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Car Technology Market Evolution and Emissions Impacts
An Example of Energy Policy Scenarios under Uncertainty

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ABSTRACT

After the Great Recession and the stark decline in crude oil prices, the transport system, in particular, the car market, is possibly facing a bifurcation point. The extent to which the car market might, in terms of propulsion technology, become more heterogeneous and environmentally-friendly remains highly uncertain. To explore this, a model grounded on dynamic econometrics and system dynamics is developed. The model encompasses nine car technologies powered by seven types of fuel: gasoline, diesel, flex-fuel, liquefied petroleum gas, natural gas, hybrid, plug-in hybrid, electric and fuel cell. Model-based policy analysis is performed and the impacts of several types of car-mix until 2030 are derived. The model is applied to China, France, Germany, India, Japan and the US. The resulting main environmental impact, greenhouse gas emissions, is presented using two reporting boundaries. The key conclusion is that policies that target at electric vehicle market deployment and disregard clean electricity generation are possibly a source of policy failure. Our policy recommendation for the analysed countries, in the context of car technology, centres on the need to conceive a coherent energy, transport and environmental policy package, while acknowledging uncertainty.

Keywords: *system dynamics, energy scenarios, environmental policy, car technologies, multi-country analysis*

1. INTRODUCTION

After the Great Recession and the stark decline in crude oil prices, the transport system, is possibly facing a bifurcation point. Will it remain on the road to *economic efficiency*, narrowly defined, or will it take a path towards *sustainability*? In particular, the car market may continue to remain locked-in in conventional technology, albeit more efficient, or may diversify its sources of propulsion. The exploration of these possibilities calls for a model-based analysis of policies and impacts. A major impact of interest is greenhouse gas (GHG) emissions. Transport generated directly 7.0 gigatons of CO_{2eq} in 2010 (IPCC, 2015). In the car market, this results from the demand for gasoline and diesel fuels to meet travel needs. Taking steps towards sustainability makes the problem of drastically reducing emissions from car travel activities explicit. The outcome of the recent 21st Conference of Parties (COP) in Paris revealed commitment at the international level to fight against climate change. The means by which this may be achieved comprise mitigation measures in transport, including the deployment of cleaner technology in the car market. A specific shift from the internal combustion engine (ICE) to the electric drive continues to be under discussion. In September 2015, there were 1 million electric vehicles (EVs) worldwide (ICCT, 2015). The prevailing international target is to achieve 20 million EVs on the world's roads by 2020 (EVI, 2015). The extent to which rapid growth in global EV market penetration is achieved remains uncertain.

The main objective of this paper is to explore energy policy scenarios in key car markets. The focus of this study is on alternative car propulsion technologies, especially on EVs, and their market deployment. The perspective offered is international, with the scope limited to a set of 6 relevant countries: China, France, Germany, India, Japan and the US. The rest of the paper has the following structure: section 2 offers a view on previous work; some methodological considerations are included in section 3; the model is introduced in section 4; conclusions are drawn and discussion takes place in section 5. The paper ends with an appendix.

2. PREVIOUS WORK

This section is kept intentionally short, because a review of existing similar work has been given by the authors elsewhere (see (Gómez Vilchez et al., 2015) (Gómez Vilchez et al., 2014)). The survey of model-based studies included in those references range from global transport/energy, system dynamics, diffusion and discrete choice models, all of which are relevant to this work.

This paper builds on early modelling exercises (see the references mentioned in the previous paragraph for more modelling details). In particular, the modelling exercise presented in section 4 contains two developments with respect to the models introduced in those precedent papers: (i) a model extension to include the French, Indian and Japanese markets; and (ii) a dynamic econometric sub-model to estimate aggregate car stock in each of the six countries of interest.

The model extension to incorporate additional countries can be explained by the interest in offering an international perspective and comparing different county-specific policy measures. Concerning the use of econometrics, a research gap was identified from surveying previous similar work: the need to provide more sophisticated modelling of the variable ‘car stock’ (i.e. number of passenger cars in circulation in a given market in a certain year). In previous studies, this variable is assumed to remain constant in mature car markets, with Little’s formula (Little, 1961) being in some cases invoked (e.g. (Wansart, 2012)).

The main part of the modelling exercise is based on dynamic simulation. Although the problem of interest is highly complex (see (Strogatz, 2014) for examples of spatio-temporal complexity), complexity is kept at a manageable size. This is achieved by considering, for each country, only the temporal dimension and a high level of aggregation. Consequently, the application of agent-based modelling is beyond scope. For an agent-based model dealing with technologies displaying increasing returns to adoption, see (Arthur, 2014). For a recent review of agent-based models within the context of plug-in hybrid electric vehicles, see (Gnann, 2015).

Concerning the choice of technology, between the extreme cases of a representative agent and agent-based simulation, a midway modelling approach has been chosen. The important aspect is to incorporate the possibility of some interaction among at least two groups of agents. This idea is captured by epidemic and diffusion models of the Bass type (Bass, 1969) (Mahajan et al., 1991).

Finally, the concept of feedback underlies this type of studies. In economics, (Richardson, 1999) distinguishes between those who use(d) this concept implicitly and those who modell(ed) it explicitly. An interesting example of the former is (Einstein, 2005), writing in 1930 about the world economic crisis. An early explicit formulation in economics was given by (Myrdal, 1944) through ‘the principle of (circular) cumulation’. The pioneering computer modelling work of (Forrester, 1999), influenced by Brown’s servomechanism ideas (Brown and Campbell, 1948) (Richardson, 1999), resulted in the establishment of the system dynamics (SD) modelling approach/method. Following developments in time-series econometrics, a tradition in Britain emerged that explicitly acknowledges feedback processes, stressing that “there is a close relationship between error correction formulations and “servomechanism” control rules [see Phillips (1954, 1957)]” (Hendry et al., 1984) (p. 1069). See also (Engle and Granger, 1991) and (Banerjee, 1993).

3. METHODOLOGICAL REMARKS

The area of this research topic may be seen as lying between the realms of the transport system and the energy system (perhaps more generally, the environmental system). Systems theory (Boulding, 1956) (Bertalanffy, 1973) (Meadows and Wright, 2008) is adopted by the authors as a guiding scientific principle in this study. However, it is not our aim to model a system, but to build a model for a given problem (Sterman, 2000). The problem was stated in section 1 and we do not pretend our model will solve this complex problem. Instead, it is our hope that the developed model may provide some orientation about possible futures. This is in line with the idea of model-based energy scenarios (Dieckhoff, 2011). In our view, the developed model might even, following (Colander and Kupers, 2014), deliver visions, but not definite answers, to policy. (Manski, 2013) highlights "the immense difficulty of predicting policy outcomes" (p. 115) and suggests an "honest portrayal of partial knowledge" (p. 3) in policy analysis. Complex problems transcend academic boundaries and thus require a holistic vision (Laszlo, 1996) and interdisciplinary research. Although we have attempted to incorporate concepts from other disciplines, we acknowledge that our main perspective comes from the economic discipline. And even within that discipline, several worldviews co-exist. As a result, methods from different schools of thought are available in economics, including SD (Radzicki, 1990) (Lavoie, 2014).

In this work, we attempt to integrate two different methods from the realm of dynamic economics: dynamic econometrics and SD. An econometric model is generally based on the idea of a stochastic linear system in equilibrium. In contrast, an SD model reflects the modeller's attempt to represent disequilibrium arising from a deterministic nonlinear system. Mathematically seen, the former essentially uses difference equations and a statistical estimator that computationally optimizes key values; the latter simulate behavior over time based on a structure defined by ordinary differential equations. In SD, the modelled system is discretized, and a computer is also used, to efficiently solve the system of equations. For this task, numerical methods, such as Euler or Runge-Kutta integration (see e.g. (Braun, 1992)), are commonly employed. Meadows in (Randers, 1980) considered these two methods as possibly complementary, but acknowledged the difficulty in integrating both philosophies in a single model. We identify two reasons why this difficulty may diminish: (i) different "methodologies" co-exist within econometrics, and some are more consistent with the view of systems having inertia; and (ii) the literature on non-stationarity (see (Nelson and Plosser, 1982)), unit roots and cointegration has largely developed after Meadow's article.

4. MODELLING EXERCISE

The developed model consists of two differentiated sub-models: a dynamic econometric sub-model and a SD one. Most of the modelling exercise is conducted in a SD platform.

Econometric Sub-model and Model Linkage

Six individual time series sub-models, one for each country, are specified. The purpose of these is to estimate aggregate car stock in each market and use these as forecasts in the modelling exercise. Historical country-specific data on various available variables (see Table 1) is used to obtain estimates. The dependent variable is 'car ownership', represented by the ratio of car stock and population. The key independent variable is real per capita income. Non-stationarity and the possibility of structural breaks are checked using several unit root tests. For these modelling tasks and estimation, EViews® is employed. Prior to estimation, the single-equations were specified as autoregressive distributed lags (ADLs). See (Gómez Vilchez et al., 2016) for further details.

Table 1 – Econometric Model Variables and Data Sources

	China	France	Germany	India	Japan	US
Years	1980-2013	1960-2014	1970-2014	1980-2013	1960-2014	1960-2013
Car Stock	(UN, 2016) (IRF, 2016)	(Insee, 2016)	(Eurostat, 2016) (IRF, 2016) (KBA, 2016)	(GOI, 2016)	(Stat, 2016)	(FHWA, 2016) (IRF, 2016)
Population	UN (2015)					
GDP	(WB, 2016)					

De facto, the output of the econometric exercise is fed as an exogenous input into the SD sub-model. Figure 1 shows point estimates of the projected car ownership by country. These values are assumed to be the forecasts for the rest of the modelling exercise. The database used to feed the SD sub-model is available in a single Excel file.

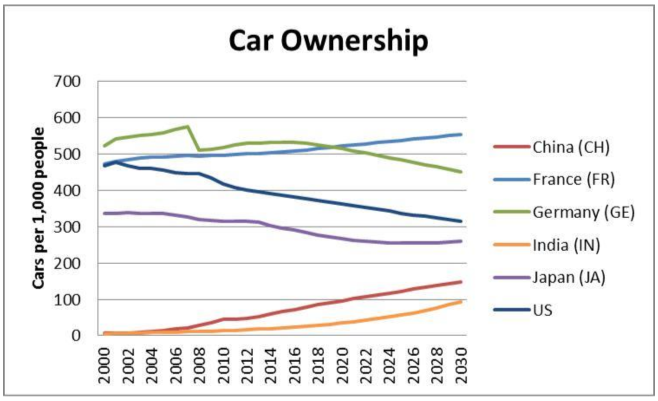

Figure 1 – Projected Car Ownership by Country (2000-2030)

The link between the aggregate econometric values and the SD values resulting from the stock-and-flow formulation is made by capturing the idea of car stock desired by the industry. It is assumed that the automotive industry relies on the econometric forecasts and devotes marketing efforts as needed. In essence, a basic first-order negative process is formulated (see Figure 2). In addition, in the context of such a stock adjustment loop, an ‘expected loss rate’ formulation has been included to mitigate steady state error (Sterman, 2000).

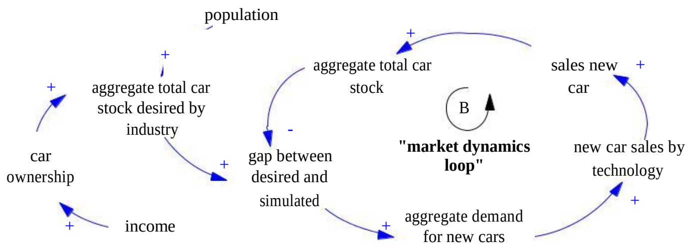

Figure 2 – Key ‘Market Dynamics’ Feedback Loop (Gómez Vilchez et al., 2016)

System Dynamics Sub-model

The core of the modelling exercise is represented by an SD sub-model, conveniently structured into nine modules. Figure 3 illustrates its conceptual arrangement. In this paper, the ‘Technology Choice’ module is briefly described (see Section 2 and Appendix for additional information about this sub-model).

To allow for interaction among prospective car purchasers, market segmentation is performed. For this task, three stocks representing groups of agents are created. The classification is based on the ‘innovativeness’ criterion (Rogers, 2003). Figure 4 shows how the market represented in the model is segmented. Each segment represents a fraction of the market, with the sum of the segments being equal to 1. It is assumed that the fraction of slow adopters increases over time, influenced by social exposure to an increasing number of technologies available in the market. Throughout the simulation, it is assumed that 0.8% of the market can be characterised as ‘innovators’. The initial value of the non-adopters is 80%.

Each market segment uses the following decision rules to choose car technology:

- Innovators: who make their decision based on a degree of innovativeness, represented by a stock-and-flow structure. When a new car technology is introduced in the market, the stock of innovativeness for that technology increases rapidly. This degree of innovativeness then decreases as time goes by.
- Slow adopters: two different choice formulations are employed. Until 2014, the level of attractiveness of each *available* technology depends on relative purchase cost and energy cost per km, with a respective weight of 0.6 and 0.4. After 2015, the results of a discrete choice study (Hackbarth and Madlener, 2013) are used to set up a modelling framework that derives market shares by technology based on a series of attributes: purchase cost, energy cost per km, fuelling time, range and emissions.
- Non-adopters: the scrappage rate determines replacement sales. It is assumed that 10% of those scrappaging their cars are no longer willing to buy a new car. The rest (90%) purchase the same car technology that was scrappaged.

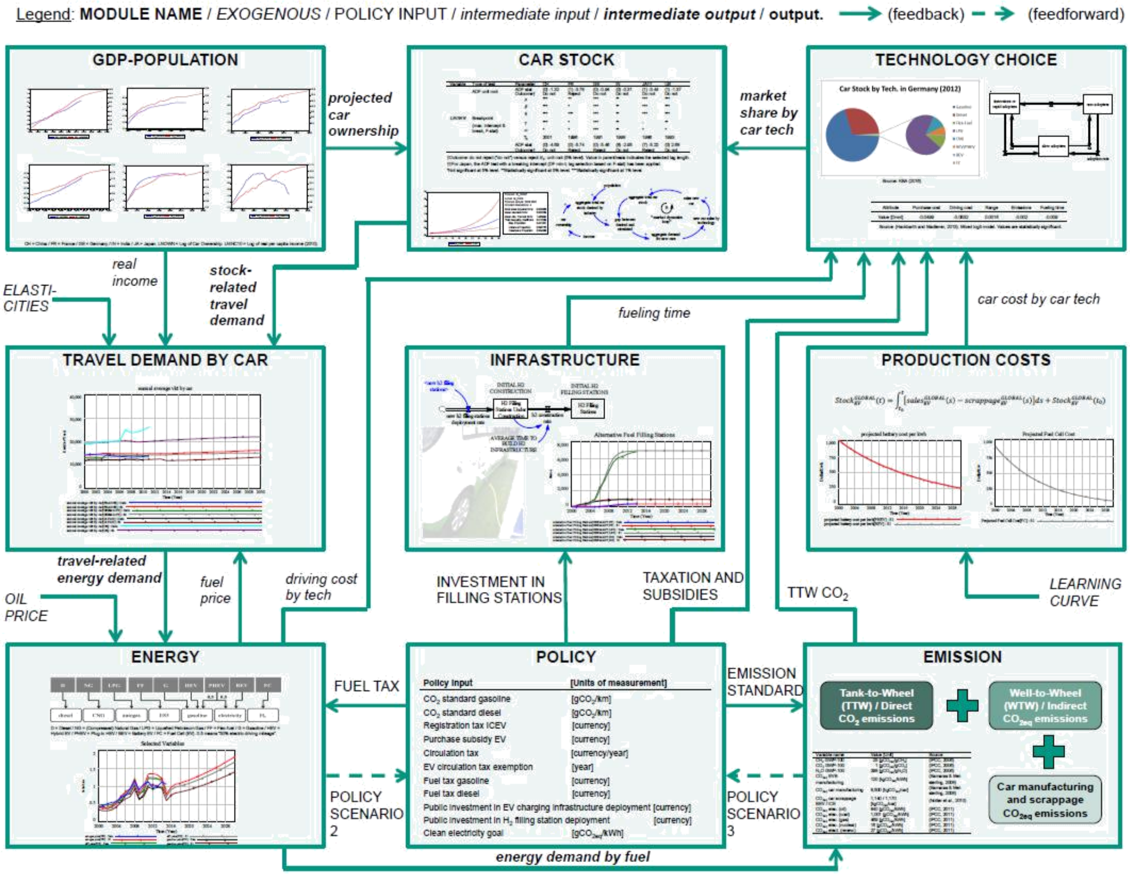

Figure 3 – Modular Overview of the SD Model

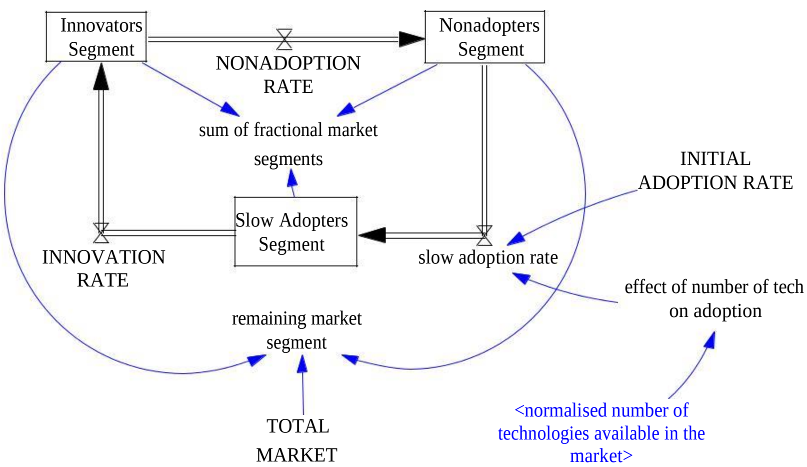

Figure 4 – Three Market Segments: Innovators, Slow Adopters and Non-Adopters

In addition to the crude oil price scenario assumptions, two important assumptions affecting technology choice are the cost of EV battery and fuel cells as well as infrastructure availability (i.e. number of filling stations or charging points).

The assumed cost reductions for EV battery and fuel cells are modelled using the concept of cumulative experience and learning curves (cf. (Sterman, 2000)). To obtain cumulative experience, it is assumed that the target of 20 million EVs on the world's roads by 2020 (EVI, 2013) is met. For the EV battery, a learning curve of 8%, consistent with the range of values shown by (Nykvist and Nilsson, 2015), is assumed. See (DOE, 2016) for some fuel cell targets. The resulting cost projections can be seen in Figure 5.

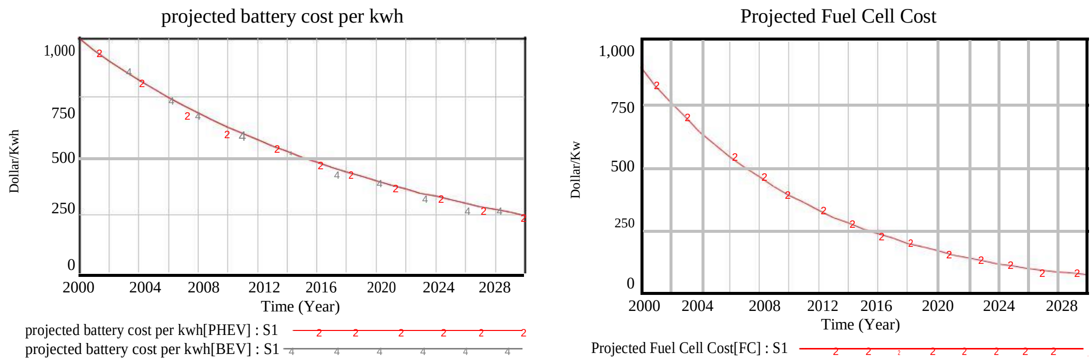

Figure 5 – Assumed Cost Reductions for EV Battery and Fuel Cells

The availability of filling/charging infrastructure compatible with a given technology is crucial to increase the attractiveness of that technology. Assumptions are made concerning the number of filling stations / charging points available for each of the seven types of fuels considered (see Figure 6 for an example of the assumed alternative fuel vehicle infrastructure in Germany). For electricity and hydrogen, the model user sets the amount of investment that can be made to increase the number of public stations, thus affecting attractiveness of electric and fuel cell cars.

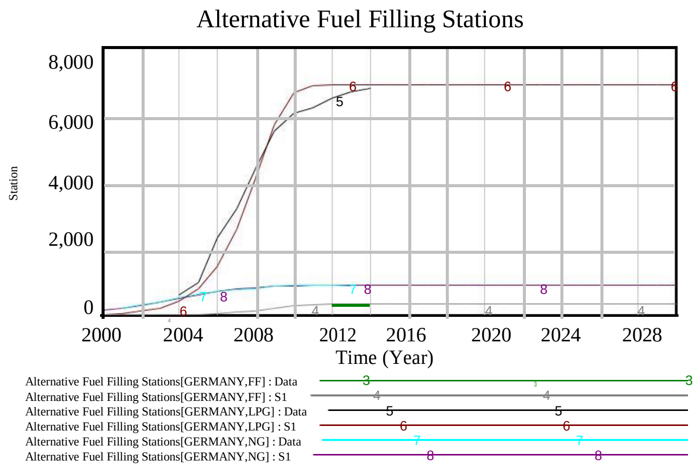

Figure 6 – Assumed Alternative Fuel Filling Stations in Germany

Because of discontinuities present in the model, Euler integration is chosen to solve the equations (Sterman, 2000), using a one-year time step in Vensim®. Although model validation precedes scenario and policy analysis, this issue is covered in section 5.

Scenarios and Policy Analysis

To illustrate the results of model simulation runs, three scenarios are chosen and analysed. These can be succinctly described as follows:

- Scenario 1 (S1) – Base-run (Business-as-usual / Reference / Do-nothing): "Policies currently under implementation and planned remain in place. No new policies are introduced by the model user".
- Scenario 2 (S2) – Oil reduction: "New policies targeting oil demand reduction from car use, disregarding clean electricity generation, are implemented".
- Scenario 3 (S3) – GHG emissions reduction: "In addition to policies supported under S2, new policies targeting fuel cell cars and clean electricity generation are implemented".

Figure 7 illustrates key simulation output for Scenario 3. The results are shown using two different reporting boundaries: direct or tank-to-wheel (TTW) and non-direct or well-to-tank (WTW) emissions, including car manufacturing and scrappage. The choice of the reporting metric is important, as differences between them are remarkable.

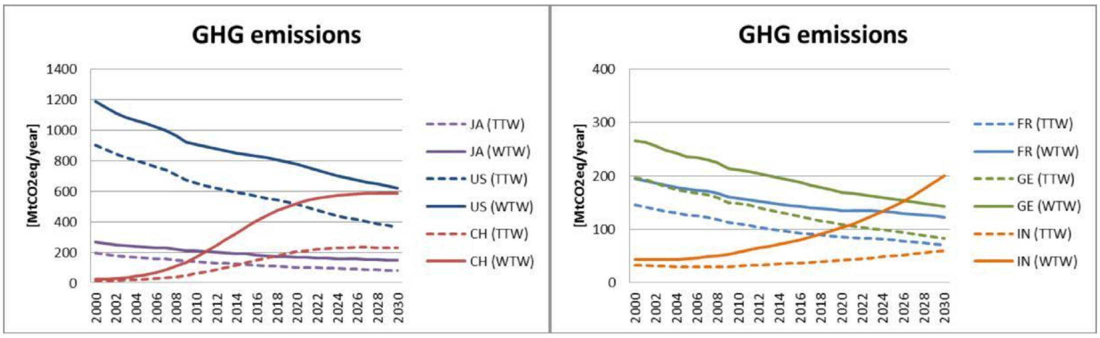

Figure 7 – Key Simulation Output

In practice, policy-makers are supposed to be interested in obtaining some information concerning the economic implications of specific plans or policies. This can, to some extent, be captured by the idea of a dedicated fund. The balancing of a fund, regarded as a stock influenced by revenues and expenditures, was used in an early SD paper by (Ford, 1995). In the current version of the model, a basic stock-and-flow structure has been set up to enable further analysis about the economic consequences of policy inputs determined by the model user.

5. CONCLUSIONS AND DISCUSSION

Summary and Conclusions

In this paper, an attempt to combine two different methods (dynamic econometrics and system dynamics) in one model has been made. The developed model depicts the evolution of nine car propulsion technologies and seven types of fuels from 2000 to

2030 in six countries. The purpose of such model is to allow for policy analysis in the international context of environmental pressure to reduce GHG emissions from car travel.

The key conclusion is that policies that target at electric vehicle market deployment and disregard clean electricity generation are possibly a source of policy failure. In countries with high carbon-intensive electricity systems, the promotion of electric vehicles on environmental grounds turns out to be deceptive. Our general policy recommendation for the analysed countries, in the context of car technology, centres on the need to conceive a coherent energy, transport and environmental policy package.

Finally, the decision to expand the reporting boundaries to include non-direct GHG emissions sheds additional light on the impact of car technology. A related issue is that of regulatory oversight, temporary or permanent, of driving cycles' results. The recent case of diesel cars exceeding the amount of nitrogen oxides legally permitted in the US and in the EU (Oldenkamp et al., 2016) illustrates this point. Although not shown in section 4, the model contains a variable that enables the model user to simply specify the desired degree of compliance with the prevailing test driving cycle. Perhaps, an interesting remark is the recent proposal for the World-wide harmonized Light duty Test Cycle (WLTC), a new global test cycle using real-world driving data (Tutuianu et al., 2015).

Discussion of Limitations and Future Research Needs

Three basic limitations of this work are: (i) only the car market is considered, neglecting other vehicle markets and the role of public transport alternatives within the wider transport system; (ii) the impact of EVs on local power grids is not analysed; and (iii) only aggregate (average) emissions from the electricity grid are taken into account, ignoring the effect of marginal emissions.

With regards to model validation, suggestions of possible tests for system dynamics models are offered by (Barlas, 1996) (Sterman, 2000) and (Bossel, 2007). Here, the issue of historical fit is highlighted. Before being used for post-sample forecasting purposes, an econometric model is usually estimated and the accuracy of its within-sample forecasts compared with historical data. However, it is important to note that good within-sample fit is no guarantee that the model will perform adequately beyond sample. The same is, in our view, applicable to dynamic simulation models such as those based on system dynamics. Although the model developed in this study provides, for key variables, a reasonable fit to historical data and we are thus, to some extent, confident about the structure of the model, good historical fit is no indication of successful ex-ante simulation. (Bunge, 1982) highlights an important aspect of forecasts in the engineering and social sciences that is worth mentioning here: the possibility of self-fulfilling forecasts (cf. Figure 2 and related discussion). In connection with this idea, he distinguishes between 'active' and 'passive' forecasts, the latter being testable.

Further research is needed to improve the behavioural assumptions employed to derive the market shares of each technology, by also including additional country-specific information. A discrete choice modelling framework has been included in the model. Two remarks about this framework: (i) an important methodological maintained (i.e. non-testable) assumption in discrete choice modelling relates to the use of numerical utilities (i.e. cardinal utilities) (see (Hensher et al., 2005)). The application of this type of utilities in scientifically-sounded models is, however, not without controversy; and
(ii) for a discrete choice model such as the mixed logit to be estimated, the assumption that the error term is independent and identically Gumbel distributed (Hackbarth and Madlener, 2013) needs to be made a priori by the modeller. The adoption of particular types of probability distributions for decision-making under uncertainty is not without its conceptual problems (see Figure 8).

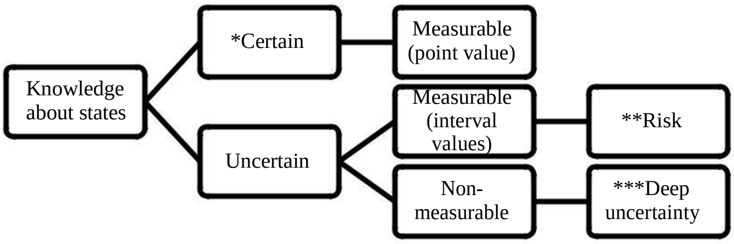

Figure 8 – A workable taxonomy of concepts related to uncertainty

*In collecting data for this model, different historical values of the *same* variable were reported by different sources of data. Thus we are forced to proceed further without certainty that the chosen historical value is the correct one. **If projected into the future, a maintained assumption of ergodicity is needed. ***Other terms commonly found in the literature to express this concept are: fundamental, Knightian, Keynesian, irreducible, radical uncertainty or, to some, even ambiguity.

The recent drastic decrease in crude oil prices came about as a surprise to many. As (Scheffer et al., 2012) note, in complex systems characterized by critical transitions or tipping points, surprises will continue to appear. It is unknown what the future crude oil price will be. What was clear from the oil shocks in the 1970s is that a homogeneous car-mix with only conventional technology is not very resilient. The response at that time was to improve efficiency, but there are technical limits to this. In addition to the emissions argument presented above, oil importing countries, such as those considered in this paper, have the possibility to reduce oil dependence by promoting diversification of the car-mix. Whether social interaction results in a tipping point, the moment of critical mass (Gladwell, 2006), that facilitates the market up-take of alternative car technology, and when this may happen, is a different story.

Finally, from a methodological perspective, it seems to us that there is an ongoing trend within the system dynamics community to encourage the application of analytical methods that may support the development of better SD models (see e.g. (Rahmandad et al., 2015)). The extent to which SD and econometrics can be successfully combined remains unclear. (Sterman, 2000) cautions about integrating an econometric formulation, mainly for mathematical reasons, within a SD model (p. 438). But he acknowledges that the use of econometric techniques, at least in the context of estimation of delay duration and distributions, may be helpful (p. 467). In principle, we see the possibility of enriching SD models with dynamic econometric techniques of the British tradition. This avenue of research needs, however, further exploration.

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APPENDIX

In line with suggestions made by (Bossel, 2007) and (Rahmandad and Sterman, 2012) on model transparency and reproducibility, this appendix is devoted to model documentation. Given space limitations, only the 'Model Assessment Results' using the SDM-Doc ((Martinez-Moyano, 2012); see also http://tools.systemdynamics.org/sdm-doc/) are shown in Figure 9 below. For those interested in the model code, which is available upon request, the usage of the SDM-Doc is recommended.

Model Information	Number
Total Number of Variables	472
Total Number of State Variables (Level+Smooth+Delay Variables)	26 (5.5%)
Total Number of Stocks (Stocks in Level+Smooth+Delay Variables) †	429 (90.9%)
Total Number of Macros	0
Variables with Source Information	121 (25.6%)
Variables with Dimensionless Units	102 (21.6%)
Variables without Predefined Min or Max Values	433 (91.7%)
Function Sensitivity Parameters	0
Data Lookup Tables	0
Time Unit	Year
Initial Time	2000
Final Time	2030
Reported Time Interval	1
Time Step	1
Model Is Fully Formulated	Yes
Modeler-Defined Groups	- **No** -
VPM File Available	- **No** -

Warnings	Number
Undocumented Equations	198 (41.9%)
Equations with Embedded Data (0 and 1 constants ignored)	14 (3%)
Equations With Unit Errors or Warnings	Unavailable
Variables Not in Any View	0
Incompletely Defined Subscripted Variables	0
Nonmonotonic Lookup Functions	0
Cascading (Chained) Lookup Functions	0
Non-Zero End Sloped Lookup Functions	0
Equations with "IF THEN ELSE" Functions	10 (2.1%)
Equations with "MIN" or "MAX" Functions	2 (0.4%)
Equations with "STEP", "PULSE", or Related Functions	0

Potential Omissions	Number
Unused Variables	17
Supplementary Variables	18
Supplementary Variables Being Used	3
Complex Variable Formulations (Richardson's Rule = 3)	15
Complex Stock Formulations	0

List of 18 Views and Their 478 Variables

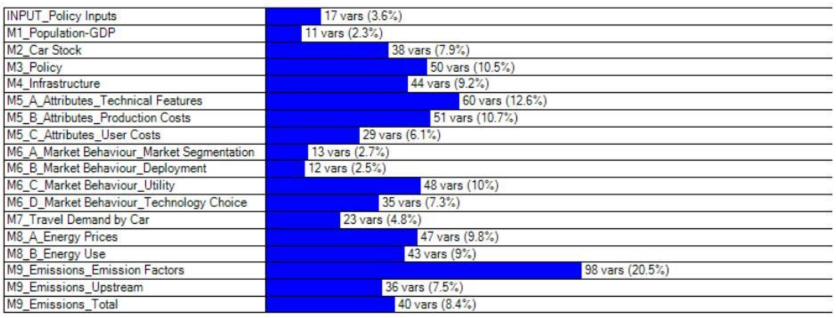

Figure 9 – Model Assessment Results
Source: Own Model Applying SDM-Doc