the reaction to the same change at graduation point 22F and 23M. The last two graphs show the similar reaction to a change a graduation points 31F and 31M. There is no reaction in low qualified labour types in the last two cases, since at these graduation points people shift from medium to high qualification level. For technical reasons the graphs have to start on the next page.

Hours worked by labour type BaseDifAbs | 18_1990_2040

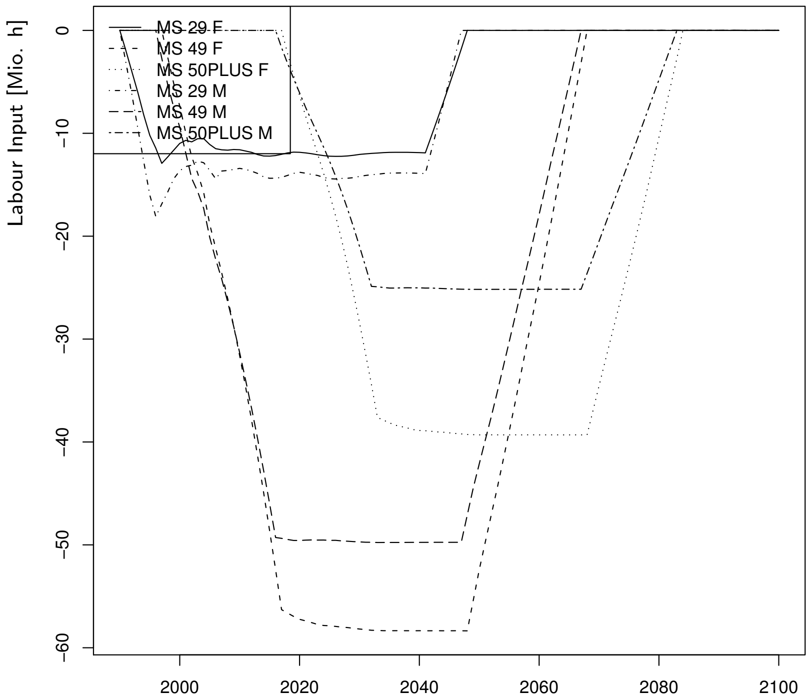


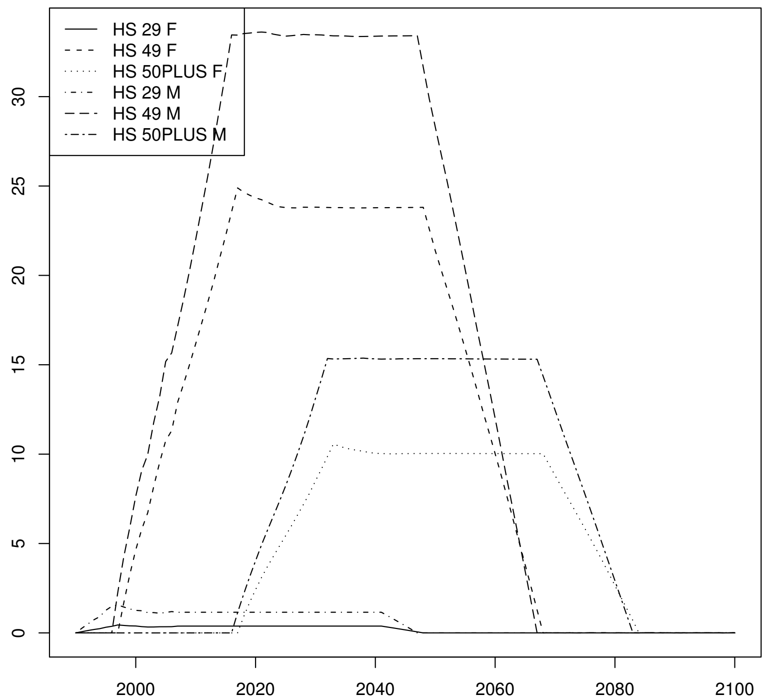


Hours worked by labour type BaseDifAbs | 18_1990_2040

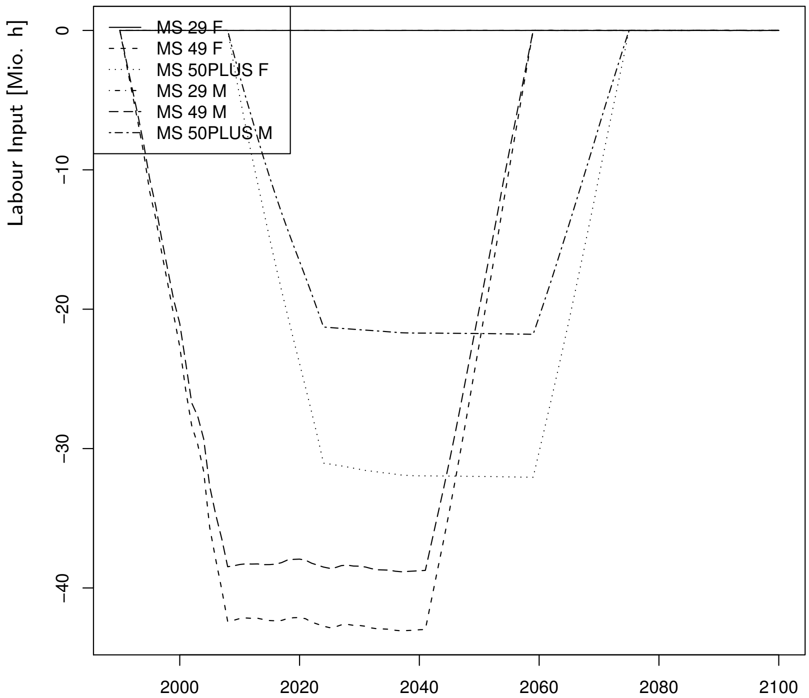


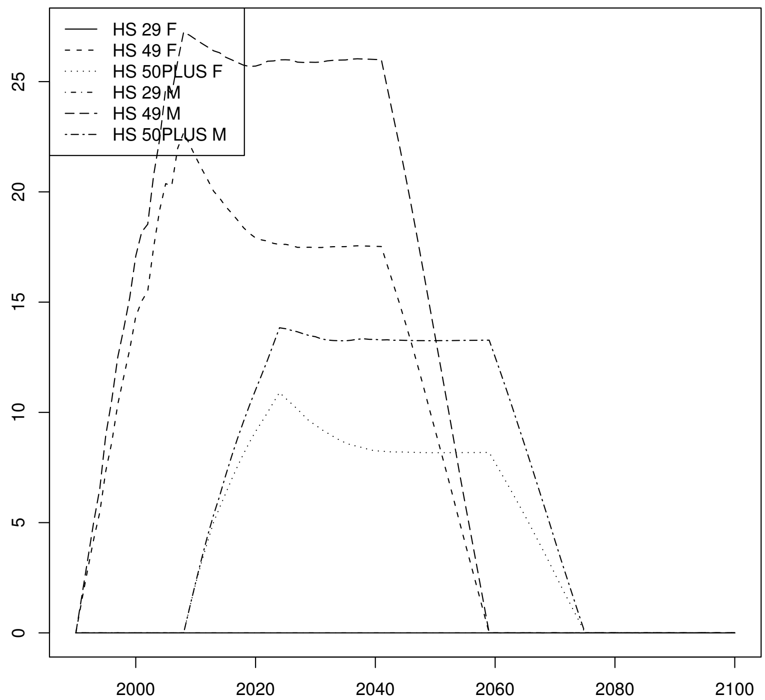
Hours worked by labour type BaseDifAbs | 22_1990_2040





Hours worked by labour type BaseDifAbs | 31_1990_2040





C.5.6 Graduation Probability → Gross Output

Only for consistency in section numbering needed. All relevant information contained in the main part of the thesis.

C.5.7 Population Composition → Labour Input

Only for consistency in section numbering needed. All relevant information contained in the main part of the thesis.

C.5.8 Population Composition → Gross Output

The following table contains supplementary information for section 5.3.8 on page 132. It contains the relative figures of the changes given as absolute values in table 5.7 on page 133.

Table C.7
Sectoral output change [1/1000%] due to a change of 1000 persons in population by ISCED group

[1/1000 %]	*1992*			*1995*			*2000*			*2005*		
	low	*med*	*high*	*low*	*med*	*high*	*low*	*med*	*high*	*low*	*med*	*high*
AtB	0.0	3.0	0.0	0.0	4.0	0.0	0.0	4.0	0.0	0.0	4.0	0.0
C	-0.2	2.0	0.0	-0.3	2.0	0.0	-0.5	4.0	1.0	-0.5	4.0	1.0
15t16	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17t19	-0.2	1.0	0.0	-0.3	2.0	0.0	-0.4	3.0	0.0	-0.5	4.0	1.0
20	-0.4	1.0	0.0	-0.3	1.0	0.0	-0.3	1.0	0.0	-0.4	1.0	0.0
21t22	-0.1	1.0	0.0	-0.1	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0
23	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
24	-0.1	1.0	0.0	-0.1	1.0	0.0	-0.1	1.0	0.0	-0.1	1.0	0.0
25	0.0	1.0	1.0	0.0	1.0	1.0	0.0	1.0	1.0	0.0	1.0	1.0
26	-0.1	1.0	0.0	-0.1	1.0	0.0	-0.2	1.0	0.0	-0.2	1.0	0.0
27t28	0.0	1.0	0.0	0.0	1.0	0.0	-0.1	1.0	0.0	0.0	0.0	0.0
29	0.0	1.0	0.0	-0.1	1.0	0.0	0.0	1.0	0.0	-0.1	1.0	0.0
30t33	-0.1	1.0	0.0	-0.1	1.0	1.0	-0.1	1.0	1.0	-0.1	1.0	1.0
34t35	0.0	1.0	1.0	0.0	1.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0
36t37	-0.1	1.0	0.0	-0.1	1.0	0.0	-0.1	1.0	0.0	-0.1	1.0	0.0
E	-0.1	1.0	0.0	-0.1	1.0	0.0	-0.1	1.0	0.0	-0.1	1.0	0.0
F	0.0	1.0	0.0	0.0	1.0	0.0	-0.1	1.0	0.0	-0.1	1.0	0.0
50	-0.9	2.0	1.0	-1.1	2.0	2.0	-1.0	2.0	1.0	-1.0	2.0	1.0
51	-0.2	1.0	0.0	-0.2	1.0	0.0	-0.3	1.0	0.0	-0.3	1.0	0.0
52	-0.9	1.0	1.0	-0.9	1.0	1.0	-0.9	1.0	1.0	-1.0	1.0	1.0
H	-1.3	3.0	2.0	-1.3	3.0	2.0	-1.2	3.0	1.0	-1.3	3.0	2.0
60t63	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0	0.0	1.0	0.0
64	0.0	2.0	0.0	0.0	2.0	0.0	0.0	2.0	0.0	0.0	2.0	0.0
J	-0.1	1.0	2.0	-0.1	1.0	2.0	-0.1	1.0	1.0	-0.1	1.0	1.0
70	-0.2	0.0	1.0	-0.2	0.0	1.0	-0.1	0.0	1.0	-0.2	0.0	1.0
71t74	-1.4	6.0	6.0	-1.3	6.0	6.0	-1.2	5.0	5.0	-1.4	5.0	5.0
L	-0.6	1.0	0.0	-0.6	1.0	0.0	-0.7	1.0	0.0	-0.7	1.0	0.0
M	-0.8	4.0	7.0	-0.7	3.0	7.0	-0.6	3.0	7.0	-0.6	3.0	6.0
N	-0.4	7.0	2.0	-0.4	6.0	2.0	-0.3	5.0	2.0	-0.3	5.0	1.0
O	-1.4	1.0	1.0	-1.3	1.0	1.0	-1.1	1.0	1.0	-1.0	1.0	1.0

Reaction to a change of 1000 persons in the population distinguished by sector and ISCED group. - 1000 in low, + 1000 in medium and high qualified labour types.

C.5.9 Labour Input → Gross Output

The following tables contains supplementary information for section 5.3.9 on page 134.

Table C.8
Sectoral output change [‰] due to a 1% change in labour input by ISCED group

[‰]	1992			1995			2000			2005		
	low	med	high	low	med	high	low	med	high	low	med	high
AtB	-1.02	4.11	0.44	-1.06	3.80	0.45	-1.30	2.99	0.35	-1.35	2.49	0.33
C	-0.89	2.51	0.40	-0.70	2.52	0.46	-0.78	3.34	0.62	-0.66	2.48	0.66
15t16	-0.51	1.14	0.07	-0.51	1.27	0.09	-0.52	1.35	0.12	-0.50	1.27	0.12
17t19	-0.77	1.72	0.11	-0.75	1.85	0.13	-0.68	1.75	0.15	-0.64	1.60	0.15
20	-1.00	2.44	0.36	-0.85	2.31	0.38	-0.69	1.99	0.34	-0.55	1.68	0.34
21t22	-0.74	1.79	0.26	-0.72	1.98	0.32	-0.56	1.61	0.28	-0.49	1.52	0.31
23	-0.16	0.39	0.06	-0.13	0.34	0.06	-0.12	0.36	0.06	-0.06	0.20	0.04
24	-0.77	1.87	0.27	-0.66	1.80	0.29	-0.53	1.54	0.27	-0.44	1.34	0.27
25	-0.77	1.88	0.27	-0.71	1.95	0.32	-0.65	1.90	0.33	-0.55	1.70	0.34
26	-0.81	1.97	0.29	-0.71	1.93	0.32	-0.67	1.95	0.34	-0.60	1.84	0.37
27t28	-0.88	2.14	0.31	-0.81	2.22	0.36	-0.72	2.08	0.36	-0.55	1.70	0.34
29	-0.92	2.23	0.33	-0.84	2.30	0.38	-0.74	2.14	0.37	-0.63	1.95	0.39
30t33	-0.65	2.30	0.59	-0.56	2.33	0.69	-0.45	2.02	0.61	-0.39	1.90	0.70
34t35	-0.48	1.70	0.44	-0.43	1.79	0.53	-0.32	1.46	0.44	-0.26	1.30	0.48
36t37	-0.85	2.40	0.38	-0.75	2.69	0.49	-0.55	2.35	0.43	-0.52	1.95	0.52
E	-0.57	1.60	0.26	-0.46	1.65	0.30	-0.36	1.55	0.29	-0.30	1.12	0.30
F	-0.71	2.83	0.24	-0.68	2.73	0.25	-0.71	2.61	0.27	-0.84	2.54	0.32
50	-0.81	3.77	0.29	-0.92	4.25	0.37	-1.11	4.17	0.40	-1.25	3.81	0.45
51	-0.67	3.08	0.24	-0.65	3.02	0.27	-0.80	3.01	0.29	-0.94	2.86	0.34
52	-1.05	4.85	0.38	-1.10	5.10	0.45	-1.19	4.50	0.43	-1.32	4.03	0.47
H	-0.79	3.66	0.28	-0.83	3.82	0.34	-0.97	3.64	0.35	-1.16	3.53	0.41
60t63	-0.72	2.72	0.21	-0.70	2.67	0.22	-0.65	2.30	0.19	-0.74	1.91	0.20
64	-0.83	3.14	0.24	-0.74	2.82	0.23	-0.55	1.94	0.16	-0.47	1.22	0.13
J	-0.29	3.10	0.41	-0.24	2.96	0.46	-0.20	2.45	0.46	-0.19	2.09	0.44
70	-0.06	0.24	0.11	-0.06	0.24	0.11	-0.09	0.25	0.13	-0.09	0.22	0.12
71t74	-0.42	1.64	0.72	-0.47	1.75	0.83	-0.68	1.91	0.96	-0.80	1.95	1.12
L	-0.76	4.08	1.08	-0.74	4.16	1.13	-0.63	4.22	1.06	-0.54	4.08	1.11
M	-0.66	3.72	3.21	-0.61	3.70	3.62	-0.63	3.72	3.64	-0.61	3.44	3.54
N	-0.72	3.81	1.12	-0.65	3.78	0.99	-0.60	3.76	1.01	-0.65	3.68	1.01
O	-0.71	2.09	0.81	-0.71	2.11	0.87	-0.81	2.12	0.80	-0.84	2.14	0.87

SEGESD results. Reaction to a 1% change in the labour input by sector and ISCED group. - 1% in low, + 1% in medium and high qualified labour types. Sectors sorted by knowledge intensity in table 5.8 on page 135.

Table C.9
Sectoral output change [Mio €] due to a 1% change in labour input by ISCED group

[Mio €]	1992			1995			2000			2005		
	low	med	high	low	med	high	low	med	high	low	med	high
AtB	-49.4	198.7	21.4	-48.9	174.5	20.7	-58.9	136.1	15.7	-48.4	89.3	11.7
C	-23.4	66.1	10.6	-15.6	55.7	10.2	-9.5	40.7	7.5	-6.7	25.1	6.7
15t16	-70.5	156.5	9.7	-64.4	158.4	10.8	-63.2	163.0	14.0	-58.9	148.4	13.8
17t19	-33.3	74.0	4.6	-24.5	60.3	4.1	-19.4	50.0	4.3	-13.4	33.7	3.1
20	-19.6	47.5	6.9	-19.0	52.0	8.5	-13.9	40.2	6.9	-9.8	30.4	6.1
21t22	-56.8	138.0	20.2	-51.9	141.7	23.2	-44.1	127.6	21.9	-33.5	103.4	20.8
23	-4.2	10.1	1.5	-2.9	7.9	1.3	-4.5	13.1	2.2	-3.1	9.7	1.9
24	-78.1	189.6	27.7	-69.1	188.7	30.9	-60.6	175.3	30.1	-48.4	149.2	30.0
25	-36.8	89.5	13.1	-32.9	90.0	14.7	-31.4	90.8	15.6	-26.4	81.5	16.4
26	-32.1	78.1	11.4	-29.4	80.3	13.2	-24.8	71.9	12.4	-17.6	54.4	10.9
27t28	-122.4	297.4	43.4	-108.2	295.6	48.4	-99.5	287.8	49.5	-80.9	249.6	50.2
29	-132.7	322.3	47.0	-112.8	308.0	50.5	-107.8	311.8	53.6	-94.3	291.0	58.5
30t33	-94.6	336.1	86.4	-70.4	292.0	86.1	-71.4	320.4	96.5	-56.5	277.2	101.5
34t35	-76.7	272.7	70.1	-63.7	264.2	77.9	-71.9	322.8	97.2	-65.1	319.2	116.9
36t37	-27.8	78.6	12.6	-22.4	80.0	14.6	-17.7	75.7	14.0	-14.1	53.1	14.2
E	-39.3	111.1	17.8	-31.0	110.9	20.3	-22.5	96.1	17.7	-24.4	92.3	24.7
F	-161.2	639.8	54.9	-166.9	667.4	61.5	-148.7	544.5	55.8	-128.1	387.6	48.2
50	-33.7	156.1	12.1	-35.5	164.0	14.4	-46.0	173.4	16.7	-55.4	169.3	19.9
51	-95.3	441.2	34.3	-97.1	448.4	39.5	-115.8	436.9	42.0	-123.0	375.5	44.1
52	-117.4	544.0	42.3	-124.9	576.8	50.8	-149.9	565.4	54.4	-155.5	474.9	55.8
H	-44.5	206.2	16.0	-47.6	219.6	19.4	-57.5	216.8	20.8	-60.4	184.3	21.7
60t63	-94.0	353.4	26.6	-89.6	343.2	27.7	-98.8	350.9	29.6	-114.9	297.4	31.7
64	-41.4	155.8	11.7	-38.3	146.7	11.8	-35.3	125.4	10.6	-34.0	87.9	9.4
J	-38.0	406.9	53.7	-34.4	421.6	66.3	-33.7	413.3	77.4	-36.8	397.0	83.6
70	-13.6	52.9	23.2	-16.4	60.6	28.8	-23.2	65.2	32.9	-23.1	56.0	32.1
71t74	-104.3	406.0	178.0	-123.5	457.1	217.0	-216.3	606.9	306.1	-262.8	638.3	366.4
L	-121.0	647.2	171.7	-116.2	651.3	177.5	-97.0	650.6	163.2	-80.2	604.6	164.1
M	-55.0	311.1	268.3	-52.9	322.4	315.6	-59.1	351.0	343.3	-59.5	334.2	343.9
N	-99.2	523.7	154.5	-100.0	580.7	152.5	-101.8	635.6	171.5	-110.9	633.9	173.4
O	-82.2	242.4	94.0	-86.7	258.0	105.8	-111.8	291.9	109.4	-108.3	276.2	111.5
Total	-1,998.7	7,553.1	1,545.4	-1,897.0	7,678.3	1,723.9	-2,016.0	7,750.7	1,892.8	-1,954.3	6,924.6	1,993.3
Ratios	-3.8	4.9	-0.8	-4.0	4.5	-0.9	-3.8	4.1	-0.9	-3.5	3.5	-1.0

SEGESD results. Reaction to a 1% change in the labour input by sector and ISCED group. - 1% in low, + 1% in medium and high qualified labour types.

Appendix D

SEGESD Model Code

This is the code of the complete implementation of *SEGESD* as a system dynamics model in the software *Vensim*.

```
********************************************************
	.Control
********************************************************~
		Simulation Control Parameters
	|

Add_Hours_worked_by_labour_type_BaseDeltaRel[labour_types_low] = 0 ~~|
Add_Hours_worked_by_labour_type_BaseDeltaRel[labour_types_med] = 0 ~~|
Add_Hours_worked_by_labour_type_BaseDeltaRel[labour_types_high]=	0
	~	Dmnl
	~	Factor for multiplication with \
		Hours_worked_by_sector_and_labour_type_BaseDifAbs
	|

Add_Pop_by_labour_type_RelDif_Exponential_Base[LS_29_M]	=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[LS_29_F]	=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[LS_49_M]	=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[LS_49_F]	=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[LS_50PLUS_M]=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[LS_50PLUS_F]=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[MS_29_M]	=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[MS_29_F]	=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[MS_49_M]	=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[MS_49_F]	=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[MS_50PLUS_M]=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[MS_50PLUS_F]=1 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[HS_29_M]	=1.01 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[HS_29_F]	=1.01 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[HS_49_M]	=1.01 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[HS_49_F]	=1.01 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[HS_50PLUS_M]=1.01 ~~|
Add_Pop_by_labour_type_RelDif_Exponential_Base[HS_50PLUS_F]=1.01
	~	Dmnl
	~	Yearly additional population. Multiplied yearly -> exponential increase.
		For analysis of effect of population structure change on gross output.
	|

Additional_Education_Spending_BaseDeltaRel=
	0.01
	~	Dmnl
	~		|

Additional_Education_Spending_switch_ISCED[ISCED_low]=
	0 ~~|
Additional_Education_Spending_switch_ISCED[ISCED_med]=
	1 ~~|
Additional_Education_Spending_switch_ISCED[ISCED_high]=
	1
	~	Dmnl
	~	Factor for Additional Education spending, ISCED specific.
	|

Additional_Qualified_Persons_per_labour_type_Abs[labour_types_low]	= 0 ~~|
Additional_Qualified_Persons_per_labour_type_Abs[labour_types_med]	= 0 ~~|
Additional_Qualified_Persons_per_labour_type_Abs[labour_types_high] = 1
	~	Person*Tsd
	~	Added to "Qualification Level BaseDifAbs". Use only for impact analysis of change in \
		population structure.
		Defined on [labour_types]
	|

Change_End_Year=
```

```
        2040
        ~       Dmnl
        ~               |

Change_Start_Year=
        1990
        ~       Dmnl
        ~               |

FINAL_TIME  = 2100
        ~       Year
        ~       The final time for the simulation.
        |

Impact_Quali_on_LabIn_per_labour_type_Age[labour_types_29]=
        1 ~~|
Impact_Quali_on_LabIn_per_labour_type_Age[labour_types_49]=
        1 ~~|
Impact_Quali_on_LabIn_per_labour_type_Age[labour_types_50PLUS]=
        1
        ~       Dmnl
        ~               |

Impact_Quali_on_LabIn_per_labour_type_ISCED[labour_types_low]=
        1 ~~|
Impact_Quali_on_LabIn_per_labour_type_ISCED[labour_types_med]=
        1 ~~|
Impact_Quali_on_LabIn_per_labour_type_ISCED[labour_types_high]=
        1
        ~       Dmnl
        ~               |

INITIAL_TIME  = 1970
        ~       Year
        ~       The initial time for the simulation.
        |

LowerBoundary_weak_or_moderate=
        1
        ~       Dmnl
        ~       1: weak
                2 (or any other) : moderate
        |

Probability_to_raise_Qualification_AbsoluteChange_10PC_moderate[age18,sex_f]=0.0210162\
                ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_moderate[age18,sex_m]=0.0073461\
                ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_moderate[age22,sex_f]=0.0116152\
                ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_moderate[age23,sex_m]=0.00608011\
                ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_moderate[age31,sex_f]=0.00395491\
                ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_moderate[age31,sex_m]=0.00041819\
                ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_moderate[ages_yearly_no_gp,sexes\
               ]=0 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_moderate[age22,sex_m]=0 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_moderate[age23,sex_f]=0
        ~       Dmnl
        ~       defined on: [ages_yearly, sexes]
                Values for 10% additional spending per student. Linear in percentage.
        |

Probability_to_raise_Qualification_AbsoluteChange_10PC_strong[age18,sex_f]=0.0484301 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_strong[age18,sex_m]=0.018224 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_strong[age22,sex_f]=0.0304537 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_strong[age23,sex_m]=0.0105169 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_strong[age31,sex_f]=0.0148073 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_strong[age31,sex_m]=0.00212885\
                ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_strong[ages_yearly_no_gp,sexes\
               ]=0 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_strong[age22,sex_m]=0 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_strong[age23,sex_f]=0
        ~       Dmnl
        ~       defined on: [ages_yearly, sexes]
                Values for 10% additional spending per student. Linear in percentage.
        |

Probability_to_raise_Qualification_AbsoluteChange_10PC_weak[age18,sex_f]=0.00371965 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_weak[age18,sex_m]=0.0016786 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_weak[age22,sex_f]=0.00205578 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_weak[age23,sex_m]=0.00138932 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_weak[age31,sex_f]=0.00068472 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_weak[age31,sex_m]=0.00037776 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_weak[ages_yearly_no_gp,sexes]=\
                0 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_weak[age22,sex_m]=0 ~~|
Probability_to_raise_Qualification_AbsoluteChange_10PC_weak[age23,sex_f]=0
        ~       Dmnl
        ~       defined on: [ages_yearly, sexes]
                Values for 10% additional spending per student. Linear in percentage.
        |

Probability_to_raise_Qualification_AbsoluteChange_fixed[age18,sex_f]=0.01 ~~|
Probability_to_raise_Qualification_AbsoluteChange_fixed[age18,sex_m]=0.01 ~~|
Probability_to_raise_Qualification_AbsoluteChange_fixed[age22,sex_f]=0.01 ~~|
Probability_to_raise_Qualification_AbsoluteChange_fixed[age23,sex_m]=0.01 ~~|
```

```
Probability_to_raise_Qualification_AbsoluteChange_fixed[age31,sex_f]=0.01 ~~|
Probability_to_raise_Qualification_AbsoluteChange_fixed[age31,sex_m]=0.01 ~~|
Probability_to_raise_Qualification_AbsoluteChange_fixed[ages_yearly_no_gp,sexes]=0 ~~|
Probability_to_raise_Qualification_AbsoluteChange_fixed[age22,sex_m]=0 ~~|
Probability_to_raise_Qualification_AbsoluteChange_fixed[age23,sex_f]=0
	~	Dmnl
	~	defined on: [ages_yearly, sexes]
	|

Probability_to_raise_Qualification_Activate_Change[age18,sex_f]=0 ~~|
Probability_to_raise_Qualification_Activate_Change[age18,sex_m]=0 ~~|
Probability_to_raise_Qualification_Activate_Change[age22,sex_f]=0 ~~|
Probability_to_raise_Qualification_Activate_Change[age23,sex_m]=0 ~~|
Probability_to_raise_Qualification_Activate_Change[age31,sex_f]=0 ~~|
Probability_to_raise_Qualification_Activate_Change[age31,sex_m]=0 ~~|
Probability_to_raise_Qualification_Activate_Change[ages_yearly_no_gp,sexes]=0 ~~|
Probability_to_raise_Qualification_Activate_Change[age22,sex_m]=0 ~~|
Probability_to_raise_Qualification_Activate_Change[age23,sex_f]=0
	~	Dmnl
	~	additional graduation probability per graduation point.
		0: switched off
		1: switched on
	|

Probability_to_raise_Qualification_Change_Intervall_Current_Step=
	0
	~	Dmnl
	~	In the case of 4 SubIntervalls the steps are the lower (0) and upper (4) \
		boundary of the intervall and 3 intermediate points within the intervall.
	|

Probability_to_raise_Qualification_Change_SubIntervalls=
	4
	~	Dmnl
	~	4 subintervalls (equally long) mean 5 intervall steps. The steps are then \
		the lower (0) and upper (4) boundary of the intervall and 3 (1, 2, 3) \
		intermediate points within the intervall.
	|

SAVEPER  =
	TIME_STEP
	~	Year [0,?]
	~	The frequency with which output is stored.
	|

Switch_Analyse_Quali_Level_Abs_Change=
	1
	~	Dmnl
	~	0 : taking population structure change from "Population by Labour type BaseDifRel
		1: use isolated absolute changes from
		    "Additional Qualified Persons per labour type Abs Effective"
	|

Switch_Analyse_Quali_Level_Rel_Change=
	0
	~	Dmnl
	~	1: Analyse Exponential Rel Change of Population
		0: Use Change in Population as calculated in Pop Cohort Model
	|

Switch_Baseline=
	0
	~
	~	1: Calculation of baseline
		0: Calculation of scenarios
	|

Switch_GradProb_AbsChange_Fixed_or_GP_specific=
	1
	~	Dmnl
	~	1: fixed
		2 (or any other): GP specific
	|

TIME_STEP  = 1
	~	Year [0,?]
	~	The time step for the simulation.
	|

********************************************************
	.EducPopulation
********************************************************~
		Educated Population Cohort Model
	|

Add_Pop_by_labour_type_RelDif_Exponential_Exponent=
	IF_THEN_ELSE(
	  Time < Change_Start_Year :OR: Time > Change_End_Year,
	  0 ,
	  Time -  Change_Start_Year + 1
	)
	~	Dmnl
	~		|

Births_Next_Year=
	SUM( Births_Next_Year_by_age_yearly_of_mother[ages_yearly_reproduction!] )
	~	Person
	~		|

Births_Next_Year_by_age_yearly_of_mother[ages_yearly_reproduction]=
	Women_in_reproduction_age[ages_yearly_reproduction]
	* Fertility_Rate_by_age_yearly[ages_yearly_reproduction]
	~	Person
```

```
        ~                |

Births_Next_Year_by_sex_Endog[sexes]=
        Births_Next_Year * Sex_split_of_newborns_Eurostat[sexes]
        ~       Person
        ~                |

Births_Next_Year_Eurostat
        ~       Person
        ~       shift of one year in exog data file (value for 1949 are born children in \
                1950) due to integration. births enter age00 in population conveyor \
                delayed by one year. Probably delay by timestep, which is set to 1 year.
        |

Births_Next_Year_RelDifEndogExog=
        Births_Next_Year / Births_Next_Year_Eurostat
        ~       Dmnl
        ~                |

Death_Probability_by_age_yearly_and_sex_Eurostat[sexes,ages_yearly]
        ~       Dmnl
        ~       per 100.000 persons
        |

Deaths_by_age_yearly_and_sex[sexes,ages_yearly]=
        SUM(Deaths_by_age_yearly_and_sex_and_Isced_groups[sexes,ages_yearly,isced_groups!])
        ~       Person
        ~                |

Deaths_by_age_yearly_and_sex_and_Isced_groups[sexes,ages_yearly,isced_groups]=
        Educated_Population_Conveyor[ages_yearly,sexes,isced_groups]
        * ( Death_Probability_by_age_yearly_and_sex_Eurostat[sexes,ages_yearly] / 100000)
        ~       Person
        ~                |

Deaths_by_age_yearly_and_sex_Eurostat[sexes,ages_yearly]
        ~       Person
        ~                |

Deaths_by_age_yearly_and_sex_RelDiffEndogExog[sexes,ages_yearly]=
        Deaths_by_age_yearly_and_sex[sexes,ages_yearly]
        / Deaths_by_age_yearly_and_sex_Eurostat[sexes,ages_yearly]
        ~       Dmnl
        ~                |

Distribution_of_ISCED_groups_in_init_pop[age00,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age00,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age00,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age00,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age00,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age00,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age01,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age01,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age01,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age01,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age01,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age01,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age02,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age02,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age02,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age02,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age02,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age02,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age03,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age03,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age03,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age03,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age03,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age03,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age04,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age04,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age04,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age04,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age04,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age04,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age05,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age05,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age05,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age05,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age05,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age05,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age06,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age06,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age06,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age06,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age06,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age06,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age07,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age07,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age07,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age07,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age07,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age07,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age08,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age08,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age08,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age08,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age08,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age08,sex_m,ISCED_med]=0 ~~|
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Distribution_of_ISCED_groups_in_init_pop[age09,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age09,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age09,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age09,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age09,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age09,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age10,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age10,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age10,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age10,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age10,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age10,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age11,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age11,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age11,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age11,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age11,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age11,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age12,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age12,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age12,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age12,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age12,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age12,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age13,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age13,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age13,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age13,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age13,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age13,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age14,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age14,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age14,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age14,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age14,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age14,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age15,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age15,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age15,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age15,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age15,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age15,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age16,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age16,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age16,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age16,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age16,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age16,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age17,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age17,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age17,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age17,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age17,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age17,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age18,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age18,sex_f,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age18,sex_f,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age18,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age18,sex_m,ISCED_low]=1 ~~|
Distribution_of_ISCED_groups_in_init_pop[age18,sex_m,ISCED_med]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age19,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age19,sex_f,ISCED_low]=0.22072 ~~|
Distribution_of_ISCED_groups_in_init_pop[age19,sex_f,ISCED_med]=0.77928 ~~|
Distribution_of_ISCED_groups_in_init_pop[age19,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age19,sex_m,ISCED_low]=0.11048 ~~|
Distribution_of_ISCED_groups_in_init_pop[age19,sex_m,ISCED_med]=0.88952 ~~|
Distribution_of_ISCED_groups_in_init_pop[age20,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age20,sex_f,ISCED_low]=0.22521 ~~|
Distribution_of_ISCED_groups_in_init_pop[age20,sex_f,ISCED_med]=0.77479 ~~|
Distribution_of_ISCED_groups_in_init_pop[age20,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age20,sex_m,ISCED_low]=0.10982 ~~|
Distribution_of_ISCED_groups_in_init_pop[age20,sex_m,ISCED_med]=0.89018 ~~|
Distribution_of_ISCED_groups_in_init_pop[age21,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age21,sex_f,ISCED_low]=0.23631 ~~|
Distribution_of_ISCED_groups_in_init_pop[age21,sex_f,ISCED_med]=0.76369 ~~|
Distribution_of_ISCED_groups_in_init_pop[age21,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age21,sex_m,ISCED_low]=0.11404 ~~|
Distribution_of_ISCED_groups_in_init_pop[age21,sex_m,ISCED_med]=0.88596 ~~|
Distribution_of_ISCED_groups_in_init_pop[age22,sex_f,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age22,sex_f,ISCED_low]=0.24742 ~~|
Distribution_of_ISCED_groups_in_init_pop[age22,sex_f,ISCED_med]=0.75258 ~~|
Distribution_of_ISCED_groups_in_init_pop[age22,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age22,sex_m,ISCED_low]=0.11826 ~~|
Distribution_of_ISCED_groups_in_init_pop[age22,sex_m,ISCED_med]=0.88174 ~~|
Distribution_of_ISCED_groups_in_init_pop[age23,sex_f,ISCED_high]=0.16281 ~~|
Distribution_of_ISCED_groups_in_init_pop[age23,sex_f,ISCED_low]=0.25852 ~~|
Distribution_of_ISCED_groups_in_init_pop[age23,sex_f,ISCED_med]=0.57697 ~~|
Distribution_of_ISCED_groups_in_init_pop[age23,sex_m,ISCED_high]=0 ~~|
Distribution_of_ISCED_groups_in_init_pop[age23,sex_m,ISCED_low]=0.12248 ~~|
Distribution_of_ISCED_groups_in_init_pop[age23,sex_m,ISCED_med]=0.87752 ~~|
Distribution_of_ISCED_groups_in_init_pop[age24,sex_f,ISCED_high]=0.15681 ~~|
Distribution_of_ISCED_groups_in_init_pop[age24,sex_f,ISCED_low]=0.26963 ~~|
Distribution_of_ISCED_groups_in_init_pop[age24,sex_f,ISCED_med]=0.57129 ~~|
Distribution_of_ISCED_groups_in_init_pop[age24,sex_m,ISCED_high]=0.29451 ~~|
Distribution_of_ISCED_groups_in_init_pop[age24,sex_m,ISCED_low]=0.12671 ~~|
Distribution_of_ISCED_groups_in_init_pop[age24,sex_m,ISCED_med]=0.57879 ~~|
Distribution_of_ISCED_groups_in_init_pop[age25,sex_f,ISCED_high]=0.15081 ~~|
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Distribution_of_ISCED_groups_in_init_pop[age25,sex_f,ISCED_low]=0.28073 ~~|
Distribution_of_ISCED_groups_in_init_pop[age25,sex_f,ISCED_med]=0.56562 ~~|
Distribution_of_ISCED_groups_in_init_pop[age25,sex_m,ISCED_high]=0.29206 ~~|
Distribution_of_ISCED_groups_in_init_pop[age25,sex_m,ISCED_low]=0.13093 ~~|
Distribution_of_ISCED_groups_in_init_pop[age25,sex_m,ISCED_med]=0.57701 ~~|
Distribution_of_ISCED_groups_in_init_pop[age26,sex_f,ISCED_high]=0.14481 ~~|
Distribution_of_ISCED_groups_in_init_pop[age26,sex_f,ISCED_low]=0.29184 ~~|
Distribution_of_ISCED_groups_in_init_pop[age26,sex_f,ISCED_med]=0.55995 ~~|
Distribution_of_ISCED_groups_in_init_pop[age26,sex_m,ISCED_high]=0.28962 ~~|
Distribution_of_ISCED_groups_in_init_pop[age26,sex_m,ISCED_low]=0.13515 ~~|
Distribution_of_ISCED_groups_in_init_pop[age26,sex_m,ISCED_med]=0.57523 ~~|
Distribution_of_ISCED_groups_in_init_pop[age27,sex_f,ISCED_high]=0.13881 ~~|
Distribution_of_ISCED_groups_in_init_pop[age27,sex_f,ISCED_low]=0.30294 ~~|
Distribution_of_ISCED_groups_in_init_pop[age27,sex_f,ISCED_med]=0.55427 ~~|
Distribution_of_ISCED_groups_in_init_pop[age27,sex_m,ISCED_high]=0.28717 ~~|
Distribution_of_ISCED_groups_in_init_pop[age27,sex_m,ISCED_low]=0.13937 ~~|
Distribution_of_ISCED_groups_in_init_pop[age27,sex_m,ISCED_med]=0.57346 ~~|
Distribution_of_ISCED_groups_in_init_pop[age28,sex_f,ISCED_high]=0.13281 ~~|
Distribution_of_ISCED_groups_in_init_pop[age28,sex_f,ISCED_low]=0.31405 ~~|
Distribution_of_ISCED_groups_in_init_pop[age28,sex_f,ISCED_med]=0.5486 ~~|
Distribution_of_ISCED_groups_in_init_pop[age28,sex_m,ISCED_high]=0.28473 ~~|
Distribution_of_ISCED_groups_in_init_pop[age28,sex_m,ISCED_low]=0.14359 ~~|
Distribution_of_ISCED_groups_in_init_pop[age28,sex_m,ISCED_med]=0.57168 ~~|
Distribution_of_ISCED_groups_in_init_pop[age29,sex_f,ISCED_high]=0.12681 ~~|
Distribution_of_ISCED_groups_in_init_pop[age29,sex_f,ISCED_low]=0.32515 ~~|
Distribution_of_ISCED_groups_in_init_pop[age29,sex_f,ISCED_med]=0.54292 ~~|
Distribution_of_ISCED_groups_in_init_pop[age29,sex_m,ISCED_high]=0.28229 ~~|
Distribution_of_ISCED_groups_in_init_pop[age29,sex_m,ISCED_low]=0.14781 ~~|
Distribution_of_ISCED_groups_in_init_pop[age29,sex_m,ISCED_med]=0.5699 ~~|
Distribution_of_ISCED_groups_in_init_pop[age30,sex_f,ISCED_high]=0.12081 ~~|
Distribution_of_ISCED_groups_in_init_pop[age30,sex_f,ISCED_low]=0.33626 ~~|
Distribution_of_ISCED_groups_in_init_pop[age30,sex_f,ISCED_med]=0.53725 ~~|
Distribution_of_ISCED_groups_in_init_pop[age30,sex_m,ISCED_high]=0.27984 ~~|
Distribution_of_ISCED_groups_in_init_pop[age30,sex_m,ISCED_low]=0.15203 ~~|
Distribution_of_ISCED_groups_in_init_pop[age30,sex_m,ISCED_med]=0.56813 ~~|
Distribution_of_ISCED_groups_in_init_pop[age31,sex_f,ISCED_high]=0.11481 ~~|
Distribution_of_ISCED_groups_in_init_pop[age31,sex_f,ISCED_low]=0.34736 ~~|
Distribution_of_ISCED_groups_in_init_pop[age31,sex_f,ISCED_med]=0.53158 ~~|
Distribution_of_ISCED_groups_in_init_pop[age31,sex_m,ISCED_high]=0.2774 ~~|
Distribution_of_ISCED_groups_in_init_pop[age31,sex_m,ISCED_low]=0.15625 ~~|
Distribution_of_ISCED_groups_in_init_pop[age31,sex_m,ISCED_med]=0.56635 ~~|
Distribution_of_ISCED_groups_in_init_pop[age32,sex_f,ISCED_high]=0.10881 ~~|
Distribution_of_ISCED_groups_in_init_pop[age32,sex_f,ISCED_low]=0.35847 ~~|
Distribution_of_ISCED_groups_in_init_pop[age32,sex_f,ISCED_med]=0.5259 ~~|
Distribution_of_ISCED_groups_in_init_pop[age32,sex_m,ISCED_high]=0.27495 ~~|
Distribution_of_ISCED_groups_in_init_pop[age32,sex_m,ISCED_low]=0.16048 ~~|
Distribution_of_ISCED_groups_in_init_pop[age32,sex_m,ISCED_med]=0.56457 ~~|
Distribution_of_ISCED_groups_in_init_pop[age33,sex_f,ISCED_high]=0.10281 ~~|
Distribution_of_ISCED_groups_in_init_pop[age33,sex_f,ISCED_low]=0.36957 ~~|
Distribution_of_ISCED_groups_in_init_pop[age33,sex_f,ISCED_med]=0.52023 ~~|
Distribution_of_ISCED_groups_in_init_pop[age33,sex_m,ISCED_high]=0.27251 ~~|
Distribution_of_ISCED_groups_in_init_pop[age33,sex_m,ISCED_low]=0.1647 ~~|
Distribution_of_ISCED_groups_in_init_pop[age33,sex_m,ISCED_med]=0.5628 ~~|
Distribution_of_ISCED_groups_in_init_pop[age34,sex_f,ISCED_high]=0.09682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age34,sex_f,ISCED_low]=0.38068 ~~|
Distribution_of_ISCED_groups_in_init_pop[age34,sex_f,ISCED_med]=0.51456 ~~|
Distribution_of_ISCED_groups_in_init_pop[age34,sex_m,ISCED_high]=0.27006 ~~|
Distribution_of_ISCED_groups_in_init_pop[age34,sex_m,ISCED_low]=0.16892 ~~|
Distribution_of_ISCED_groups_in_init_pop[age34,sex_m,ISCED_med]=0.56102 ~~|
Distribution_of_ISCED_groups_in_init_pop[age35,sex_f,ISCED_high]=0.09082 ~~|
Distribution_of_ISCED_groups_in_init_pop[age35,sex_f,ISCED_low]=0.39178 ~~|
Distribution_of_ISCED_groups_in_init_pop[age35,sex_f,ISCED_med]=0.50888 ~~|
Distribution_of_ISCED_groups_in_init_pop[age35,sex_m,ISCED_high]=0.26762 ~~|
Distribution_of_ISCED_groups_in_init_pop[age35,sex_m,ISCED_low]=0.17314 ~~|
Distribution_of_ISCED_groups_in_init_pop[age35,sex_m,ISCED_med]=0.55924 ~~|
Distribution_of_ISCED_groups_in_init_pop[age36,sex_f,ISCED_high]=0.08482 ~~|
Distribution_of_ISCED_groups_in_init_pop[age36,sex_f,ISCED_low]=0.40289 ~~|
Distribution_of_ISCED_groups_in_init_pop[age36,sex_f,ISCED_med]=0.50321 ~~|
Distribution_of_ISCED_groups_in_init_pop[age36,sex_m,ISCED_high]=0.26517 ~~|
Distribution_of_ISCED_groups_in_init_pop[age36,sex_m,ISCED_low]=0.17736 ~~|
Distribution_of_ISCED_groups_in_init_pop[age36,sex_m,ISCED_med]=0.55747 ~~|
Distribution_of_ISCED_groups_in_init_pop[age37,sex_f,ISCED_high]=0.07882 ~~|
Distribution_of_ISCED_groups_in_init_pop[age37,sex_f,ISCED_low]=0.41399 ~~|
Distribution_of_ISCED_groups_in_init_pop[age37,sex_f,ISCED_med]=0.49754 ~~|
Distribution_of_ISCED_groups_in_init_pop[age37,sex_m,ISCED_high]=0.26273 ~~|
Distribution_of_ISCED_groups_in_init_pop[age37,sex_m,ISCED_low]=0.18158 ~~|
Distribution_of_ISCED_groups_in_init_pop[age37,sex_m,ISCED_med]=0.55569 ~~|
Distribution_of_ISCED_groups_in_init_pop[age38,sex_f,ISCED_high]=0.07282 ~~|
Distribution_of_ISCED_groups_in_init_pop[age38,sex_f,ISCED_low]=0.4251 ~~|
Distribution_of_ISCED_groups_in_init_pop[age38,sex_f,ISCED_med]=0.49186 ~~|
Distribution_of_ISCED_groups_in_init_pop[age38,sex_m,ISCED_high]=0.26028 ~~|
Distribution_of_ISCED_groups_in_init_pop[age38,sex_m,ISCED_low]=0.1858 ~~|
Distribution_of_ISCED_groups_in_init_pop[age38,sex_m,ISCED_med]=0.55391 ~~|
Distribution_of_ISCED_groups_in_init_pop[age39,sex_f,ISCED_high]=0.07063 ~~|
Distribution_of_ISCED_groups_in_init_pop[age39,sex_f,ISCED_low]=0.43595 ~~|
Distribution_of_ISCED_groups_in_init_pop[age39,sex_f,ISCED_med]=0.48393 ~~|
Distribution_of_ISCED_groups_in_init_pop[age39,sex_m,ISCED_high]=0.25714 ~~|
Distribution_of_ISCED_groups_in_init_pop[age39,sex_m,ISCED_low]=0.18793 ~~|
Distribution_of_ISCED_groups_in_init_pop[age39,sex_m,ISCED_med]=0.55493 ~~|
Distribution_of_ISCED_groups_in_init_pop[age40,sex_f,ISCED_high]=0.06844 ~~|
Distribution_of_ISCED_groups_in_init_pop[age40,sex_f,ISCED_low]=0.44681 ~~|
Distribution_of_ISCED_groups_in_init_pop[age40,sex_f,ISCED_med]=0.47599 ~~|
Distribution_of_ISCED_groups_in_init_pop[age40,sex_m,ISCED_high]=0.254 ~~|
Distribution_of_ISCED_groups_in_init_pop[age40,sex_m,ISCED_low]=0.19005 ~~|
Distribution_of_ISCED_groups_in_init_pop[age40,sex_m,ISCED_med]=0.55595 ~~|
Distribution_of_ISCED_groups_in_init_pop[age41,sex_f,ISCED_high]=0.06625 ~~|
Distribution_of_ISCED_groups_in_init_pop[age41,sex_f,ISCED_low]=0.45766 ~~|
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Distribution_of_ISCED_groups_in_init_pop[age41,sex_f,ISCED_med]=0.46805 ~~|
Distribution_of_ISCED_groups_in_init_pop[age41,sex_m,ISCED_high]=0.25086 ~~|
Distribution_of_ISCED_groups_in_init_pop[age41,sex_m,ISCED_low]=0.19217 ~~|
Distribution_of_ISCED_groups_in_init_pop[age41,sex_m,ISCED_med]=0.55698 ~~|
Distribution_of_ISCED_groups_in_init_pop[age42,sex_f,ISCED_high]=0.06406 ~~|
Distribution_of_ISCED_groups_in_init_pop[age42,sex_f,ISCED_low]=0.46852 ~~|
Distribution_of_ISCED_groups_in_init_pop[age42,sex_f,ISCED_med]=0.46012 ~~|
Distribution_of_ISCED_groups_in_init_pop[age42,sex_m,ISCED_high]=0.24771 ~~|
Distribution_of_ISCED_groups_in_init_pop[age42,sex_m,ISCED_low]=0.19429 ~~|
Distribution_of_ISCED_groups_in_init_pop[age42,sex_m,ISCED_med]=0.558 ~~|
Distribution_of_ISCED_groups_in_init_pop[age43,sex_f,ISCED_high]=0.06188 ~~|
Distribution_of_ISCED_groups_in_init_pop[age43,sex_f,ISCED_low]=0.47938 ~~|
Distribution_of_ISCED_groups_in_init_pop[age43,sex_f,ISCED_med]=0.45218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age43,sex_m,ISCED_high]=0.24457 ~~|
Distribution_of_ISCED_groups_in_init_pop[age43,sex_m,ISCED_low]=0.19641 ~~|
Distribution_of_ISCED_groups_in_init_pop[age43,sex_m,ISCED_med]=0.55902 ~~|
Distribution_of_ISCED_groups_in_init_pop[age44,sex_f,ISCED_high]=0.05969 ~~|
Distribution_of_ISCED_groups_in_init_pop[age44,sex_f,ISCED_low]=0.49023 ~~|
Distribution_of_ISCED_groups_in_init_pop[age44,sex_f,ISCED_med]=0.44424 ~~|
Distribution_of_ISCED_groups_in_init_pop[age44,sex_m,ISCED_high]=0.24143 ~~|
Distribution_of_ISCED_groups_in_init_pop[age44,sex_m,ISCED_low]=0.19853 ~~|
Distribution_of_ISCED_groups_in_init_pop[age44,sex_m,ISCED_med]=0.56004 ~~|
Distribution_of_ISCED_groups_in_init_pop[age45,sex_f,ISCED_high]=0.0575 ~~|
Distribution_of_ISCED_groups_in_init_pop[age45,sex_f,ISCED_low]=0.50109 ~~|
Distribution_of_ISCED_groups_in_init_pop[age45,sex_f,ISCED_med]=0.43631 ~~|
Distribution_of_ISCED_groups_in_init_pop[age45,sex_m,ISCED_high]=0.23829 ~~|
Distribution_of_ISCED_groups_in_init_pop[age45,sex_m,ISCED_low]=0.20065 ~~|
Distribution_of_ISCED_groups_in_init_pop[age45,sex_m,ISCED_med]=0.56106 ~~|
Distribution_of_ISCED_groups_in_init_pop[age46,sex_f,ISCED_high]=0.05531 ~~|
Distribution_of_ISCED_groups_in_init_pop[age46,sex_f,ISCED_low]=0.51194 ~~|
Distribution_of_ISCED_groups_in_init_pop[age46,sex_f,ISCED_med]=0.42837 ~~|
Distribution_of_ISCED_groups_in_init_pop[age46,sex_m,ISCED_high]=0.23514 ~~|
Distribution_of_ISCED_groups_in_init_pop[age46,sex_m,ISCED_low]=0.20278 ~~|
Distribution_of_ISCED_groups_in_init_pop[age46,sex_m,ISCED_med]=0.56208 ~~|
Distribution_of_ISCED_groups_in_init_pop[age47,sex_f,ISCED_high]=0.05312 ~~|
Distribution_of_ISCED_groups_in_init_pop[age47,sex_f,ISCED_low]=0.5228 ~~|
Distribution_of_ISCED_groups_in_init_pop[age47,sex_f,ISCED_med]=0.42043 ~~|
Distribution_of_ISCED_groups_in_init_pop[age47,sex_m,ISCED_high]=0.232 ~~|
Distribution_of_ISCED_groups_in_init_pop[age47,sex_m,ISCED_low]=0.2049 ~~|
Distribution_of_ISCED_groups_in_init_pop[age47,sex_m,ISCED_med]=0.5631 ~~|
Distribution_of_ISCED_groups_in_init_pop[age48,sex_f,ISCED_high]=0.05093 ~~|
Distribution_of_ISCED_groups_in_init_pop[age48,sex_f,ISCED_low]=0.53365 ~~|
Distribution_of_ISCED_groups_in_init_pop[age48,sex_f,ISCED_med]=0.4125 ~~|
Distribution_of_ISCED_groups_in_init_pop[age48,sex_m,ISCED_high]=0.22886 ~~|
Distribution_of_ISCED_groups_in_init_pop[age48,sex_m,ISCED_low]=0.20702 ~~|
Distribution_of_ISCED_groups_in_init_pop[age48,sex_m,ISCED_med]=0.56412 ~~|
Distribution_of_ISCED_groups_in_init_pop[age49,sex_f,ISCED_high]=0.04874 ~~|
Distribution_of_ISCED_groups_in_init_pop[age49,sex_f,ISCED_low]=0.54451 ~~|
Distribution_of_ISCED_groups_in_init_pop[age49,sex_f,ISCED_med]=0.40456 ~~|
Distribution_of_ISCED_groups_in_init_pop[age49,sex_m,ISCED_high]=0.22572 ~~|
Distribution_of_ISCED_groups_in_init_pop[age49,sex_m,ISCED_low]=0.20914 ~~|
Distribution_of_ISCED_groups_in_init_pop[age49,sex_m,ISCED_med]=0.56514 ~~|
Distribution_of_ISCED_groups_in_init_pop[age50,sex_f,ISCED_high]=0.04655 ~~|
Distribution_of_ISCED_groups_in_init_pop[age50,sex_f,ISCED_low]=0.55536 ~~|
Distribution_of_ISCED_groups_in_init_pop[age50,sex_f,ISCED_med]=0.39662 ~~|
Distribution_of_ISCED_groups_in_init_pop[age50,sex_m,ISCED_high]=0.22258 ~~|
Distribution_of_ISCED_groups_in_init_pop[age50,sex_m,ISCED_low]=0.21126 ~~|
Distribution_of_ISCED_groups_in_init_pop[age50,sex_m,ISCED_med]=0.56616 ~~|
Distribution_of_ISCED_groups_in_init_pop[age51,sex_f,ISCED_high]=0.04437 ~~|
Distribution_of_ISCED_groups_in_init_pop[age51,sex_f,ISCED_low]=0.56622 ~~|
Distribution_of_ISCED_groups_in_init_pop[age51,sex_f,ISCED_med]=0.38869 ~~|
Distribution_of_ISCED_groups_in_init_pop[age51,sex_m,ISCED_high]=0.21943 ~~|
Distribution_of_ISCED_groups_in_init_pop[age51,sex_m,ISCED_low]=0.21338 ~~|
Distribution_of_ISCED_groups_in_init_pop[age51,sex_m,ISCED_med]=0.56718 ~~|
Distribution_of_ISCED_groups_in_init_pop[age52,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age52,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age52,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age52,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age52,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age52,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age53,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age53,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age53,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age53,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age53,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age53,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age54,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age54,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age54,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age54,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age54,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age54,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age55,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age55,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age55,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age55,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age55,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age55,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age56,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age56,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age56,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age56,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age56,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age56,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age57,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age57,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age57,sex_f,ISCED_med]=0.38075 ~~|
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Distribution_of_ISCED_groups_in_init_pop[age57,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age57,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age57,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age58,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age58,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age58,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age58,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age58,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age58,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age59,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age59,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age59,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age59,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age59,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age59,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age60,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age60,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age60,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age60,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age60,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age60,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age61,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age61,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age61,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age61,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age61,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age61,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age62,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age62,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age62,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age62,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age62,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age62,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age63,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age63,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age63,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age63,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age63,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age63,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age64,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age64,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age64,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age64,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age64,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age64,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age65,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age65,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age65,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age65,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age65,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age65,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age66,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age66,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age66,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age66,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age66,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age66,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age67,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age67,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age67,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age67,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age67,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age67,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age68,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age68,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age68,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age68,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age68,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age68,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age69,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age69,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age69,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age69,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age69,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age69,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age70,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age70,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age70,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age70,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age70,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age70,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age71,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age71,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age71,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age71,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age71,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age71,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age72,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age72,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age72,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age72,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age72,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age72,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age73,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age73,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age73,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age73,sex_m,ISCED_high]=0.21629 ~~|
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Distribution_of_ISCED_groups_in_init_pop[age73,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age73,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age74,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age74,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age74,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age74,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age74,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age74,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age75,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age75,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age75,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age75,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age75,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age75,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age76,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age76,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age76,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age76,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age76,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age76,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age77,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age77,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age77,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age77,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age77,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age77,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age78,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age78,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age78,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age78,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age78,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age78,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age79,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age79,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age79,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age79,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age79,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age79,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age80,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age80,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age80,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age80,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age80,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age80,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age81,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age81,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age81,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age81,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age81,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age81,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age82,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age82,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age82,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age82,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age82,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age82,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age83,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age83,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age83,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age83,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age83,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age83,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age84,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age84,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age84,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age84,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age84,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age84,sex_m,ISCED_med]=0.5682 ~~|
Distribution_of_ISCED_groups_in_init_pop[age85,sex_f,ISCED_high]=0.04218 ~~|
Distribution_of_ISCED_groups_in_init_pop[age85,sex_f,ISCED_low]=0.57707 ~~|
Distribution_of_ISCED_groups_in_init_pop[age85,sex_f,ISCED_med]=0.38075 ~~|
Distribution_of_ISCED_groups_in_init_pop[age85,sex_m,ISCED_high]=0.21629 ~~|
Distribution_of_ISCED_groups_in_init_pop[age85,sex_m,ISCED_low]=0.21551 ~~|
Distribution_of_ISCED_groups_in_init_pop[age85,sex_m,ISCED_med]=0.5682
        ~
        ~               |

Educated_Population_Conveyor[age00, sexes, ISCED_low]= INTEG (
        Births_Next_Year_by_sex_Endog[sexes]
        - Education_and_Aging_of_Population_Outflow[age00,sexes, ISCED_low]
        + Immigration_by_Age_yearly_and_sex_and_isced[age00,sexes,ISCED_low],
                Population_Init[age00, sexes, ISCED_low]) ~~|
Educated_Population_Conveyor[age00, sexes, ISCED_med]= INTEG (
        - Education_and_Aging_of_Population_Outflow[age00,sexes, ISCED_med]
        + Immigration_by_Age_yearly_and_sex_and_isced[age00,sexes,ISCED_med],
                Population_Init[age00, sexes, ISCED_med]) ~~|
Educated_Population_Conveyor[age00, sexes, ISCED_high]= INTEG (
        - Education_and_Aging_of_Population_Outflow[age00,sexes, ISCED_high]
        + Immigration_by_Age_yearly_and_sex_and_isced[age00,sexes,ISCED_high],
                Population_Init[age00, sexes, ISCED_high]) ~~|
Educated_Population_Conveyor[ages_yearly_subsequent, sexes, isced_groups]= INTEG (
        Education_and_Aging_of_Population_Inflow[ages_yearly_previous,sexes, isced_groups]
        - Education_and_Aging_of_Population_Outflow[ages_yearly_subsequent,sexes,isced_groups\
                ]
        - Deaths_by_age_yearly_and_sex_and_Isced_groups[sexes,ages_yearly_previous,isced_groups\
                ]
        + Immigration_by_Age_yearly_and_sex_and_isced[ages_yearly_previous,sexes,isced_groups\
```

```
                ],
                Population_Init[ages_yearly_subsequent,sexes,isced_groups])
        ~       Person
        ~       mapping of subscript ranges ages_yearly_previous to ages_yearly_subsequent \
                is essential for conveyor to work !!
        |

Educated_Population_Conveyor_Base[ages_yearly,sexes, isced_groups]
        ~       Person
        ~       Baseline
        |

Educated_Population_Conveyor_Base_Plot[ages_yearly,sexes,isced_groups]=
        Educated_Population_Conveyor_Base[ages_yearly,sexes,isced_groups]
        ~       Person
        ~       for some reason vensim puts a new time header for \
                "Educated_Population_Conveyor_Base", starting with 1900, 1950 1951 etc. \
                therefor this var. like that it comes in the same structure as all other \
                vars.
        |

Educated_Population_Conveyor_BaseDifAbs[ages_yearly,sexes,isced_groups]=
        Educated_Population_Conveyor[ages_yearly,sexes,isced_groups]
        - Educated_Population_Conveyor_Base[ages_yearly,sexes,isced_groups]
        ~       Person
        ~               |

Educated_Population_Conveyor_BaseDifRel[ages_yearly,sexes,isced_groups]=
        XIDZ(
        Educated_Population_Conveyor[ages_yearly,sexes,isced_groups] ,
        Educated_Population_Conveyor_Base[ages_yearly,sexes,isced_groups] ,
        -1
        )
        ~       Dmnl
        ~               |

Education_and_Aging_of_Population_AbsDiffOutflowInflow[ages_yearly,sexes]=
        SUM(Education_and_Aging_of_Population_Outflow[ages_yearly,sexes,isced_groups!])
        - SUM(Education_and_Aging_of_Population_Inflow[ages_yearly,sexes,isced_groups!])
        ~       Person
        ~               |

Education_and_Aging_of_Population_Inflow[ages_yearly, sexes, ISCED_low]=
        Educated_Population_Conveyor[ages_yearly,sexes, ISCED_low]
        - Graduates_by_Age_yearly_and_sex_and_ISCED[ages_yearly,sexes,ISCED_med] ~~|
Education_and_Aging_of_Population_Inflow[ages_yearly,sexes,ISCED_med]=
            Graduates_by_Age_yearly_and_sex_and_ISCED[ages_yearly,sexes,ISCED_med]
        + Educated_Population_Conveyor[ages_yearly,sexes, ISCED_med]
        -   Graduates_by_Age_yearly_and_sex_and_ISCED[ages_yearly,sexes,ISCED_high] ~~|
Education_and_Aging_of_Population_Inflow[ages_yearly,sexes,ISCED_high]=
        Educated_Population_Conveyor[ages_yearly,sexes, ISCED_high]
        + Graduates_by_Age_yearly_and_sex_and_ISCED[ages_yearly,sexes,ISCED_high]
        ~       Person
        ~               |

Education_and_Aging_of_Population_Outflow[ages_yearly, sexes, isced_groups]=
        Educated_Population_Conveyor[ages_yearly,sexes, isced_groups]
        ~       Person
        ~               |

Education_Spending_per_ISCED_Real95_Base[isced_groups]=
        IF_THEN_ELSE(
         Time < Change_Start_Year :OR: Time > Change_End_Year,
         0 ,
         Education_spending_pub_priv_Real95_Mio_Euro[isced_groups]
        )
        ~       Euro*Mio
        ~               |

Education_Spending_per_ISCED_Real95_Base_Cumulated_Lag1[isced_groups]
        = INTEG (Education_Spending_per_ISCED_Real95_Base[isced_groups],
                0)
        ~       Euro*Mio
        ~       The integral of Education spending, containing all spending till the \
                previous preiod (year t-1).
        |

Education_Spending_per_ISCED_Real95_BaseDifAbs[isced_groups]=
        Education_Spending_per_ISCED_Real95_Base[isced_groups]
        * Additional_Education_Spending_switch_ISCED[isced_groups]
        * Additional_Education_Spending_BaseDeltaRel
        ~       Euro*Mio
        ~               |

Education_Spending_per_ISCED_Real95_BaseDifAbs_Cumulated_Lag1[isced_groups]=
        Education_Spending_per_ISCED_Real95_Base_Cumulated_Lag1[isced_groups]
        * Additional_Education_Spending_switch_ISCED[isced_groups]
        * Additional_Education_Spending_BaseDeltaRel
        ~       Euro*Mio
        ~               |

Education_Spending_Real95_BaseDifAbs_Cumulated_Lag1=
        SUM( Education_Spending_per_ISCED_Real95_BaseDifAbs_Cumulated_Lag1[isced_groups!] )
        ~
        ~               |

Fertility_Rate_by_age_yearly[ages_yearly_reproduction]
        ~       Dmnl
        ~       Fraction of births per woman. Source: Eurostat. Timeshift: value in 2000 \
                is the value of 2001
        |
```

```
Graduates_by_Age_yearly_and_sex_and_ISCED[ages_yearly,sexes,ISCED_low]=
        0 ~~|
Graduates_by_Age_yearly_and_sex_and_ISCED[ages_yearly,sexes,ISCED_med]=
        Educated_Population_Conveyor[ages_yearly,sexes, ISCED_low]
        *
        Probability_to_raise_Qualification_Low_to_Med_Effective[ages_yearly,sexes] ~~|
Graduates_by_Age_yearly_and_sex_and_ISCED[ages_yearly,sexes,ISCED_high]=
        Educated_Population_Conveyor[ages_yearly,sexes, ISCED_med]
        *
        Probability_to_raise_Qualification_Med_to_High_Effective[ages_yearly,sexes]
        ~       Person
        ~               |

Graduates_by_ISCED[isced_groups]=
        SUM(Graduates_by_sex_and_ISCED[sexes!,isced_groups])
        ~       Person
        ~               |

Graduates_by_isced_and_sex_BaseDeltaRel[isced_groups,sexes]=
        zidz(
        Graduates_by_isced_and_sex_BaseDifAbs[isced_groups, sexes],
        Graduates_by_sex_and_ISCED_Base[sexes,isced_groups]
        )
        ~       Dmnl
        ~               |

Graduates_by_isced_and_sex_BaseDifAbs[isced_groups,sexes]=
        Graduates_by_sex_and_ISCED[sexes,isced_groups]
        - Graduates_by_sex_and_ISCED_Base[sexes,isced_groups]
        ~       Person
        ~               |

Graduates_by_isced_and_sex_BaseDifRel[isced_groups, sexes]=
        XIDZ(
        Graduates_by_sex_and_ISCED[sexes,isced_groups],
        Graduates_by_sex_and_ISCED_Base[sexes,isced_groups] ,
        -1
        )
        ~       Dmnl
        ~               |

Graduates_by_ISCED_Exog[ISCED_low]=
        0 ~~|
Graduates_by_ISCED_Exog[ISCED_med]=
        GRADUATES_eurostat[ISCED_3]
        + GRADUATES_eurostat[ISCED_4] ~~|
Graduates_by_ISCED_Exog[ISCED_high]=
            GRADUATES_eurostat[ISCED_5A1]
        + GRADUATES_eurostat[ISCED_5A2]
        + GRADUATES_eurostat[ISCED_5B]
        + GRADUATES_eurostat[ISCED_6]
        ~       Person
        ~       aggregation acc. to
                data\human_resources\LFS_original_age\MAPPING ICESD GROUP - ISCED97.xlsx
        |

Graduates_by_ISCED_RelDifEnEx[isced_groups]=
        XIDZ(
        Graduates_by_ISCED[isced_groups],
        Graduates_by_ISCED_Exog[isced_groups],
        -1)
        ~       Dmnl
        ~       Break after 2004 in exog data. 1998 to 2004 very good fit.
        |

Graduates_by_sex_and_ISCED[sexes,isced_groups]=
        SUM(Graduates_by_Age_yearly_and_sex_and_ISCED[ages_yearly!,sexes,isced_groups])
        ~       Person
        ~               |

Graduates_by_sex_and_ISCED_Base[sexes,isced_groups]
        ~       Person
        ~       Baseline
        |

Immigration=
        SUM(Immigration_by_sex[sexes!])
        ~       Person
        ~               |

Immigration_by_Age_yearly_and_sex_and_isced[ages_yearly,sexes, isced_groups]=
        Immigration_by_Age_yearly_and_sex_Endog_Data_Loop[ages_yearly,sexes]
        * Qualificiation_Distribution_by_Age_yearly_and_sex[ages_yearly,sexes,isced_groups]
        ~       Person
        ~               |

Immigration_by_Age_yearly_and_sex_Endog_Data_Loop[ages_yearly,sexes]
        ~       Person
        ~       data loop. calculated based on Population_AbsDiff_Endog_Exog. Residual of \
                endog and exog data defined as migration.
        |

Immigration_by_sex[sexes]=
        SUM( Immigration_by_sex_and_Isced_groups[sexes,isced_groups!] )
        ~       Person
        ~               |

Immigration_by_sex_and_Isced_groups[sexes, isced_groups]=
        SUM( Immigration_by_Age_yearly_and_sex_and_isced[ages_yearly_previous!,sexes,isced_groups\
                ] )
```

```
	~	Person
	~	all ages but age85, because that contains all aggregates of previous \
		cohorts
	|

ISCED_Distr_in_Population_by_Age_Groups_Lfs_and_sex[age_groups_lfs,sexes,isced_groups\
		]=
	Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups[age_groups_lfs,sexes,isced_groups\
		]
	/ Population_by_Age_Groups_Lfs_and_sex[age_groups_lfs,sexes]
	~	Dmnl
	~		|

ISCED_Distr_in_Population_by_Age_Groups_Lfs_and_sex_Exog[age_groups_lfs,sexes,isced_groups\
		]=
	XIDZ(
	QUALI_LEVEL_POP_ORIG_AGE_lfs[isced_groups,sexes,age_groups_lfs] ,
	Population_by_Age_Groups_Lfs_and_sex_Exog[age_groups_lfs,sexes] ,
	-1
	)
	~	Dmnl
	~		|

ISCED_Distr_in_Population_by_Age_Groups_Lfs_and_sex_RelDiffEnEx[age_groups_lfs,sexes,\
		isced_groups]=
	ISCED_Distr_in_Population_by_Age_Groups_Lfs_and_sex[age_groups_lfs,sexes,isced_groups\
		]
	/ ISCED_Distr_in_Population_by_Age_Groups_Lfs_and_sex_Exog[age_groups_lfs,sexes,isced_groups\
		]
	~	Dmnl
	~		|

Population=
	SUM( Population_by_Isced_groups[isced_groups!] )
	~	Person
	~		|

Population_5year_1year_split_Destatis[ages_5years,ages_yearly]
	~	Dmnl
	~	starting 1970
	|

Population_5years_by_sex_Eurostat[sexes]=
	SUM(Population_5years_Eurostat[sexes,ages_5years!])
	~	Person
	~		|

Population_5years_Eurostat[sexes,ages_5years]
	~	Person
	~	starts 1960
	|

Population_Age_yearly_Destatis[ages_yearly]
	~	Person
	~	problems in data - break in 1989
	|

Population_by_Age_5year_and_Age_yearly_and_sex_Exog[ages_5years,ages_yearly,sexes]=
	Population_5years_Eurostat[sexes,ages_5years]
	*
	Population_5year_1year_split_Destatis[ages_5years,ages_yearly]
	~	Person
	~		|

Population_by_Age_Group_Lfs[age_groups_lfs]=
	SUM(Population_by_Age_Groups_Lfs_and_Isced_groups[age_groups_lfs,isced_groups!])
	~	Person
	~		|

Population_by_Age_Group_Lfs_RelDifEnEx[age_groups_lfs]=
	XIDZ(
	Population_by_Age_Group_Lfs[age_groups_lfs] ,
	Population_by_Age_Groups_Lfs_Exog[age_groups_lfs] ,
	-1
	)
	~
	~		|

Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups[age_groups_euklems,sexes,isced_groups\
		]=
	SUM(Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups_mapped[age_groups_euklems\
		,ages_yearly!,sexes,isced_groups] )
	~	Person
	~		|

Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups_Base[age_groups_euklems,sexes\
		,isced_groups]
	~	Person
	~		|

Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups_BaseDifAbs[age_groups_euklems\
		,sexes,isced_groups]=
	Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups[age_groups_euklems,sexes,isced_groups\
		]
	- Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups_Base[age_groups_euklems,\
		sexes,isced_groups]
	~	Person
	~		|

Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups_BaseDifRel[age_groups_euklems\
		,sexes,isced_groups]=
```

```
        XIDZ(
        Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups[age_groups_euklems,sexes,isced_groups\
                ] ,
        Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups_Base[age_groups_euklems,sexes\
                ,isced_groups] ,
        -1
        )
        ~       Dmnl
        ~               |

Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups_mapped[age_groups_euklems,ages_yearly\
                ,sexes, isced_groups]=
        Educated_Population_Conveyor[ages_yearly,sexes, isced_groups]
        * Mapping_Ages_Yearly_to_Age_Groups_Euklems[age_groups_euklems,ages_yearly]
        ~       Person
        ~               |

Population_by_Age_Groups_Lfs_and_Isced_groups[age_groups_lfs,isced_groups]=
        SUM(Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups[age_groups_lfs,sexes!,isced_groups\
                ])
        ~       Person
        ~               |

Population_by_Age_Groups_Lfs_and_sex[age_groups_lfs,sexes]=
        SUM( Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups[age_groups_lfs,sexes,isced_groups\
                !] )
        ~       Person
        ~               |

Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups[age_groups_lfs,sexes, isced_groups\
                ]=
        SUM( Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups_mapped[age_groups_lfs,ages_yearly\
                !,sexes, isced_groups] )
        ~       Person
        ~               |

Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups_Base[age_groups_lfs,sexes, isced_groups\
                ]
        ~       Person
        ~               |

Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups_BaseDifAbs[age_groups_lfs,sexes\
                , isced_groups]=
        Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups[age_groups_lfs,sexes,isced_groups\
                ]
        - Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups_Base[age_groups_lfs,sexes,isced_groups\
                ]
        ~       Person
        ~               |

Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups_BaseDifRel[age_groups_lfs,sexes\
                , isced_groups]=
        XIDZ(
        Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups[age_groups_lfs,sexes,isced_groups\
                ] ,
        Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups_Base[age_groups_lfs,sexes,isced_groups\
                ] ,
        -1
        )
        ~       Dmnl
        ~               |

Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups_mapped[age_groups_lfs,ages_yearly\
                ,sexes, isced_groups]=
        Educated_Population_Conveyor[ages_yearly,sexes, isced_groups]
        * Mapping_Ages_Yearly_to_Age_Groups_Lfs[age_groups_lfs,ages_yearly]
        ~       Person
        ~               |

Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups_RelDifEndogExog[age_groups_lfs,\
                sexes,isced_groups]=
        XIDZ(
        Population_by_Age_Groups_Lfs_and_sex_and_Isced_groups[age_groups_lfs,sexes,isced_groups\
                ] ,
        QUALI_LEVEL_POP_ORIG_AGE_lfs[isced_groups,sexes,age_groups_lfs] ,
        -1
        )
        ~       Dmnl
        ~               |

Population_by_Age_Groups_Lfs_and_sex_Exog[age_groups_lfs,sexes]=
        SUM( QUALI_LEVEL_POP_ORIG_AGE_lfs[isced_groups!,sexes,age_groups_lfs] )
        ~       Person
        ~               |

Population_by_Age_Groups_Lfs_and_sex_RelDiffEnEx[age_groups_lfs,sexes]=
        XIDZ(
        Population_by_Age_Groups_Lfs_and_sex[age_groups_lfs,sexes] ,
        Population_by_Age_Groups_Lfs_and_sex_Exog[age_groups_lfs,sexes] ,
        -1
        )
        ~       Dmnl
        ~               |

Population_by_Age_Groups_Lfs_Exog[age_groups_lfs]=
        SUM(Population_by_Age_Groups_Lfs_and_sex_Exog[age_groups_lfs,sexes!])
        ~       Person
        ~               |

Population_by_Age_yearly_and_Isced_groups[ages_yearly, isced_groups]=
```

```
        SUM( Educated_Population_Conveyor[ages_yearly,sexes!, isced_groups] )
        ~       Person
        ~               |

Population_by_Age_yearly_and_sex[ages_yearly,sexes]=
        SUM(Educated_Population_Conveyor[ages_yearly,sexes,isced_groups!])
        ~       Person
        ~               |

Population_by_Age_yearly_and_sex_AbsDiffEndogExog[ages_yearly,sexes]=
        Population_by_Age_yearly_and_sex_Exog[ages_yearly,sexes]
        - Population_by_Age_yearly_and_sex[ages_yearly,sexes]
        ~
        ~       used for data_loop: Imigration_Endog
        |

Population_by_Age_yearly_and_sex_Exog[ages_yearly,sexes]=
        SUM( Population_by_Age_5year_and_Age_yearly_and_sex_Exog[ages_5years!,ages_yearly,sexes\
                ] )
        ~       Person
        ~       Eurostat Masse combined with Destatis yearly age distribution
        |

Population_by_Age_yearly_and_sex_RelDiffEndogExog[ages_yearly,sexes]=
        Population_by_Age_yearly_and_sex[ages_yearly,sexes] / Population_by_Age_yearly_and_sex_Exog\
                [ages_yearly,sexes]
        ~       Dmnl
        ~               |

Population_by_isced_group[ISCED_low]=
        SUM(Population_by_Labour_type[labour_types_low!]) ~~|
Population_by_isced_group[ISCED_med]=
        SUM(Population_by_Labour_type[labour_types_med!]) ~~|
Population_by_isced_group[ISCED_high]=
        SUM(Population_by_Labour_type[labour_types_high!])
        ~       Person
        ~               |

Population_by_isced_group_Base[ISCED_low]=
        SUM(Population_by_Labour_type_Base[labour_types_low!]) ~~|
Population_by_isced_group_Base[ISCED_med]=
        SUM(Population_by_Labour_type_Base[labour_types_med!]) ~~|
Population_by_isced_group_Base[ISCED_high]=
        SUM(Population_by_Labour_type_Base[labour_types_high!])
        ~       Person
        ~               |

Population_by_Isced_group_BaseDeltaRel[isced_groups]=
        zidz(
        Population_by_isced_group_BaseDifAbs[isced_groups], Population_by_isced_group_Base[isced_groups\
                ]
        )
        ~       Dmnl
        ~               |

Population_by_isced_group_BaseDifAbs[isced_groups]=
        Population_by_isced_group[isced_groups] - Population_by_isced_group_Base[isced_groups\
                ]
        ~       Person
        ~               |

Population_by_isced_group_BaseDifRel[isced_groups]=
        zidz(
         Population_by_isced_group[isced_groups],
         Population_by_isced_group_Base[isced_groups]
        )
        ~       Dmnl
        ~               |

Population_by_Isced_groups[isced_groups]=
        SUM(Population_by_Age_yearly_and_Isced_groups[ages_yearly!, isced_groups])
        ~       Person
        ~               |

Population_by_Labour_type[HS_29_F]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age15_29,sex_f,ISCED_high] ~~|
Population_by_Labour_type[HS_29_M]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age15_29,sex_m,ISCED_high] ~~|
Population_by_Labour_type[HS_49_F]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age30_49,sex_f,ISCED_high] ~~|
Population_by_Labour_type[HS_49_M]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age30_49,sex_m,ISCED_high] ~~|
Population_by_Labour_type[HS_50PLUS_F]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age50_65,sex_f,ISCED_high] ~~|
Population_by_Labour_type[HS_50PLUS_M]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age50_65,sex_m,ISCED_high] ~~|
Population_by_Labour_type[LS_29_F]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age15_29,sex_f,ISCED_low] ~~|
Population_by_Labour_type[LS_29_M]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age15_29,sex_m,ISCED_low] ~~|
Population_by_Labour_type[LS_49_F]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age30_49,sex_f,ISCED_low] ~~|
Population_by_Labour_type[LS_49_M]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age30_49,sex_m,ISCED_low] ~~|
Population_by_Labour_type[LS_50PLUS_F]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age50_65,sex_f,ISCED_low] ~~|
Population_by_Labour_type[LS_50PLUS_M]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age50_65,sex_m,ISCED_low] ~~|
Population_by_Labour_type[MS_29_F]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age15_29,sex_f,ISCED_med] ~~|
```

```
Population_by_Labour_type[MS_29_M]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age15_29, sex_m, ISCED_med]  ~~|
Population_by_Labour_type[MS_49_F]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age30_49, sex_f, ISCED_med]  ~~|
Population_by_Labour_type[MS_49_M]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age30_49, sex_m, ISCED_med]  ~~|
Population_by_Labour_type[MS_50PLUS_F]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age50_65, sex_f, ISCED_med]  ~~|
Population_by_Labour_type[MS_50PLUS_M]=Population_by_Age_Groups_Euklems_and_sex_and_Isced_groups\
                [age50_65, sex_m, ISCED_med]
        ~       Person
        ~               |

Population_by_Labour_type_Base[labour_types]
        ~       Person
        ~               |

Population_by_Labour_type_BaseDeltaRel[labour_types]=
        zidz(
         Population_by_Labour_type_BaseDifAbs[labour_types],
         Population_by_Labour_type_Base[labour_types]
        )
        ~       Dmnl
        ~               |

Population_by_Labour_type_BaseDifAbs[labour_types]=
        Population_by_Labour_type[labour_types]
        - Population_by_Labour_type_Base[labour_types]
        ~       Person
        ~               |

Population_by_Labour_type_BaseDifRel[labour_types]=
        IF_THEN_ELSE(
          Switch_Baseline=1,
          1,
          IF_THEN_ELSE(
            Switch_Analyse_Quali_Level_Rel_Change = 1,
            POWER( Add_Pop_by_labour_type_RelDif_Exponential_Base[labour_types], Add_Pop_by_labour_type_RelDif_Exponential_Exponent\
                ) ,
            XIDZ(
              Population_by_Labour_type[labour_types] ,
              Population_by_Labour_type_Base[labour_types] ,
              -1
            )
          )
        )
        ~       Dmnl
        ~       If baseline calculation, then relative difference is 1, i.e. no difference.
        |

Population_CHECK_Age_Group_Lfs=
        SUM(Population_by_Age_Group_Lfs[age_groups_lfs!])
        ~       Person
        ~               |

Population_Check_Age_Group_Lfs_RelDifEndogExog=
        Population_CHECK_Age_Group_Lfs / Population_Eurostat
        ~       Dmnl
        ~               |

Population_Destatis=
        SUM(Population_Age_yearly_Destatis[ages_yearly!])
        ~       Person
        ~               |

Population_Eurostat=
        SUM(Population_5years_by_sex_Eurostat[sexes!])
        ~       Person
        ~               |

Population_Init[ages_yearly, sexes, isced_groups]=
        IF_THEN_ELSE(
        Time=INITIAL_TIME ,
        Population_by_Age_yearly_and_sex_Exog[ages_yearly, sexes]
        * Distribution_of_ISCED_groups_in_init_pop[ages_yearly, sexes, isced_groups],
        0
        )
        ~       Person
        ~               |

Population_RelDiffEndogExog=
        Population / Population_Eurostat
        ~       Dmnl
        ~               |

Probability_to_raise_Qualification_AbsChange[ages_yearly, sexes]=
        IF_THEN_ELSE(
        Switch_GradProb_AbsChange_Fixed_or_GP_specific = 1,
        Probability_to_raise_Qualification_AbsoluteChange_fixed[ages_yearly, sexes] ,
        Probability_to_raise_Qualification_AbsoluteChange_GP_specific[ages_yearly, sexes]
        )
        ~       Dmnl
        ~               |

Probability_to_raise_Qualification_AbsChange_Effective[ages_yearly, sexes]=
        IF_THEN_ELSE(
          Time < Change_Start_Year :OR: Time > Change_End_Year,
          0 ,
          Probability_to_raise_Qualification_AbsChange[ages_yearly, sexes]
          * Probability_to_raise_Qualification_Activate_Change[ages_yearly, sexes]
        )
```

```
        ~       Dmnl
        ~       Factor changing:
                Probability_to_raise_Qualification_Low_to_Med and
                Probability_to_raise_Qualification_Med_to_High
        |

Probability_to_raise_Qualification_AbsoluteChange_GP_specific[ages_yearly,sexes]=
        ( Probability_to_raise_Qualification_AbsoluteChangeLowerBoundary[ages_yearly,sexes]
          +
          ( Probability_to_raise_Qualification_AbsoluteChangeUpperBoundary[ages_yearly,sexes\
                ]
          - Probability_to_raise_Qualification_AbsoluteChangeLowerBoundary[ages_yearly,sexes\
                ]
          )
          / Probability_to_raise_Qualification_Change_SubIntervalls
          * Probability_to_raise_Qualification_Change_Intervall_Current_Step
        )
        * ( Additional_Education_Spending_BaseDeltaRel / 0.1 )
        ~       Dmnl
        ~       defined on: [ages_yearly, sexes]
                Probability to raise Qualificaiton AbsoluteChange
                is for 10pc spending increase. Divide Add Educ Spend BaseDeltaRel by 0.1 \
                to scale probabilities according to Spending increase.
        |

Probability_to_raise_Qualification_AbsoluteChangeLowerBoundary[ages_yearly,sexes]=
        IF_THEN_ELSE(
        LowerBoundary_weak_or_moderate=1,
        Probability_to_raise_Qualification_AbsoluteChange_10PC_weak[ages_yearly,sexes] ,
        Probability_to_raise_Qualification_AbsoluteChange_10PC_moderate[ages_yearly,sexes]
        )
        ~       Dmnl
        ~               |

Probability_to_raise_Qualification_AbsoluteChangeUpperBoundary[ages_yearly,sexes]=
        Probability_to_raise_Qualification_AbsoluteChange_10PC_strong[ages_yearly,sexes]
        ~       Dmnl
        ~               |

Probability_to_raise_Qualification_Low_to_Med[ages_yearly,sexes]
        ~       Dmnl
        ~       Compiled in "Probability_to_raise_Quali.xlsx"
        |

Probability_to_raise_Qualification_Low_to_Med_BaseDifAbs[ages_yearly,sexes]=
        Probability_to_raise_Qualification_Low_to_Med_Effective[ages_yearly,sexes]
        -
        Probability_to_raise_Qualification_Low_to_Med[ages_yearly,sexes]
        ~       Dmnl
        ~               |

Probability_to_raise_Qualification_Low_to_Med_Effective[age18,sex_f]=
        Probability_to_raise_Qualification_Low_to_Med[age18,sex_f]
        + Probability_to_raise_Qualification_AbsChange_Effective[age18,sex_f] ~~|
Probability_to_raise_Qualification_Low_to_Med_Effective[age18,sex_m]=
        Probability_to_raise_Qualification_Low_to_Med[age18,sex_m]
        + Probability_to_raise_Qualification_AbsChange_Effective[age18,sex_m] ~~|
Probability_to_raise_Qualification_Low_to_Med_Effective[age22,sex_f]=
        Probability_to_raise_Qualification_Low_to_Med[age22,sex_f] ~~|
Probability_to_raise_Qualification_Low_to_Med_Effective[age23,sex_m]=
        Probability_to_raise_Qualification_Low_to_Med[age23,sex_m] ~~|
Probability_to_raise_Qualification_Low_to_Med_Effective[age31,sex_f]=
        Probability_to_raise_Qualification_Low_to_Med[age31,sex_f] ~~|
Probability_to_raise_Qualification_Low_to_Med_Effective[age31,sex_m]=
        Probability_to_raise_Qualification_Low_to_Med[age31,sex_m] ~~|
Probability_to_raise_Qualification_Low_to_Med_Effective[ages_yearly_no_gp,sexes]=
        Probability_to_raise_Qualification_Low_to_Med[ages_yearly_no_gp,sexes] ~~|
Probability_to_raise_Qualification_Low_to_Med_Effective[age22,sex_m]=
        Probability_to_raise_Qualification_Low_to_Med[age22,sex_m] ~~|
Probability_to_raise_Qualification_Low_to_Med_Effective[age23,sex_f]=
        Probability_to_raise_Qualification_Low_to_Med[age23,sex_f]
        ~       Dmnl
        ~       defined on: [ages_yearly, sexes]
        |

Probability_to_raise_Qualification_Med_to_High[ages_yearly,sexes]
        ~       Dmnl
        ~       Compiled in "Probability_to_raise_Quali.xlsx"
        |

Probability_to_raise_Qualification_Med_to_High_BaseDifAbs[ages_yearly,sexes]=
        Probability_to_raise_Qualification_Med_to_High_Effective[ages_yearly,sexes]
        -
        Probability_to_raise_Qualification_Med_to_High[ages_yearly,sexes]
        ~       Dmnl
        ~               |

Probability_to_raise_Qualification_Med_to_High_Effective[age18,sex_f]=
        Probability_to_raise_Qualification_Med_to_High[age18,sex_f] ~~|
Probability_to_raise_Qualification_Med_to_High_Effective[age18,sex_m]=
        Probability_to_raise_Qualification_Med_to_High[age18,sex_m] ~~|
Probability_to_raise_Qualification_Med_to_High_Effective[age22,sex_f]=
        Probability_to_raise_Qualification_Med_to_High[age22,sex_f]
        +
        Probability_to_raise_Qualification_AbsChange_Effective[age22,sex_f] ~~|
Probability_to_raise_Qualification_Med_to_High_Effective[age23,sex_m]=
        Probability_to_raise_Qualification_Med_to_High[age23,sex_m]
        +
        Probability_to_raise_Qualification_AbsChange_Effective[age23,sex_m] ~~|
Probability_to_raise_Qualification_Med_to_High_Effective[age31,sex_f]=
```

```
        Probability_to_raise_Qualification_Med_to_High[age31,sex_f]
        +
        Probability_to_raise_Qualification_AbsChange_Effective[age31,sex_f] ~~|
Probability_to_raise_Qualification_Med_to_High_Effective[age31,sex_m]=
        Probability_to_raise_Qualification_Med_to_High[age31,sex_m]
        +
        Probability_to_raise_Qualification_AbsChange_Effective[age31,sex_m] ~~|
Probability_to_raise_Qualification_Med_to_High_Effective[ages_yearly_no_gp,sexes]=
        Probability_to_raise_Qualification_Med_to_High[ages_yearly_no_gp,sexes] ~~|
Probability_to_raise_Qualification_Med_to_High_Effective[age22,sex_m]=
        Probability_to_raise_Qualification_Med_to_High[age22,sex_m] ~~|
Probability_to_raise_Qualification_Med_to_High_Effective[age23,sex_f]=
        Probability_to_raise_Qualification_Med_to_High[age23,sex_f]
        ~       Dmnl
        ~       defined on: [ages_yearly, sexes]
        |

QUALI_LEVEL_POP_ORIG_AGE_lfs[isced_groups,sexes,age_groups_lfs]
        ~       Person
        ~               |

QUALI_LEVEL_POP_ORIG_AGE_lfs_CHECK[isced_groups,sexes]=
        SUM(QUALI_LEVEL_POP_ORIG_AGE_lfs[isced_groups,sexes,age_groups_lfs!])
        ~
        ~               |

Qualification_Level_of_Population_Exog[labour_types]=
        QUALIFICATION_LEVEL_POPULATION_lfs[labour_types]
        / 1000
        ~       Tsd * Person
        ~               |

Qualificiation_Distribution_by_Age_yearly_and_sex[ages_yearly,sexes,isced_groups]=
        Educated_Population_Conveyor[ages_yearly,sexes,isced_groups]
        / Population_by_Age_yearly_and_sex[ages_yearly,sexes]
        ~       Dmnl
        ~               |

Sex_split_of_newborns_Eurostat[sex_f]=
        0.48726 ~~|
Sex_split_of_newborns_Eurostat[sex_m]=
        0.51274
        ~       Dmnl
        ~       Relation of below 5 year old. Average 1970 - 2008. Eurostat data.
                \data\population\age_structure-5year-eurostat\Relation of sexes of \
                newborns.ods
        |

Spending_on_Education_Public_And_Private_by_ISCED[isced_groups]=
        Students_by_ISCED_Exog[isced_groups]
        * Spending_on_Education_Public_And_Private_per_Student_by_ISCED_Exog[isced_groups]
        ~       Tsd * Euro
        ~               |

Spending_on_Education_Public_And_Private_per_Student_by_ISCED_Exog[ISCED_low]=
        SPENDING_PER_STUDENT_eurostat[ISCED_1] ~~|
Spending_on_Education_Public_And_Private_per_Student_by_ISCED_Exog[ISCED_med]=
        SPENDING_PER_STUDENT_eurostat[ISCED_2_3_4] ~~|
Spending_on_Education_Public_And_Private_per_Student_by_ISCED_Exog[ISCED_high]=
        SPENDING_PER_STUDENT_eurostat[ISCED_5_6]
        ~       Euro / Person
        ~               |

Spending_On_Education_Public_by_ISCED_Exog[ISCED_low]=
        + PUBLIC_SPENDING_ON_EDUCATION_eurostat[ISCED_1] ~~|
Spending_On_Education_Public_by_ISCED_Exog[ISCED_med]=
        PUBLIC_SPENDING_ON_EDUCATION_eurostat[ISCED_2_3_4] ~~|
Spending_On_Education_Public_by_ISCED_Exog[ISCED_high]=
        PUBLIC_SPENDING_ON_EDUCATION_eurostat[ISCED_5_6]
        ~       Mio*Euro
        ~       PUBLIC_SPENDING_ON_EDUCATION_eurostat[ISCED_0] ignored, because not \
                available in 'per student' data. ISCED 0 is 50-70% of ISCED 1.
        |

Spending_on_Education_Ratio_Public_vs_PubPriv[isced_groups]=
        XIDZ(
        Spending_On_Education_Public_by_ISCED_Exog[isced_groups] * 1000 ,
        Spending_on_Education_Public_And_Private_by_ISCED[isced_groups] ,
        -1
        )
        ~       Dmnl
        ~       Quite good fit. Deviation plausible as private spending.
        |

SPENDING_PER_STUDENT_eurostat[ISCED_1] ~~|
SPENDING_PER_STUDENT_eurostat[ISCED_2_3_4] ~~|
SPENDING_PER_STUDENT_eurostat[ISCED_5_6]
        ~       Euro / Person
        ~       Real Values. Eurostat. 1995 - 2005. Public and Private Spending.
        |

Students_by_ISCED_Exog[ISCED_low]=
        + STUDENTS_eurostat[ISCED_1] ~~|
Students_by_ISCED_Exog[ISCED_med]=
        + STUDENTS_eurostat[ISCED_2]
        + STUDENTS_eurostat[ISCED_3]
        + STUDENTS_eurostat[ISCED_4] ~~|
Students_by_ISCED_Exog[ISCED_high]=
        + STUDENTS_eurostat[ISCED_5]
        + STUDENTS_eurostat[ISCED_6]
```

```
        ~       Person*Tsd
        ~       STUDENTS_eurostat[ISCED_0] ignored, because no data for "Spending per \
                Student Eurostat"
        |

Women_in_reproduction_age[ages_yearly_reproduction]=
        SUM(Educated_Population_Conveyor[ages_yearly_reproduction,sex_f, isced_groups!] )
        ~
        ~               |

********************************************************
        .ExogData
********************************************************~
                exogenous data from euklems
        |

Education_spending_pub_priv_Real95_Mio_Euro[isced_groups]
        ~       Euro*Mio
        ~       Education Spending Baseline Assumption
                Calculated exogenously based on population development.
                Calculated in \
                D:\projects\Dissertation\diss_rep\model\data\human_resources\education_spen\
                ding\public and private\educ_spending_pub_priv.xlsx
        |

GDP_Deflator_Euro_1995
        ~       Dmnl
        ~               |

GDP_Deflator_Euro_2000
        ~       Dmnl
        ~               |

GDP_Deflator_Euro_2005
        ~       Dmnl
        ~               |

GRADUATES_eurostat[ISCED_3] ~~|
GRADUATES_eurostat[ISCED_4] ~~|
GRADUATES_eurostat[ISCED_5A1] ~~|
GRADUATES_eurostat[ISCED_5A2] ~~|
GRADUATES_eurostat[ISCED_5B] ~~|
GRADUATES_eurostat[ISCED_6]
        ~       Person
        ~       exogenous eurostat education data. Break after 2004.
        |

PUBLIC_SPENDING_ON_EDUCATION_eurostat[ISCED_0] ~~|
PUBLIC_SPENDING_ON_EDUCATION_eurostat[ISCED_1] ~~|
PUBLIC_SPENDING_ON_EDUCATION_eurostat[ISCED_2_3_4] ~~|
PUBLIC_SPENDING_ON_EDUCATION_eurostat[ISCED_5_6]
        ~       Mio*Euro
        ~       exogenous eurostat education data.
                Real Value, based on Eurostat Deflator.
        |

QUALIFICATION_LEVEL_POPULATION_lfs[labour_types]
        ~       Person
        ~       Labour force survey data
        |

STUDENTS_eurostat[ISCED_0] ~~|
STUDENTS_eurostat[ISCED_1] ~~|
STUDENTS_eurostat[ISCED_2] ~~|
STUDENTS_eurostat[ISCED_3] ~~|
STUDENTS_eurostat[ISCED_4] ~~|
STUDENTS_eurostat[ISCED_5] ~~|
STUDENTS_eurostat[ISCED_6]
        ~       Person*Tsd
        ~       exogenous eurostat education data.
        |

********************************************************
        .ExogDataEuklems
********************************************************~
                exogenous data from euklems
        |

CAP_euklems[sectors]
        ~
        ~       exog data from EUKLEMS
        |

CAP_QI_euklems[sectors]
        ~
        ~       exog data from EUKLEMS
        |

CAPIT_euklems[sectors]
        ~
        ~       exog data from EUKLEMS
        |

CAPIT_QI_euklems[sectors]
        ~
        ~       exog data from EUKLEMS
        |

CAPIT_QPH_euklems[sectors]
        ~
        ~       exog data from EUKLEMS
        |
```

```
CAPITAL_COMPENSATION_euklems[sectors,capital_types]
	~
	~	exog data from EUKLEMS
	|

CAPITAL_CONSUMPTION_REAL1995_euklems[sectors,capital_types]
	~
	~	exog data from EUKLEMS
	|

Capital_Depreciation_Rates_euklems[CT]=0.115 ~~|
Capital_Depreciation_Rates_euklems[IT]=0.315 ~~|
Capital_Depreciation_Rates_euklems[OCon]=0.033 ~~|
Capital_Depreciation_Rates_euklems[OMach]=0.102 ~~|
Capital_Depreciation_Rates_euklems[Other]=0.102 ~~|
Capital_Depreciation_Rates_euklems[Rstruc]=0.0114 ~~|
Capital_Depreciation_Rates_euklems[Soft]=0.315 ~~|
Capital_Depreciation_Rates_euklems[TraEq]=0.196
	~
	~	based on EUKLEMS methodology paper and euklems data files. compiled in \
		"analysis of variable definitions.xlsx"
	|

CAPITAL_FORMATION_GROSS_INDEX1995_euklems[sectors,capital_types]
	~
	~	exog data from EUKLEMS
	|

CAPITAL_FORMATION_GROSS_NOMINAL_euklems[sectors,capital_types]
	~
	~	exog data from EUKLEMS
	|

CAPITAL_FORMATION_GROSS_REAL1995_euklems[sectors,capital_types]
	~
	~	exog data from EUKLEMS
	|

CAPITAL_STOCK_REAL1995_euklems[sectors,capital_types]
	~
	~	exog data from EUKLEMS
	|

CAPNIT_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

CAPNIT_QI_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

CAPNIT_QPH_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

COMP_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

EMP_euklems[sectors]
	~	Tsd * h
	~	exog data from EUKLEMS
	|

EMPE_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

GO_euklems[sectors]
	~	Euro*Mio
	~	Current prices (i.e. nominal prices)
		exog data from EUKLEMS.
	|

GO_P_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

GO_Q_euklems[sectors]
	~
	~	exog data from EUKLEMS. This var is given as percentage points, therefore \
		factor 100 higher than according to methodology.
	|

GO_QI_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

GOConH_euklems[sectors]
	~
	~	exog data from EUKLEMS. This var is given as percentage points, therefore \
		factor 100 higher than according to methodology.
	|

GOConII_euklems[sectors]
```

```
	~
	~	exog data from EUKLEMS
	|

GOConIIE_euklems[sectors]
	~
	~	exog data from EUKLEMS. This var is given as percentage points, therefore \
		factor 100 higher than according to methodology.
	|

GOConIIM_euklems[sectors]
	~
	~	exog data from EUKLEMS. This var is given as percentage points, therefore \
		factor 100 higher than according to methodology.
	|

GOConIIS_euklems[sectors]
	~
	~	exog data from EUKLEMS. This var is given as percentage points, therefore \
		factor 100 higher than according to methodology.
	|

GOConKIT_euklems[sectors]
	~
	~	exog data from EUKLEMS. This var is given as percentage points, therefore \
		factor 100 higher than according to methodology.
	|

GOConKNIT_euklems[sectors]
	~
	~	exog data from EUKLEMS. This var is given as percentage points, therefore \
		factor 100 higher than according to methodology.
	|

GOConL_euklems[sectors]=
	( GOConH_euklems[sectors] + GOConLC_euklems[sectors] ) /100
	~
	~	euklems var, not in data file, but claimed to exist according to \
		Methodology Manual.
	|

GOConLC_euklems[sectors]
	~
	~	exog data from EUKLEMS. This var is given as percentage points, therefore \
		factor 100 higher than according to methodology.
	|

GOConTFP_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

GOS_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

H_EMP_euklems[sectors]
	~	h*Mio
	~	exog data from EUKLEMS
	|

H_EMPE_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

II_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

II_P_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

II_QI_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

IIE_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

IIE_QI_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

IIM_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

IIM_QI_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

IIS_euklems[sectors]
```

```
	~
	~	exog data from EUKLEMS
	|

IIS_QI_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

INDUSTRY_RATE_OF_RETURN_ON_CAPITAL_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

LAB_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

LAB_QI_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

LAB_QPH_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

LABHS_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

LABLS_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

LABMS_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

LP_I_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

SHARES_IN_HOURS_WORKED_euklems[sectors, labour_types]
	~	Percent
	~	exog data from EUKLEMS
	|

SHARES_IN_TOT_LAB_COMP_euklems[sectors, labour_types]
	~
	~	exog data from EUKLEMS
	|

TFPgo_I_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

TFPva_I_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

TXSP_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

VA_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

VA_P_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

VA_Q_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

VA_QI_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

VAConH_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|

VAConKIT_euklems[sectors]
	~
	~	exog data from EUKLEMS
	|
```

```
VAConKNIT_euklems[sectors]
        ~
        ~       exog data from EUKLEMS
        |

VAConLC_euklems[sectors]
        ~
        ~       exog data from EUKLEMS
        |

VAConTFP_euklems[sectors]
        ~
        ~       exog data from EUKLEMS
        |

********************************************************
        .GrossOutput
********************************************************~
                Simulation Control Parameters
        |

Additional_Gross_Output_per_Additional_Education_Spending=
        zidz(
          Gross_Output_Real95_BaseDifAbs_Cumulated_Lag1 ,
          Education_Spending_Real95_BaseDifAbs_Cumulated_Lag1
        )
        ~       Dmnl
        ~               |

Gross_Output_Changed_Index_Delta[sectors]=
        IF_THEN_ELSE(
        Time > Index_Base_Year,
        Gross_Output_Changed_Index_Stock[sectors] * ( Gross_Output_Growth_Factor_Changed[sectors\
                ] - 1 ),
        0
        )
        ~
        ~       in index base year index = 100. Delta starts one year after index base \
                year. => condition term
        |

Gross_Output_Changed_Index_Stock[sectors]= INTEG (
        Gross_Output_Changed_Index_Delta[sectors],
                100)
        ~
        ~               |

Gross_Output_exog_Index_AbsDev[sectors]=
        Gross_Output_Index_exog[sectors] - GO_QI_euklems[sectors]
        ~       Dmnl
        ~               |

Gross_Output_exog_Index_Delta[sectors]=
        IF_THEN_ELSE(
        Time > Index_Base_Year,
        Gross_Output_exog_Index_Stock[sectors] * ( Gross_Output_Growth_Factor_exog[sectors] \
                - 1 ),
        0
        )
        ~
        ~       in index base year index = 100. Delta starts one year after index base \
                year. => condition term
        |

Gross_Output_exog_Index_Stock[sectors]= INTEG (
        Gross_Output_exog_Index_Delta[sectors],
                100)
        ~
        ~               |

Gross_Output_exog_RelDev[sectors]=
        Gross_Output_Index_exog[sectors] / GO_QI_euklems[sectors]
        ~       Dmnl
        ~               |

Gross_Output_Growth_BaseDifAbs[sectors]=
        Gross_Output_Growth_Changed[sectors]
        - Gross_Output_Growth_exog[sectors]
        ~
        ~       only abs change relevant. rel change useless, since gross output growth \
                oscillating around zero.
        |

Gross_Output_Growth_Changed[sectors]=
        + Growth_Contribution_to_Gross_Output_of_TFP_calculated[sectors]
        + Growth_Contribution_to_Gross_Output_of_Capital[sectors]
        + Growth_Contribution_to_Gross_Output_of_changed_Labour_Input[sectors]
        + Growth_Contribution_to_Gross_Output_of_Energy_Input[sectors]
        + Growth_Contribution_to_Gross_Output_of_Material_Input[sectors]
        + Growth_Contribution_to_Gross_Output_of_Service_Inputs[sectors]
        ~
        ~               |

Gross_Output_Growth_Factor_BaseDifAbs[sectors]=
        Gross_Output_Growth_Factor_Changed[sectors] - Gross_Output_Growth_Factor_exog[sectors\
                ]
        ~       Dmnl
        ~               |

Gross_Output_Growth_Factor_Changed[sectors]=
        EXP( Gross_Output_Growth_Changed[sectors] )
```

```
	~
	~	Gross Output(t) / Gross Output(t-1)
	|

Gross_Output_Growth_Factor_exog[sectors]=
	EXP( Gross_Output_Growth_exog[sectors] )
	~
	~	Gross Output(t) / Gross Output(t-1)
	|

Gross_Output_in_current_prices_Base=
	SUM(GO_euklems[sectors!])
	~	Euro*Mio
	~	Current prices.
	|

Gross_Output_in_current_prices_BaseDifAbs=
	Gross_Output_in_current_prices_Changed - Gross_Output_in_current_prices_Base
	~	Euro*Mio
	~		|

Gross_Output_in_current_prices_BaseDifRel=
	zidz(Gross_Output_in_current_prices_Changed, Gross_Output_in_current_prices_Base)
	~	Euro*Mio
	~		|

Gross_Output_in_current_prices_Changed=
	SUM(Gross_Output_per_sector_in_current_prices_Changed[sectors!])
	~	Euro*Mio
	~	Curernt Prices
	|

Gross_Output_Index_BaseDifAbs[sectors]=
	Gross_Output_Index_Changed[sectors] - Gross_Output_Index_exog[sectors]
	~	Dmnl
	~		|

Gross_Output_Index_BaseDifRel[sectors]=
	Gross_Output_Index_Changed[sectors] / Gross_Output_Index_exog[sectors]
	~	Dmnl
	~		|

Gross_Output_Index_Changed[sectors]=
	IF_THEN_ELSE(
	Time > Index_Base_Year,
	Gross_Output_Changed_Index_Stock[sectors] * Gross_Output_Growth_Factor_Changed[sectors\
		],
	100
	)
	~
	~	needed becaus Index Stock always one year too late. This aux var takes the \
		index value in the proper year.
	|

Gross_Output_Index_exog[sectors]=
	IF_THEN_ELSE(
	Time > Index_Base_Year,
	Gross_Output_exog_Index_Stock[sectors] * Gross_Output_Growth_Factor_exog[sectors],
	100
	)
	~
	~	needed becaus Index Stock always one year too late. This aux var takes the \
		index value in the proper year.
	|

Gross_Output_per_sector_in_current_prices_BaseDifAbs[sectors]=
	Gross_Output_per_sector_in_current_prices_Changed[sectors]
	- GO_euklems[sectors]
	~	Euro*Mio
	~		|

Gross_Output_per_sector_in_current_prices_Changed[sectors]=
	GO_euklems[sectors]
	* Gross_Output_Index_BaseDifRel[sectors]
	~	Euro*Mio
	~	Nominal Prices
	|

Gross_Output_per_sector_Real95_Base[sectors]=
	GO_euklems[sectors] * GDP_Deflator_Euro_1995
	~	Euro*Mio
	~		|

Gross_Output_per_sector_Real95_BaseDifAbs[sectors]=
	Gross_Output_per_sector_in_current_prices_BaseDifAbs[sectors]
	* GDP_Deflator_Euro_1995
	~	Euro*Mio
	~		|

Gross_Output_per_sector_Real95_BaseDifAbs_Cumulated_Lag1[sectors]= INTEG (
	Gross_Output_per_sector_Real95_BaseDifAbs[sectors],
		0)
	~	Euro*Mio
	~		|

Gross_Output_per_sector_Real95_BaseDifRel[sectors]=
	( Gross_Output_per_sector_Real95_BaseDifAbs[sectors]
	  /
	  Gross_Output_per_sector_Real95_Base[sectors]
	)
	+ 1
```

```
	~	Dmnl
	~		|

Gross_Output_per_sector_Real95_Changed[sectors]=
	Gross_Output_per_sector_Real95_Base[sectors]
	+
	Gross_Output_per_sector_Real95_BaseDifAbs[sectors]
	~	Euro*Mio
	~		|

Gross_Output_Real95_Base=
	Gross_Output_in_current_prices_Base * GDP_Deflator_Euro_1995
	~	Euro*Mio
	~		|

Gross_Output_Real95_BaseDifAbs=
	Gross_Output_Real95_Changed - Gross_Output_Real95_Base
	~	Euro*Mio
	~		|

Gross_Output_Real95_BaseDifAbs_Cumulated_Lag1= INTEG (
	Gross_Output_Real95_BaseDifAbs,
		0)
	~	Euro*Mio
	~		|

Gross_Output_Real95_BaseDifRel=
	Gross_Output_Real95_Changed / Gross_Output_Real95_Base
	~	Euro*Mio
	~		|

Gross_Output_Real95_Changed=
	Gross_Output_in_current_prices_Changed * GDP_Deflator_Euro_1995
	~	Euro*Mio
	~		|

Growth_Contribution_to_Gross_Output_of_changed_Labour_Input[sectors]=
	Labour_Value_Share_in_GrossOutput_changed_2pAvg[sectors] *
	Labour_Service_changed_Index_Delta_Log[sectors]
	~	Dmnl
	~		|

Hours_worked_by_sector_and_labour_type_BaseDeltaRel[sectors,labour_types]=
	Hours_worked_by_sector_and_labour_type_BaseDifAbs[sectors,labour_types]
	/ Hours_worked_by_labour_type_and_sector_Exog[sectors,labour_types]
	~	Dmnl
	~		|

Hours_worked_changed_by_labour_type_and_sector[sectors,labour_types]=
	Hours_worked_by_labour_type_and_sector_Exog[sectors,labour_types]
	+ Hours_worked_by_sector_and_labour_type_BaseDifAbs[sectors,labour_types]
	~	h*Mio
	~		|

Hours_worked_changed_Delta_Log[sectors,labour_types] =
	IF_THEN_ELSE(
	  Hours_worked_changed_by_labour_type_and_sector[sectors,labour_types] <= 0
	  :OR:
	  Hours_worked_changed_lag1[sectors,labour_types] <= 0 ,
	  0 ,
	  LN( Hours_worked_changed_by_labour_type_and_sector[sectors,labour_types] /		\
		Hours_worked_changed_lag1[sectors,labour_types] )
	)
	~	Dmnl
	~	for negative hours worked -> 0
		i.e. treated as "no change" in hours worked.
	|

Hours_worked_changed_lag1[sectors,labour_types]=
	DELAY_FIXED( Hours_worked_changed_by_labour_type_and_sector[sectors,labour_types] , \
		1 , Hours_worked_changed_by_labour_type_and_sector[sectors,labour_types] )
	~	h*Mio
	~		|

Hours_worked_changed_Weighted_Delta_Log[sectors,labour_types]=
	Hours_worked_changed_Delta_Log[sectors,labour_types] *
	Shares_in_Total_Labour_Compensation_changed_2pAvg[sectors,labour_types]
	~
	~		|

Labour_Compensation_by_sector_and_labour_type_euklems[sectors,labour_types]=
	LAB_euklems[sectors]
	* SHARES_IN_TOT_LAB_COMP_euklems[sectors,labour_types] / 100
	~
	~		|

Labour_Compensation_changed_by_sector_and_labour_type[sectors,labour_types]=
	Labour_Compensation_by_sector_and_labour_type_euklems[sectors,labour_types]
	* ( 1 + Hours_worked_by_sector_and_labour_type_BaseDeltaRel[sectors,labour_types] )
	~
	~		|

Labour_Service_changed_Index_Delta_Log[sectors]=
	SUM( Hours_worked_changed_Weighted_Delta_Log[sectors,labour_types!] )
	~
	~		|

Labour_Value_Share_in_GrossOutput_changed[sectors]=
	Total_Labour_Compensation_changed_by_sector[sectors]
	/ ( GO_euklems[sectors] + Labour_Compensation_by_sector_BaseDifAbs[sectors] )
	~
	~		|
```

```
Labour_Value_Share_in_GrossOutput_changed_2pAvg[sectors]=
	( Labour_Value_Share_in_GrossOutput_changed[sectors] + Labour_Value_Share_in_GrossOutput_changed_lag1\
		[sectors] ) /2
	~
	~	2 periode average
	|

Labour_Value_Share_in_GrossOutput_changed_lag1[sectors]=
	DELAY_FIXED(
	Labour_Value_Share_in_GrossOutput_changed[sectors] ,
	1 ,
	Labour_Value_Share_in_GrossOutput_changed[sectors] )
	~
	~	value of last year (t-1)
	|

Shares_in_Total_Labour_Compensation_changed[sectors,labour_types]=
	Labour_Compensation_changed_by_sector_and_labour_type[sectors,labour_types] / Total_Labour_Compensation_changed_by_sector\
		[sectors]
	~
	~		|

Shares_in_Total_Labour_Compensation_changed_2pAvg[sectors,labour_types]=
	(  Shares_in_Total_Labour_Compensation_changed[sectors,labour_types]
	 + Shares_in_Total_Labour_Compensation_changed_lag1[sectors,labour_types] ) /2
	~
	~		|

Shares_in_Total_Labour_Compensation_changed_lag1[sectors,labour_types]= DELAY_FIXED (
	Shares_in_Total_Labour_Compensation_changed[sectors,labour_types],
	1 ,
	Shares_in_Total_Labour_Compensation_changed[sectors,labour_types])
	~
	~		|

Total_Labour_Compensation_changed_by_sector[sectors]=
	SUM ( Labour_Compensation_changed_by_sector_and_labour_type[sectors,labour_types!] )
	~
	~		|

********************************************************
	.LabourInput
********************************************************~
		Simulation Control Parameters
	|

Add_Hours_worked_by_sector_and_labour_type_BaseDifAbs[sectors,labour_types]=
	IF_THEN_ELSE(
	  Time < Change_Start_Year :OR: Time > Change_End_Year,
	  0 ,
	  Add_Hours_worked_by_labour_type_BaseDeltaRel[labour_types] * Hours_worked_by_labour_type_and_sector_Exog\
		[sectors,labour_types]
	)
	~	Mio*h
	~	For partial analysis:
		(9) Labour Input -> Output
	|

Additional_Qualified_Persons_per_labour_type_Abs_Effective[labour_types]=
	IF_THEN_ELSE(
	  Time < Change_Start_Year :OR: Time > Change_End_Year,
	  0 ,
	  Additional_Qualified_Persons_per_labour_type_Abs[labour_types]
	)
	~	Person*Tsd
	~		|

Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,HS_29_F]= 0.729 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,HS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,MS_29_M]= 0.952 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,MS_29_F]= 0.956 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,LS_29_F]= 0.08 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_AtB,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,HS_29_M]= 0.826 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,HS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,MS_29_M]= 0.938 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,MS_29_F]= 0.924 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C,LS_29_F]= 0 ~~|
```

```
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C ,LS_49_F]= 0.044 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C ,LS_50PLUS_M]= 0.193 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_C ,LS_50PLUS_F]= 0.607 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,HS_49_M]= 0.695 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,HS_49_F]= 0.912 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,HS_50PLUS_M]= 0.773 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,HS_50PLUS_F]= 0.813 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,MS_29_M]= 0.906 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,MS_29_F]= 0.834 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,MS_50PLUS_F]= 0.754 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_15t16 ,LS_50PLUS_F]= 0.366 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,HS_29_M]= 0.748 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,HS_29_F]= 0.727 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,HS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,MS_29_M]= 0.916 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,MS_29_F]= 0.909 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,LS_49_F]= 0.029 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,LS_50PLUS_M]= 0.202 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_17t19 ,LS_50PLUS_F]= 0.58 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,HS_29_M]= 0.743 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,HS_29_F]= 0.405 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,HS_49_F]= 0.762 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,HS_50PLUS_F]= 0.78 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,MS_29_M]= 0.748 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,MS_29_F]= 0.805 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,LS_49_F]= 0.286 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,LS_50PLUS_M]= 0.386 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_20 ,LS_50PLUS_F]= 0.71 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,HS_29_M]= 0.558 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,HS_29_F]= 0.189 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,HS_49_F]= 0.757 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,HS_50PLUS_F]= 0.762 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,MS_29_M]= 0.926 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,MS_29_F]= 0.917 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,MS_50PLUS_F]= 0.15 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,LS_49_F]= 0.046 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,LS_50PLUS_M]= 0.047 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_21t22 ,LS_50PLUS_F]= 0.531 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,HS_29_M]= 0.566 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,HS_29_F]= 0.581 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,HS_50PLUS_F]= 0.338 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,MS_29_M]= 0.916 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,MS_29_F]= 0.884 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,LS_50PLUS_M]= 0.059 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_23 ,LS_50PLUS_F]= 0.5 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,HS_29_M]= 0.675 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,HS_29_F]= 0.412 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,HS_49_M]= 0 ~~|
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Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,HS_49_F]= 0.607 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,HS_50PLUS_F]= 0.728 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,MS_29_M]= 0.92 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,MS_29_F]= 0.902 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,LS_49_F]= 0.065 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,LS_50PLUS_M]= 0.117 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_24 ,LS_50PLUS_F]= 0.559 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,HS_49_M]= 0.755 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,HS_49_F]= 0.93 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,HS_50PLUS_M]= 0.904 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,HS_50PLUS_F]= 0.84 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,MS_29_M]= 0.587 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,MS_29_F]= 0.632 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,MS_49_M]= 0.381 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,MS_49_F]= 0.305 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,MS_50PLUS_M]= 0.886 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,MS_50PLUS_F]= 0.876 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,LS_49_F]= 0.12 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_25 ,LS_50PLUS_F]= 0.42 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,HS_29_M]= 0.821 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,HS_29_F]= 0.495 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,HS_49_F]= 0.753 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,HS_50PLUS_F]= 0.734 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,MS_29_M]= 0.881 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,MS_29_F]= 0.912 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,LS_49_F]= 0.164 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,LS_50PLUS_M]= 0.23 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_26 ,LS_50PLUS_F]= 0.64 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,HS_49_M]= 0.453 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,HS_49_F]= 0.897 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,HS_50PLUS_M]= 0.778 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,HS_50PLUS_F]= 0.819 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,MS_29_M]= 0.841 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,MS_29_F]= 0.827 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,MS_50PLUS_M]= 0.192 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,MS_50PLUS_F]= 0.652 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,LS_49_F]= 0.076 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_27t28 ,LS_50PLUS_F]= 0.497 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,HS_29_M]= 0.373 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,HS_29_F]= 0.129 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,HS_49_F]= 0.745 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,HS_50PLUS_M]= 0.181 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,HS_50PLUS_F]= 0.781 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,MS_29_M]= 0.896 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,MS_29_F]= 0.858 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,MS_50PLUS_F]= 0.263 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,LS_49_F]= 0.018 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,LS_50PLUS_M]= 0.03 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_29 ,LS_50PLUS_F]= 0.494 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33 ,HS_29_M]= 0.838 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33 ,HS_29_F]= 0.416 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33 ,HS_49_F]= 0.158 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33 ,HS_50PLUS_F]= 0.626 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33 ,MS_29_M]= 0.876 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33 ,MS_29_F]= 0.883 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33 ,MS_49_F]= 0 ~~|
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Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33,MS_50PLUS_F]= 0.006 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33,LS_49_F]= 0.071 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_30t33,LS_50PLUS_F]= 0.503 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,HS_29_M]= 0.528 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,HS_49_M]= 0.554 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,HS_49_F]= 0.809 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,HS_50PLUS_M]= 0.794 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,HS_50PLUS_F]= 0.809 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,MS_29_M]= 0.221 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,MS_29_F]= 0.671 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,MS_49_M]= 0.294 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,MS_50PLUS_M]= 0.81 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,MS_50PLUS_F]= 0.713 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,LS_49_F]= 0.173 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_34t35,LS_50PLUS_F]= 0.397 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,HS_29_M]= 0.758 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,HS_50PLUS_F]= 0.821 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,MS_29_M]= 0.869 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,MS_29_F]= 0.821 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,MS_50PLUS_F]= 0.247 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,LS_49_F]= 0.063 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,LS_50PLUS_M]= 0.15 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_36t37,LS_50PLUS_F]= 0.583 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,HS_29_M]= 0.681 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,HS_49_F]= 0.17 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,HS_50PLUS_M]= 0.014 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,HS_50PLUS_F]= 0.814 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,MS_29_M]= 0.882 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,MS_29_F]= 0.832 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,MS_50PLUS_F]= 0.384 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,LS_49_F]= 0.053 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,LS_50PLUS_M]= 0.134 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_E,LS_50PLUS_F]= 0.572 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,HS_29_M]= 0.736 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,HS_29_F]= 0.361 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,HS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,MS_29_M]= 0.739 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,MS_29_F]= 0.704 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,LS_49_F]= 0.362 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,LS_50PLUS_M]= 0.21 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_F,LS_50PLUS_F]= 0.035 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,HS_49_M]= 0.767 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,HS_49_F]= 0.795 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,HS_50PLUS_M]= 0.872 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,HS_50PLUS_F]= 0.842 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,MS_29_M]= 0.167 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,MS_29_F]= 0.505 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,MS_49_M]= 0.714 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,MS_49_F]= 0.571 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,MS_50PLUS_M]= 0.891 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,MS_50PLUS_F]= 0.805 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,LS_29_M]= 0.08 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,LS_29_F]= 0.06 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,LS_49_M]= 0.602 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50,LS_50PLUS_M]= 0 ~~|
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Correlation_Hours_worked_Quali_level_CorrCoeff[sector_50 ,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,HS_29_M]= 0.293 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,HS_29_F]= 0.049 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,HS_49_M]= 0.261 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,HS_49_F]= 0.111 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,HS_50PLUS_M]= 0.744 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,HS_50PLUS_F]= 0.769 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,MS_29_M]= 0.867 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,MS_29_F]= 0.891 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,LS_49_M]= 0.568 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,LS_49_F]= 0.182 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_51 ,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,HS_49_M]= 0.751 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,HS_49_F]= 0.69 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,HS_50PLUS_M]= 0.849 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,HS_50PLUS_F]= 0.827 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,MS_29_M]= 0.693 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,MS_29_F]= 0.767 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,MS_50PLUS_F]= 0.163 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,LS_49_M]= 0.681 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_52 ,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,HS_49_M]= 0.815 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,HS_49_F]= 0.865 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,HS_50PLUS_M]= 0.882 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,HS_50PLUS_F]= 0.869 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,MS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,MS_49_M]= 0.905 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,MS_49_F]= 0.809 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,MS_50PLUS_M]= 0.833 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,MS_50PLUS_F]= 0.777 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,LS_29_M]= 0.113 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,LS_29_F]= 0.1 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,LS_49_M]= 0.691 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_H ,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,HS_29_M]= 0.025 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,HS_49_F]= 0.542 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,HS_50PLUS_F]= 0.728 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,MS_29_M]= 0.838 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,MS_29_F]= 0.849 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,MS_50PLUS_M]= 0.484 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,LS_49_M]= 0.163 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_60t63 ,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,HS_29_M]= 0.539 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,HS_50PLUS_F]= 0.332 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,MS_29_M]= 0.958 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,MS_29_F]= 0.963 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_64 ,LS_50PLUS_F]= 0.564 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,HS_29_M]= 0.355 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,HS_49_M]= 0.704 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,HS_49_F]= 0.916 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,HS_50PLUS_M]= 0.925 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,HS_50PLUS_F]= 0.924 ~~|
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Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,MS_29_M]= 0.633 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,MS_29_F]= 0.665 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,MS_49_F]= 0.181 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,MS_50PLUS_M]= 0.873 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,MS_50PLUS_F]= 0.918 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,LS_29_M]= 0.09 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,LS_49_M]= 0.438 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,LS_49_F]= 0.203 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,LS_50PLUS_M]= 0.003 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_J ,LS_50PLUS_F]= 0.67 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,HS_49_M]= 0.774 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,HS_49_F]= 0.959 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,HS_50PLUS_M]= 0.899 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,HS_50PLUS_F]= 0.925 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,MS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,MS_49_M]= 0.874 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,MS_49_F]= 0.795 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,MS_50PLUS_M]= 0.691 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,MS_50PLUS_F]= 0.809 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,LS_29_M]= 0.226 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,LS_49_M]= 0.71 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,LS_49_F]= 0.027 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_70 ,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,HS_49_M]= 0.772 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,HS_49_F]= 0.944 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,HS_50PLUS_M]= 0.953 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,HS_50PLUS_F]= 0.914 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,MS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,MS_49_M]= 0.942 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,MS_49_F]= 0.95 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,MS_50PLUS_M]= 0.869 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,MS_50PLUS_F]= 0.897 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,LS_29_M]= 0.412 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,LS_29_F]= 0.246 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,LS_49_M]= 0.651 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_71t74 ,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,HS_29_F]= 0.145 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,HS_50PLUS_M]= 0.64 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,HS_50PLUS_F]= 0.734 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,MS_29_M]= 0.902 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,MS_29_F]= 0.868 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,MS_50PLUS_F]= 0.72 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,LS_49_F]= 0.323 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,LS_50PLUS_M]= 0.372 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_L ,LS_50PLUS_F]= 0.71 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,HS_49_F]= 0.719 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,HS_50PLUS_M]= 0.797 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,HS_50PLUS_F]= 0.957 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,MS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,MS_49_M]= 0.559 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,MS_49_F]= 0.863 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,MS_50PLUS_M]= 0.905 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,MS_50PLUS_F]= 0.898 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,LS_29_M]= 0.319 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,LS_49_M]= 0.786 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_M ,LS_50PLUS_F]= 0.446 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,HS_49_F]= 0.736 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,HS_50PLUS_M]= 0.568 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,HS_50PLUS_F]= 0.85 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,MS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,MS_49_M]= 0.952 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,MS_49_F]= 0.901 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,MS_50PLUS_M]= 0.798 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,MS_50PLUS_F]= 0.882 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,LS_29_M]= 0.464 ~~|
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Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,LS_29_F]= 0.705 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,LS_49_M]= 0.734 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,LS_50PLUS_M]= 0.091 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_N ,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,HS_29_M]= 0.25 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,HS_49_F]= 0.865 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,HS_50PLUS_M]= 0.577 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,HS_50PLUS_F]= 0.941 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,MS_29_F]= 0.7 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,MS_50PLUS_M]= 0.862 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,MS_50PLUS_F]= 0.875 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,LS_29_M]= 0.49 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,LS_29_F]= 0.372 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,LS_49_M]= 0.713 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_CorrCoeff[sector_O ,LS_50PLUS_F]= 0
        ~
        ~                   |

Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,HS_29_F]= 0.006477 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,HS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,MS_29_M]= 0.09907 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,MS_29_F]= 0.063153 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,LS_29_F]= 0.001105 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_AtB ,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,HS_29_M]= 0.002295 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,HS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,MS_29_M]= 0.015526 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,MS_29_F]= 0.005644 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,LS_49_F]= 0.001568 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,LS_50PLUS_M]= 0.004482 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_C ,LS_50PLUS_F]= 0.003896 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,HS_49_M]= 0.003718 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,HS_49_F]= 0.005682 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,HS_50PLUS_M]= 0.001846 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,HS_50PLUS_F]= 0.001406 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,MS_29_M]= 0.011607 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,MS_29_F]= 0.025521 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,MS_50PLUS_F]= 0.007342 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_15t16 ,LS_50PLUS_F]= 0.005378 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,HS_29_M]= 0.00126 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,HS_29_F]= 0.004729 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,HS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,MS_29_M]= 0.022077 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,MS_29_F]= 0.034189 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,LS_49_F]= 0.00402 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_17t19 ,LS_50PLUS_M]= 0.005822 ~~|
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Correlation_Hours_worked_Quali_level_Inclination[sector_17t19,LS_50PLUS_F]= 0.013066 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,HS_29_M]= 0.001135 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,HS_29_F]= 0.000921 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,HS_49_F]= 0.000739 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,HS_50PLUS_F]= 0.00031 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,MS_29_M]= 0.0085 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,MS_29_F]= 0.003987 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,LS_49_F]= 0.007156 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,LS_50PLUS_M]= 0.004442 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_20,LS_50PLUS_F]= 0.002558 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,HS_29_M]= 0.001453 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,HS_29_F]= 0.000794 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,HS_49_F]= 0.002715 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,HS_50PLUS_F]= 0.001049 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,MS_29_M]= 0.025089 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,MS_29_F]= 0.011289 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,MS_50PLUS_F]= 0.000714 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,LS_49_F]= 0.003328 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,LS_50PLUS_M]= 0.00154 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_21t22,LS_50PLUS_F]= 0.005789 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,HS_29_M]= 0.00024 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,HS_29_F]= 0.000287 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,HS_50PLUS_F]= 1.6e-005 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,MS_29_M]= 0.002655 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,MS_29_F]= 0.001152 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,LS_50PLUS_M]= 0.00024 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_23,LS_50PLUS_F]= 0.000546 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,HS_29_M]= 0.001937 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,HS_29_F]= 0.001601 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,HS_49_F]= 0.001424 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,HS_50PLUS_F]= 0.000746 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,MS_29_M]= 0.024273 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,MS_29_F]= 0.010852 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,LS_49_F]= 0.004417 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,LS_50PLUS_M]= 0.003943 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_24,LS_50PLUS_F]= 0.005875 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,HS_49_M]= 0.006969 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,HS_49_F]= 0.003808 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,HS_50PLUS_M]= 0.002033 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,HS_50PLUS_F]= 0.000893 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,MS_29_M]= 0.003777 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,MS_29_F]= 0.001909 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,MS_49_M]= 0.004299 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,MS_49_F]= 0.001309 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,MS_50PLUS_M]= 0.005655 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,MS_50PLUS_F]= 0.003005 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,LS_49_F]= 0.002861 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_25,LS_50PLUS_F]= 0.001252 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26,HS_29_M]= 0.001659 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26,HS_29_F]= 0.001413 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26,HS_49_F]= 0.000632 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26,HS_50PLUS_F]= 0.000406 ~~|
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Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,MS_29_M]= 0.014867 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,MS_29_F]= 0.006795 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,LS_49_F]= 0.006458 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,LS_50PLUS_M]= 0.004378 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_26 ,LS_50PLUS_F]= 0.00379 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,HS_49_M]= 0.006678 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,HS_49_F]= 0.008181 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,HS_50PLUS_M]= 0.00328 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,HS_50PLUS_F]= 0.00221 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,MS_29_M]= 0.024927 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,MS_29_F]= 0.011482 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,MS_50PLUS_M]= 0.00348 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,MS_50PLUS_F]= 0.005563 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,LS_49_F]= 0.007158 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_27t28 ,LS_50PLUS_F]= 0.006686 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,HS_29_M]= 0.001666 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,HS_29_F]= 0.000854 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,HS_49_F]= 0.005678 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,HS_50PLUS_M]= 0.000774 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,HS_50PLUS_F]= 0.001953 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,MS_29_M]= 0.040884 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,MS_29_F]= 0.018182 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,MS_50PLUS_F]= 0.002855 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,LS_49_F]= 0.00235 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,LS_50PLUS_M]= 0.001855 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_29 ,LS_50PLUS_F]= 0.009769 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,HS_29_M]= 0.025484 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,HS_29_F]= 0.007145 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,HS_49_F]= 0.00112 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,HS_50PLUS_F]= 0.001153 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,MS_29_M]= 0.041699 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,MS_29_F]= 0.026348 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,MS_50PLUS_F]= 5.3e-005 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,LS_49_F]= 0.011245 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,LS_50PLUS_M]= 7e-006 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_30t33 ,LS_50PLUS_F]= 0.009922 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,HS_29_M]= 0.008292 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,HS_49_M]= 0.021427 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,HS_49_F]= 0.006324 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,HS_50PLUS_M]= 0.005978 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,HS_50PLUS_F]= 0.001546 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,MS_29_M]= 0.002929 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,MS_29_F]= 0.007919 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,MS_49_M]= 0.014823 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,MS_50PLUS_M]= 0.018756 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,MS_50PLUS_F]= 0.004463 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,LS_49_F]= 0.013442 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_34t35 ,LS_50PLUS_F]= 0.003254 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,HS_29_M]= 0.002134 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,HS_50PLUS_F]= 0.00078 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,MS_29_M]= 0.015859 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,MS_29_F]= 0.005054 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,MS_50PLUS_F]= 0.000589 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37 ,LS_29_M]= 0 ~~|
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Correlation_Hours_worked_Quali_level_Inclination[sector_36t37,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37,LS_49_F]= 0.002729 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37,LS_50PLUS_M]= 0.003685 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_36t37,LS_50PLUS_F]= 0.004271 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,HS_29_M]= 0.002013 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,HS_49_F]= 0.000232 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,HS_50PLUS_M]= 3.4e-005 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,HS_50PLUS_F]= 0.000883 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,MS_29_M]= 0.015397 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,MS_29_F]= 0.00484 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,MS_50PLUS_F]= 0.001083 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,LS_49_F]= 0.00222 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,LS_50PLUS_M]= 0.003116 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_E,LS_50PLUS_F]= 0.00403 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,HS_29_M]= 0.012076 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,HS_29_F]= 0.0032 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,HS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,MS_29_M]= 0.198657 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,MS_29_F]= 0.021547 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,LS_49_F]= 0.00993 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,LS_50PLUS_M]= 0.020993 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_F,LS_50PLUS_F]= 0.000293 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,HS_49_M]= 0.011363 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,HS_49_F]= 0.003871 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,HS_50PLUS_M]= 0.002804 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,HS_50PLUS_F]= 0.001925 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,MS_29_M]= 0.00092 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,MS_29_F]= 0.003871 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,MS_49_M]= 0.016359 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,MS_49_F]= 0.010749 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,MS_50PLUS_M]= 0.01066 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,MS_50PLUS_F]= 0.009532 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,LS_29_M]= 0.001237 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,LS_29_F]= 0.000647 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,LS_49_M]= 0.0385 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_50,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,HS_29_M]= 0.00183 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,HS_29_F]= 0.000591 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,HS_49_M]= 0.002318 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,HS_49_F]= 0.000493 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,HS_50PLUS_M]= 0.002201 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,HS_50PLUS_F]= 0.002543 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,MS_29_M]= 0.045622 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,MS_29_F]= 0.061221 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,LS_49_M]= 0.025558 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,LS_49_F]= 0.006945 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_51,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,HS_49_M]= 0.021283 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,HS_49_F]= 0.006523 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,HS_50PLUS_M]= 0.006072 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,HS_50PLUS_F]= 0.004956 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,MS_29_M]= 0.03448 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,MS_29_F]= 0.051981 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,MS_50PLUS_F]= 0.002435 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,LS_49_M]= 0.087253 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_52,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,HS_29_F]= 0 ~~|
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Correlation_Hours_worked_Quali_level_Inclination[sector_H,HS_49_M]= 0.022067 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,HS_49_F]= 0.007096 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,HS_50PLUS_M]= 0.004808 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,HS_50PLUS_F]= 0.00319 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,MS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,MS_49_M]= 0.048884 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,MS_49_F]= 0.035613 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,MS_50PLUS_M]= 0.018534 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,MS_50PLUS_F]= 0.015913 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,LS_29_M]= 0.003431 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,LS_29_F]= 0.002236 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,LS_49_M]= 0.07598 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_H,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,HS_29_M]= 0.000242 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,HS_49_F]= 0.003445 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,HS_50PLUS_F]= 0.002663 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,MS_29_M]= 0.07011 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,MS_29_F]= 0.048542 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,MS_50PLUS_M]= 0.017085 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,LS_49_M]= 0.015277 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_60t63,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,HS_29_M]= 0.002096 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,HS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,HS_50PLUS_F]= 0.000223 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,MS_29_M]= 0.035826 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,MS_29_F]= 0.025578 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,MS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_64,LS_50PLUS_F]= 0.001915 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,HS_29_M]= 0.00822 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,HS_49_M]= 0.038371 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,HS_49_F]= 0.02592 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,HS_50PLUS_M]= 0.011002 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,HS_50PLUS_F]= 0.006071 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,MS_29_M]= 0.013014 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,MS_29_F]= 0.040169 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,MS_49_F]= 0.00387 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,MS_50PLUS_M]= 0.009911 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,MS_50PLUS_F]= 0.023538 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,LS_29_M]= 0.000153 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,LS_49_M]= 0.004216 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,LS_49_F]= 0.014216 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,LS_50PLUS_M]= 1.7e-005 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_J,LS_50PLUS_F]= 0.01345 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,HS_49_M]= 0.024428 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,HS_49_F]= 0.010392 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,HS_50PLUS_M]= 0.004371 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,HS_50PLUS_F]= 0.002344 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,MS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,MS_49_M]= 0.024826 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,MS_49_F]= 0.014282 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,MS_50PLUS_M]= 0.006761 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,MS_50PLUS_F]= 0.005107 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,LS_29_M]= 0.00196 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,LS_49_M]= 0.02828 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,LS_49_F]= 0.001471 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_70,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,HS_49_M]= 0.306805 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,HS_49_F]= 0.125513 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,HS_50PLUS_M]= 0.060881 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,HS_50PLUS_F]= 0.027078 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,MS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,MS_49_M]= 0.340079 ~~|
```

```
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,MS_49_F]= 0.237703 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,MS_50PLUS_M]= 0.109308 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,MS_50PLUS_F]= 0.079797 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,LS_29_M]= 0.038284 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,LS_29_F]= 0.02047 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,LS_49_M]= 0.285682 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_71t74,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,HS_29_F]= 0.005737 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,HS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,HS_50PLUS_M]= 0.006958 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,HS_50PLUS_F]= 0.021043 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,MS_29_M]= 0.017381 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,MS_29_F]= 0.046675 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,MS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,MS_50PLUS_F]= 0.024697 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,LS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,LS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,LS_49_F]= 0.076773 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,LS_50PLUS_M]= 0.047205 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_L,LS_50PLUS_F]= 0.061021 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,HS_49_F]= 0.072353 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,HS_50PLUS_M]= 0.033999 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,HS_50PLUS_F]= 0.087532 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,MS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,MS_49_M]= 0.010821 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,MS_49_F]= 0.051231 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,MS_50PLUS_M]= 0.026661 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,MS_50PLUS_F]= 0.05086 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,LS_29_M]= 0.004628 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,LS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,LS_49_M]= 0.033439 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_M,LS_50PLUS_F]= 0.010248 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,HS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,HS_49_F]= 0.074797 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,HS_50PLUS_M]= 0.020974 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,HS_50PLUS_F]= 0.02074 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,MS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,MS_49_M]= 0.104281 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,MS_49_F]= 0.269417 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,MS_50PLUS_M]= 0.027485 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,MS_50PLUS_F]= 0.131333 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,LS_29_M]= 0.005597 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,LS_29_F]= 0.019876 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,LS_49_M]= 0.034691 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,LS_50PLUS_M]= 0.001754 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_N,LS_50PLUS_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,HS_29_M]= 0.00196 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,HS_29_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,HS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,HS_49_F]= 0.017518 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,HS_50PLUS_M]= 0.006872 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,HS_50PLUS_F]= 0.011699 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,MS_29_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,MS_29_F]= 0.012377 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,MS_49_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,MS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,MS_50PLUS_M]= 0.015941 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,MS_50PLUS_F]= 0.022374 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,LS_29_M]= 0.015987 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,LS_29_F]= 0.014139 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,LS_49_M]= 0.112764 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,LS_49_F]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,LS_50PLUS_M]= 0 ~~|
Correlation_Hours_worked_Quali_level_Inclination[sector_O,LS_50PLUS_F]= 0
	~
	~		|

Growth_Contribution_to_Gross_Output_of_Labour_Input_BaseDifAbs[sectors]=
	Growth_Contribution_to_Gross_Output_of_changed_Labour_Input[sectors]
	- Growth_Contribution_to_Gross_Output_of_Labour[sectors]
	~	Dmnl
	~	only abs change relevant. rel change useless, since growth contribution \
		negative
	|

Hours_worked_BaseDeltaRel=
	Hours_worked_BaseDifAbs / Hours_worked_Exog
	~	Dmnl
	~		|

Hours_worked_BaseDifAbs=
```

```
SUM( Hours_worked_by_sector_BaseDifAbs[sectors!] )
~        h*Mio
~                |
```

The view definitions after the formula definitions in the model file are omitted. These define the layout of the visualisation of the formulas in Vensim. They are not needed for running the model.

Appendix E

MindMap2LaTeX

The content of this document was created with *MindManager*, which enables the creation of a tree document, so called *Mindmaps*. That file, available as XML data, is automatically transformed into LaTeX source code using an self-developed XSLT script. That LaTeX code is then compiled into this PDF document. This workflow is the contrary of *What you see is what you get* editing. The large advantage is twofold: first, it fosters the development of well structured documents and second it releases the author from the pains of Microsoft Word or similar editors.

For applying this XSLT to the Mindmap with the contents of this thesis, I used the open-source version of the Saxon parser, version B 9.1 available at http://saxon.sourceforge.net .

This is the complete source code of that XSLT script:

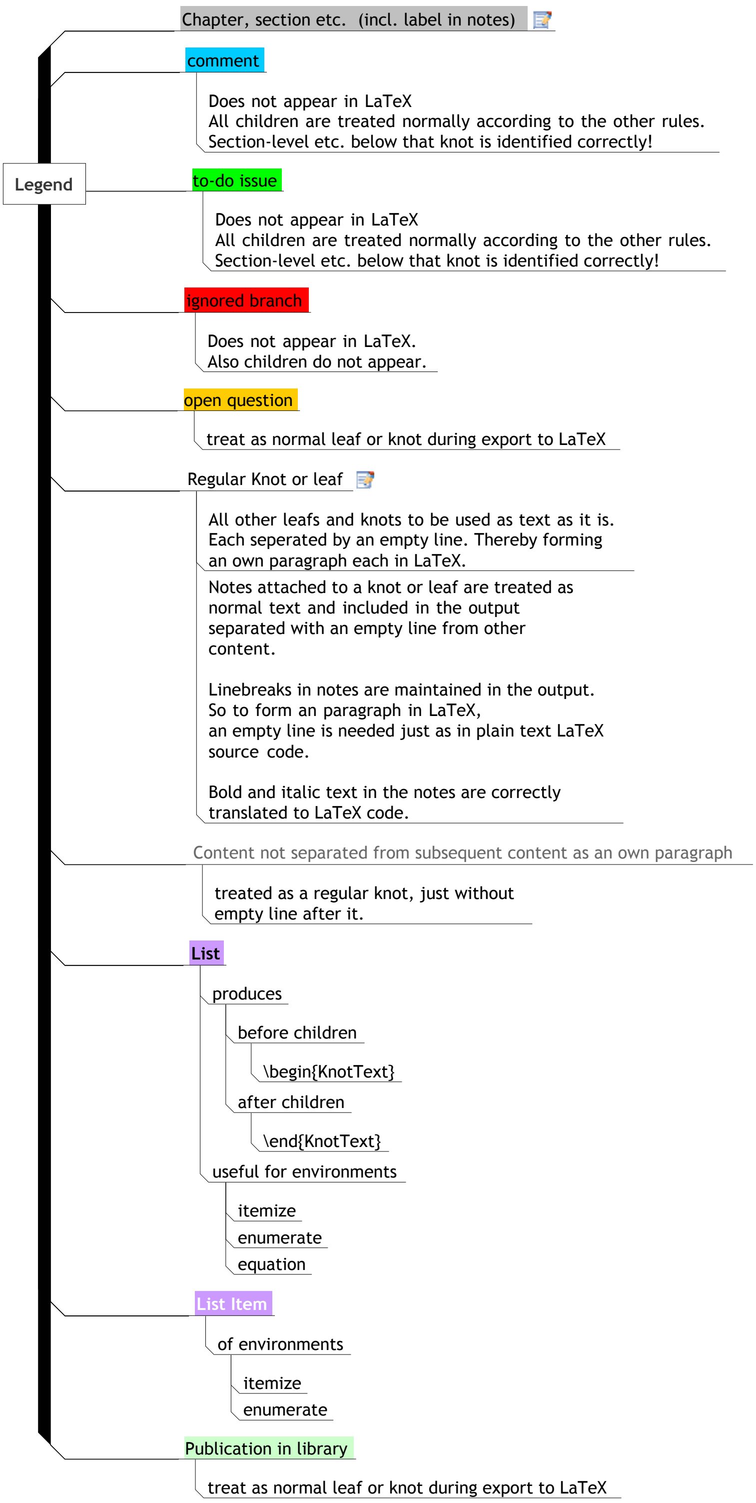
```
<?xml version="1.0" encoding="UTF-8"?>
<xsl:stylesheet version="1.0"
xmlns:xsl="http://www.w3.org/1999/XSL/Transform"
xmlns:xhtml="http://www.w3.org/1999/xhtml"
xmlns:ap="http://schemas.mindjet.com/MindManager/Application/2003"
xmlns:cor="http://schemas.mindjet.com/MindManager/Core/2003"
xmlns:html="http://www.w3.org/1999/xhtml">

<xsl:output method="text" />

<!-- &#32;&#xA;&#xD; - space; carriage return; line feed (maybe...but it works as line break in case only &#xA does not work-->

<!-- ================================================================ -->
<!-- Dealing with a Knot of the Mindmap...                             -->
<!-- ================================================================ -->

<xsl:template match="ap:Topic">

        <xsl:choose>

            <!-- Test for chapter knot-->
                <xsl:when test="ap:Color/@FillColor='ffc0c0c0'">
                        <!-- This is a chapter knot-->

                        <xsl:call-template name="WriteChapterTitel">
                        <xsl:with-param name="topic" select="." />
                        </xsl:call-template>

                        <!-- go ahead with child topics -->
                        <xsl:apply-templates/>
                </xsl:when>

            <!-- Test for 'comment' knot-->
                <xsl:when test="ap:Color/@FillColor='ff00ccff'">
                        <!-- This is a comment knot. Do nothing... -->

                        <!-- ...but go ahead with child topics -->
```

```
                <xsl:apply-templates/>
            </xsl:when>

        <!-- Test for 'to-do issue' knot-->
        <xsl:when test="ap:Color/@FillColor='ff00ff00'">
            <!-- This is a comment knot. Do nothing... -->

            <!-- ...but go ahead with child topics -->
            <xsl:apply-templates/>
        </xsl:when>

        <!-- Test for 'ignored branch' knot-->
           <xsl:when test="ap:Color/@FillColor='ffff0000'">
           <!-- This is a 'ignored branch' knot. Do nothing... -->

           <!-- ...and also irgnore children -->

        </xsl:when>

        <!-- Test for 'List' or 'List Item' knot-->
        <xsl:when test="ap:Color/@FillColor='ffcc99ff'">

            <xsl:call-template name="ListOrListItem">
                <xsl:with-param name="topic" select="." />
            </xsl:call-template>

        </xsl:when>


            <xsl:otherwise>
                <!-- This is a content knot -->
                <xsl:call-template name="WriteContentKnot">
                    <xsl:with-param name="topic" select="." />
                </xsl:call-template>

                <!-- go ahead with child topics -->
                <xsl:apply-templates/>
            </xsl:otherwise>

        </xsl:choose>

</xsl:template>

<!-- ============================================================ -->
<!-- 'List' or 'List Item'                                        -->
<!-- ============================================================ -->
<xsl:template name="ListOrListItem">
  <xsl:param name="topic" />

    <xsl:choose>

       <!-- White Text => List Item -->
       <xsl:when test="ap:Text/ap:Font/@Color='ffffffff'">

         <xsl:text> \item </xsl:text> <!-- on item of the list in LaTeX -->

         <xsl:call-template name="WriteContentKnot">
           <xsl:with-param name="topic" select="." />
         </xsl:call-template>

         <!-- go ahead with child topics -->
         <xsl:apply-templates/>

       </xsl:when>

       <!-- Other color => LaTeX environment with knot text-->
       <xsl:otherwise>

         <xsl:text>\begin{</xsl:text> <!-- begin environment -->
         <xsl:value-of select="$topic/ap:Text/@PlainText"/>
         <xsl:text>}</xsl:text>
         <xsl:text>&#xA;</xsl:text> <!-- one carriage returns -->

         <!-- go ahead with child topics -->
         <xsl:apply-templates/>

         <xsl:text>\end{</xsl:text> <!-- end environment -->
         <xsl:value-of select="$topic/ap:Text/@PlainText"/>
         <xsl:text>}</xsl:text>
         <xsl:text>&#xA;</xsl:text> <!-- one carriage returns -->

       </xsl:otherwise>
    </xsl:choose>

</xsl:template>



<!-- ============================================================ -->
<!-- Writing the content to the output                            -->
<!-- ============================================================ -->
<xsl:template name="WriteContentKnot">
        <xsl:param name="topic" />

    <!-- Write unformatted Text in Knot -->
    <xsl:value-of select="$topic/ap:Text/@PlainText"/>

    <!-- grey text (in knot) does not form an own paragraph. only one carriage return -->
    <!-- all other colored text forms an own paragraph. two carriage retrurns -->
    <xsl:choose>
       <xsl:when test="ap:Text/ap:Font/@Color='ff696969'">
         <xsl:text>&#xA;</xsl:text> <!-- one carriage return -->
       </xsl:when>
```

```
        <xsl:otherwise>
          <xsl:text>&#xA;&#xA;</xsl:text> <!-- two carriage returns -->
        </xsl:otherwise>
     </xsl:choose>

         <!-- if there is a note, write plain text to output -->
     <xsl:if test="$topic/ap:NotesGroup/ap:NotesXhtmlData">

         <!-- obviously the text leafs are written to the output stream... -->
         <xsl:apply-templates select="$topic/ap:NotesGroup/ap:NotesXhtmlData"/>
         <xsl:text>&#xA;&#xA;</xsl:text> <!-- two carriage returns -->

     </xsl:if>

</xsl:template>


<!-- It seems that text leafs are written automatically while the parser traversers thought the xml tree -->
<!-- Therefore, knots that do not need any special treatment do not need a dedicated template. -->
<!-- The parser automatically continues with the children of these knots. -->

<!-- Such knots are:  span - p - u - br -->

<!-- the 'html' tag (in the mindmap) is the root of the html data in the notes. but it seems -->
<!-- this is never called, since in a test with debug text that text never appeared. maybe this is because -->
<!-- this tag is ONLY a namespace declaration and therefore not treated as a regular knot -->

<!-- The only two tag that are treated in a special way are for italic and bold text-->

<!-- italic text -->
<xsl:template match="html:i">
      <xsl:text>\emph{</xsl:text> <!-- start of LaTeX italic command -->
      <xsl:apply-templates/> <!-- go ahead with children -->
      <xsl:text>}</xsl:text> <!-- end of LaTeX italic command -->
</xsl:template>

<!-- bold text -->
<xsl:template match="html:b">
      <xsl:text>\textbf{</xsl:text> <!-- start of LaTeX bold command -->
      <xsl:apply-templates/> <!-- go ahead with children -->
      <xsl:text>}</xsl:text> <!-- end of LaTeX bold command -->
</xsl:template>


<!-- rudimentary table support
     create only rows automaticalls
     horizontal lines too complex to determine...
     I prefer mixing \hline with HTML tables. Works fine enough :-)
 -->
<xsl:template match="html:tr">
      <xsl:apply-templates/> <!-- go ahead with children -->
      <xsl:text>\\</xsl:text> <!-- end of Table Row in LaTeX -->
</xsl:template>

<xsl:template match="html:td">

       <!-- write '&', seperating table columns in LaTeX
            one in front of every cell except the first cell  -->
      <xsl:if test="position() &gt; 2">
          <xsl:text>&#38;</xsl:text> <!-- the character '&' -->
       </xsl:if>

       <!-- translate colspan (HTML) to mulitcolumn (LaTeX), if available
        -->
      <xsl:choose>
        <xsl:when test="@colspan">
          <xsl:text>\multicolumn{</xsl:text>
          <xsl:value-of select="@colspan"/>
          <xsl:text>}{l}{</xsl:text> <!-- the alignment within the mulicolumn cell -->
          <xsl:apply-templates/> <!-- go ahead with children -->
          <xsl:text>}</xsl:text>
        </xsl:when>
        <xsl:otherwise>
          <xsl:apply-templates/> <!-- go ahead with children -->
        </xsl:otherwise>
      </xsl:choose>
</xsl:template>


<!-- List support
     HTML list item tag translated to \item command in LaTeX -->
<xsl:template match="html:li">
      <xsl:text>\item </xsl:text> <!-- on item of the list in LaTeX -->
      <xsl:apply-templates/> <!-- go ahead with children -->
</xsl:template>



<!-- ========================================================== -->
<!-- Write Chapter Titel (with lable)-->
<!-- ========================================================== -->

<xsl:template name="WriteChapterTitel">
        <xsl:param name="topic" />

    <!-- finds all ancestor knots named 'ap:Topic' with children 'ap:Color' -->
    <!-- having the attribute 'FillColor' set to the value 'ffc0c0c0', which -->
    <!-- corresponds to the color used to mark chpater, sections etc. -->
        <xsl:variable name="level" select="count( ($topic/ancestor::ap:Topic)/ap:Color[@FillColor='ffc0c0c0'] )" />

    <!-- indentify chapter level -->
        <xsl:choose>
                <xsl:when test="$level = 0">
                <xsl:text>\chapter{</xsl:text>
                </xsl:when>
```

```
            <xsl:when test="$level = 1">
            <xsl:text>\section{</xsl:text>
            </xsl:when>
            <xsl:when test="$level = 2">
            <xsl:text>\subsection{</xsl:text>
            </xsl:when>
            <xsl:when test="$level = 3">
            <xsl:text>\subsubsection{</xsl:text>
            </xsl:when>
            <xsl:when test="$level = 4">
            <xsl:text>\paragraph{</xsl:text>
            </xsl:when>
            <xsl:when test="$level = 5">
            <xsl:text>\subparagraph{</xsl:text>
            </xsl:when>
      <xsl:otherwise> <!-- just in case... -->
          <xsl:text>\subparagraph{</xsl:text>
      </xsl:otherwise>
      </xsl:choose>

   <!-- Write chapter Titel-->
   <xsl:value-of select="$topic/ap:Text/@PlainText"/>
   <xsl:text>}</xsl:text>
      <xsl:text>&#xA;</xsl:text> <!-- own carriage return -->

   <!-- Write lable for reference to section, if lable is defined in notes of section knot -->
   <xsl:if test="$topic/ap:NotesGroup">
     <xsl:text>\label{</xsl:text>
     <xsl:value-of select="$topic/ap:NotesGroup/ap:NotesXhtmlData/@PreviewPlainText"/>
     <xsl:text>}</xsl:text>
     <xsl:text>&#xA;</xsl:text> <!-- own carriage return -->
   </xsl:if>

   <xsl:text>&#xA;</xsl:text> <!-- own carriage return -->

</xsl:template>

<!-- ============================================================ -->
<!-- Ignore the following nodes -->
<!-- ============================================================ -->

<xsl:template match="ap:NotesGroup" />
<xsl:template match="ap:DocumentGroup" />
<xsl:template match="ap:StyleGroup" />
<xsl:template match="ap:MapViewGroup" />
<xsl:template match="ap:MarkersSetGroup" />
<xsl:template match="ap:FloatingTopics/ap:Topic" />
<xsl:template match="ap:OneImage" />
<xsl:template match="cor:Base64" />

</xsl:stylesheet>
```

The layout standards which have to be followed in the content mindmap for the XSLT script to work are shown on the following page.


Legend
Chapter, section etc. (incl. label in notes)
comment
Does not appear in LaTeX
All children are treated normally according to the other rules.
Section-level etc. below that knot is identified correctly!
to-do issue
Does not appear in LaTeX
All children are treated normally according to the other rules.
Section-level etc. below that knot is identified correctly!
ignored branch
Does not appear in LaTeX.
Also children do not appear.
open question
treat as normal leaf or knot during export to LaTeX
Regular Knot or leaf
All other leafs and knots to be used as text as it is.
Each seperated by an empty line. Thereby forming
an own paragraph each in LaTeX.
Notes attached to a knot or leaf are treated as
normal text and included in the output
separated with an empty line from other
content.
Linebreaks in notes are maintained in the output.
So to form an paragraph in LaTeX,
an empty line is needed just as in plain text LaTeX
source code.
Bold and italic text in the notes are correctly
translated to LaTeX code.
Content not separated from subsequent content as an own paragraph
treated as a regular knot, just without
empty line after it.
List
produces
before children
\begin{KnotText}
after children
\end{KnotText}
useful for environments
itemize
enumerate
equation
List Item
of environments
itemize
enumerate
Publication in library
treat as normal leaf or knot during export to LaTeX

Appendix F

Document status

FINAL

Document revision number

1651

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