Biases and Forecast Efficiency in Corporate Finance

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List of Abbreviations

A&A	Anchoring and Adjustment
AP	Agricultural Products
ape	Absolute Percentage Error
BWM	Bandwidth Model
CoFiPot	Corporate Financial Portal
Cor	Correlation
DV	Diverse
EBIT	Earnings Before Interest and Taxes
EBITDA	Earnings Before Interest, Taxes, Depreciation, and Amortization
exp	Exponential Function
GDP	Gross Domestic Product
G7	Group of Seven
HP	Health and Pharmaceuticals
ID	Identification
II	Invoices Issued
IM	Industrial Materials
IR	Invoices Received
KPI	Key Performance Indicator
LBWM	Logistic Bandwidth Model
mape	Mean Absolute Percentage Error
mrse	Root Mean Squared Error
mse	Mean Squared Error
Obs	Observations
pe	Percentage Error
RQ	Research Question

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Part I

Foundations

Chapter 1

Introduction

This chapter introduces briefly the motivation behind forecast processes, forecast analyses, and forecast correction in the area of corporate financial controlling. Based on the general tasks of corporate financial controlling, important challenges of forecasting research are expounded on the basis of a series of research questions. The chapter concludes with the structure of the thesis.

1.1 Motivation

Multinational, diversified corporations typically generate forecasts for cash flow items on a regular basis (e.g., monthly or quarterly), at different organizational levels, in different currencies, and for different business divisions and countries. Often they implement revolving forecasting processes: at each forecast date, a set of revisions of previously generated forecasts and new forecasts is generated. Corporate financial controlling is responsible for providing accurate forecasts. Typically, this operating unit collects forecasts that stem from experts at local subsidiaries. That is because these experts are expected to have profound knowledge of their individual business developments in order to generate reliable forecasts from the knowledge, novel information and intuition they have. For this purpose, business units and subsidiaries send thousands of item-level forecasts and revisions in a decentralized fashion to corporate headquarters. These forecasts are consolidated, aggregated, and provide the basis for corporate-wide forecasting to perform tasks required in the finance department. These tasks cover, for instance, the determination of foreign-exchange risks resulting from foreign business activities, the consolidation of liquidity planning, and the generation of *key performance indicators* (KPIs), together with respective proactive managerial actions based on these expectations.

The pivotal role of cash flows of multinational firms received attention in several research papers stating the importance of cash flow forecasting in corporate finance (Kaplan and Ruback, 1995; Martin and Morgan, 1988; Kim et al., 1998; Graham and Harvey, 2001; DeFond and Hung, 2003). For instance, scientific researchers try to access the company's stock market value with cash flow forecasts (Kaplan and Ruback, 1995). Considering the importance of financing and for corporation's market value (Stulz, 1990; Almeida et al., 2004; Lim and Wang, 2007), surprisingly little research on cash flow forecast quality has been published so far.

This is particularly surprising since accuracy of forecasts is essential for organizational units, such as the financial planning department, and those business–related forecasts generally depend on lead time and also on individual and on organizational influences. For example, research from domains such as macroeconomics and sales indicate that individual forecast revision processes often exhibit statistically conspicuous systematic patterns, such as anchoring and adjustment (Lawrence et al., 2006), and that they are linked to lower forecast accuracy. That is why such influences with systematic patterns are designated as *(individual level) biases* (Hogarth and Makridakis, 1981). But, in addition, the forecast accuracy is most likely influenced by organizational prerequisites within the corporation. These preconditions, such as earnings management policies or personal objectives for financial incentives (Healy, 1985; Burgstahler and Dichev, 1997), can alter the forecasters' prediction and are consequently referred to as *organizational biases*. In contrast to the individual level biases, these organizational-level biases can exhibit systematic patterns in the distribution of a large group of forecasts, since the organizational biases set the forecasts of one process in dependence to the other forecast processes (see e.g. in Burgstahler and Dichev, 1997).

The diagnosis of such individual and organizational biases usually requires a large database of existing forecasting processes. If data of such forecasting processes are not available or if specific preconditions have to be met – for example, for the theoretical analysis of dependencies of different biases – scientific researchers commonly utilize synthetic data sets instead of real world data to evaluate statistical metrics (Bartz-Beielstein et al., 2010). Dana and Dawes (2004) conclude, for instance, that regressions should only be applied to data with at least 100 samples, which one could transfer to real forecasting processes. The analysis of synthetic data and the transfer of findings into the real world may require the transformation of individual level forecast processes to a function of aggregate level forecast processes. This applies in particular to the analysis of organizational biases that are assumed to exist on an higher level.

However, these synthetic data sets can only represent known patterns and biases, which means unknown dependencies of biases cannot be put into context. In order to detect new biases and dependencies at such high levels and to further relate them to the individual level, it is therefore necessary and inevitably to analyze large real world databases.

Detecting such human and organizational biases in cash flows provides means to improve business performance, especially as corporations rely on risk minimization methods, such as currency hedging for the conservation of future cash flow values (Stulz, 1996). As one of the consequences of inaccuracies in these cash flow forecasts, the inadequate hedging of foreign currency risks can lead to increased costs for hedging options or uncovered currency risks.

The statistically measurable patterns in forecasts and their accuracy are usually understood as implications from the theory of forecast efficiency. This theory states that in order to be efficient, all available information must be considered within a forecast. In general, efficient forecasts in the so-called "efficiency hypothesis" (Fama, 1970) are expected to be more accurate than inefficient forecasts, since efficient forecasts fully reflect the available information. If forecasts in this sense of the efficiency hypothesis are inefficient, the occurrence of statistical patterns (and biases) can be observed. For example, if a forecast is repeatedly revised upwards, a revision pattern is indicated. This means that the next forecast is predictable and due to the fact that this important information of the pattern is omitted during the forecast generation, the forecast process is inefficient. The consideration of such patterns, based on historical data, is referred to as "weak form efficiency" (Nordhaus, 1987) which posits that efficient revisions should describe a random walk.

However, inefficient forecasts with observable patterns can be fed back to individual forecasters or used to remove biases from forecasts with statistical tools to mitigate biases or its impact on planning and decision making (Givoly and Lakonishok, 1979; Timmermann and Granger, 2004). Furthermore, statistical means can help to correct the forecasts based on the history and current information. Correction means here that, compared to the previous forecast, a smaller deviation between new forecast and realization outcome. The requirement of optimally adjusting a correction based on the history and current information is challenging because often many influences have an effect on forecasts at the same time. The better understanding of the interplay between organizational prerequisites and forecasting processes can help to provide more reliable forecast correction.

The understanding of dependencies on forecasts is crucial for a reliable service of the finance department. But, to date, there has not been a comprehensive analysis of cash flow forecast revision patterns and how they relate to individual and organizational biases.

1.2 Research Outline

This thesis aims to analyze the links between biases and forecast efficiency as well as predictive purposes. These links are considered on the basis of empirical analyses and forecasting techniques as well as organizational understanding. The research objects have been considered because they are found in many forecasting cases and are known to matter in business' organizations, and can create perspectives to improve forecast reliability and forecast correction techniques in the future. To establish these links, I choose an empirical approach that examines a large real world database. This data stems from the financial controlling department of a corporation in the biochemical industry. The records of the data provide the corresponding basic features for a long period of time, e.g. forecasts for realization volumes, and are stored at a highly differentiated level, for example per company and currency. Gaining access to a large comprehensive data set and preprocessing and understanding of the data is a matter of years rather than months, as data and inherent structures often change over time with the company (Davenport and Short, 2003). This might explain the lack of published empirical studies on internal cash flow forecasting in corporate settings.

The analysis of large amounts of data almost forces the statistical consideration of dependencies. Referring to the efficiency theory for markets (Fama, 1970), the concept of "weak form efficiency" has been developed for forecast processes. This term describes whether the errors of the forecast with revisions and the revisions among each other are statistically independent, i.e. whether with the knowledge about a set of revisions, the dependence on future revisions or even the error is ascertainable. Assuming that new information is integrated into forecasts at some point in time to improve forecasts, such shorter forecast horizons would result in decreased forecast errors. If not, this would suggest structures that exhibit inefficiency. From this, in application to the corporation's forecasts, the following *research question* (RQ) arises:

RQ 1. **Forecast Efficiency — Revision Process**
Are revisions of cash flow forecasts weak form efficient in a multinational corporation?

RQ 1.A *If forecasts are not weak efficient, which forecast patterns are detectable?*

RQ 1.B *To what extent does the reduction of lead time reduce the forecast error?*

The efficiency hypothesis, understood as the theory of efficient markets, states that if forecasts contain all available information, they will not reveal any trading opportunities. In other words, in case of forecast processes, the forecast errors must solely depend on the forecasts that were produced with the available information, which also means that the forecast accuracy solely depends on the information being integrated into the forecasts. The accuracy may have low or even zero dependency on integrated information that is unimportant. However, integrated important information must have positive dependency on the accuracy, because otherwise omitting this information would give rise to trading opportunities and violating the efficiency hypothesis.

On this basis, this thesis raises the question of whether the efficiency hypothesis is valid in the case of corporate internal forecasts. Are there any influences (i.e., earnings management) that affect or even violate the efficiency hypothesis? A violation of the efficiency hypothesis would mean that inefficiencies, e.g. omitting important information during the forecasting process, are beneficial. One would then expect inefficient forecasts to be associated with higher accuracy, which leads to the research questions:

RQ 2. **Forecast Efficiency — Efficiency Hypothesis**
Is the forecast efficiency hypothesis valid in the data of corporate financial controlling?

RQ 2.A *Do forecast processes exist that entail or even violate the efficiency theorem, resulting in inefficient forecasts that are positively associated with forecast accuracy?*

RQ 2.B *Given that influences can entail or even violate the efficiency hypothesis, can the efficiency hypothesis help to provide a explaining framework to associate the violations to such influences?*

The weak forecast efficiency raises the question about a detailed discussion of the influencing reasons. Studies suggest that patterns such as dependencies between revisions hint at individual cognitive biases such as anchoring and adjustment (A&A) heuristics, which can be summarized as the focus of forecasts by means of one or more reference points. These individual biases are commonly associated with lower forecast accuracy, but the detection of such characteristics is challenging. Inadequate detection approaches may deny the A&A pattern, although A&A is existent. This questions how the metrics of A&A approaches can be improved to provide explanatory power for forecast correction, and how the underlying statistical dimensions of time, volume and direction of adaptation interact. Providing evidences for detection in forecast processes addresses the third set of research questions.

RQ 3. **Revision Process — Anchoring & Adjustment**
Is corporate internal forecasting entailed by Anchoring & Adjustment?

RQ 3.A **Revision Process — Identifying Metric**
Do distinct Anchoring & Adjustment patterns exist and which metric can improve identification?

RQ 3.B **Revision Process — Forecast Correction**
To what extent can Anchoring & Adjustment metrics improve judgmental forecast prediction?

RQ 3.C **Revision Process — Concentration Measures**
Is the error of the forecast data related to descriptive metrics for temporal adjustments, revision pattern, and direction?

In corporate finance planning, operative business is highly time-dependent. Business years usually start in January and end in December. Within these limits, it is usually necessary for the various organizational units to fulfill their tasks, to consolidate results, and to pass them on to responsible authorities – for instance, annual financial statements or hedging against monthly currency risks. A consistent conclusion would be that organizational influences and targets somehow partially predefine the forecasts of the organizations. For instance, earnings management could be used to achieve targets of annual returns. While single focused data-driven assessment might be even misleading in the case of individual level forecasts, organizational objectives on the aggregate level may be the key to providing explanatory information for potentially ambiguous results (in efficiency analysis). This motivates the following set of questions for my research:

RQ 4. **Revision Process — Organizational Influence**
Does aggregate level revisioning behavior of experts that produce forecasts for corporate finance depend on organizational influences?

RQ 4.A *Does the revisioning behavior of experts differ over the annual cycle?*

RQ 4.B *Can annual return targets explain the revisioning behavior of experts?*

RQ 4.C *Do organizational influences exist that mask or distort the revisioning behavior of experts?*

RQ 4.D *Is the aggregate level revision process different from the individual level revision process of experts, stated in terms of weak forecast efficiency?*

When various influences on the forecasts have been identified, the general question arises as to whether and to what degree this knowledge is usable. Especially when considering that organizational business information could increase the explanatory power, they should not be left unattended for correction approaches on the aggregate level. Very rarely, statistical dependencies and organizational biases receive attention at the same time. This results in a research gap for the correction of cognitive–statistical biases (*statistical debiasing*) and organizational biases (*organizational debiasing*), so that further research on the impact and comparability of statistical and organizational debiasing approaches are necessary. This results in the following research question:

RQ 5. **Organizational Influence — Forecast Correction**
Do organizational influences provide predictive value and are they beneficially usable in aggregate level forecast correction to remove forecast biases?

Although corrections usually only serve the purpose of error minimization, an assessment should be made based on the aforementioned efficiency concept. Only when the efficiency of the prediction is improved by a correction, meaning that there are fewer statistical dependencies in the predictions after the correction procedure, a correction can be considered "successful" and meaningful in terms of removing biases. For this purpose, the efficiency concept should be extended in order to enable a detailed comparison of the meaningfulness and differences of several correction methods. This thesis addresses this gap in research with the following research questions:

RQ 6. **Forecast Correction — Forecast Efficiency**
Does the correction of forecasts to remove biases influence the aggregate level forecast efficiency?

RQ 6.A *To what extent does the correction of forecasts influence the temporal pattern of revisions, stated in terms of weak forecast efficiency?*

RQ 6.B *Exist additional temporal patterns in revisions that explain the type of forecast correction, expressed in an extension of weak forecast efficiency?*

In addition to the identification of correction potentials (RQ 1.), efficiency can thus be interpreted as an evaluation criterion for the validity and meaningfulness of the correction (RQ 6.). Based on this evaluation criterion, it will be possible to compare the correction approaches in a consistent manner using efficiency theory. At this point the circle of research questions is completed (with RQ 1., RQ 4., RQ 5., and RQ 6.), while certain topics (in RQ. 2, RQ. 3) address important research questions. The full list of research questions and results can be found in Appendix A.

Parts of the work at hand and the research results presented therein are based on existing publications and working papers. The results have been published at international conferences with research presentations held at the *OR (2014, 2016, 2017)* conferences, the articles (Knöll et al., 2016; Knöll and Simko, 2017; Knöll et al., 2018; Knöll and Roßbach, 2018a,b) which has been presented at the *MKWI Conference 2016*, *ITAT Conference 2017*, *HICSS Conference 2018* and *MKWI Conference 2018*. Further, the results base on the working papers (Knöll, 2018; Knöll and Huber, 2018; Knöll and Shapoval, 2018; Knöll et al., 2018).

1.3 Structure of the Thesis

The remainder of this thesis is organized as follows. In the following chapters of Part I (Foundations), basic information and biases on cash flow forecasts is provided for the forecasting in corporate finance. Chapter 2 provides information for the forecast processes that enable the calculation of revisions. This chapter also introduces the efficiency concept that will be used throughout the thesis, which is based on the related work on forecasting processes and finance theory. Furthermore, an overview is given of the academic literature on possible cognitive–behavioral and organizational influences.

Part II (Business Characteristics Extraction) provides notations and develops the research models for the thesis. Chapter 3 introduces the notations, followed by the research model to identify cognitive–behavioral biases that are detectable in individual level forecasts. Chapter 4 describes the research model to identify possibly existing organizational biases at aggregate level forecasts. Based on the organizational biases, several models are described to analyze the different effects of organizational influences. Moreover, the research model for analyzing the predictive value of the described models is shown in Chapter 5.

Part III (Application in Practice and Empirical Evaluation) provides details on the empirical data used in this thesis (Chapter 6) and the cash flow forecasting processes of a multinational sample corporation, together with an examination of the defined research questions. The examination of the forecasting processes covers the analyses from Part II for individual level characteristics (Chapter 7), aggregate business characteristics (Chapter 8), and evaluation of the predictive value (Chapter 9). The analyses of these last three chapters each are followed by an interpretation of the results.

Part IV (Finale) summarizes the interpretations of the empirical results to conclusions and discusses implications and potential future approaches to rethink organizational structures, biases, and future research topics. Figure 1.1 represents the overall structure of this dissertation.

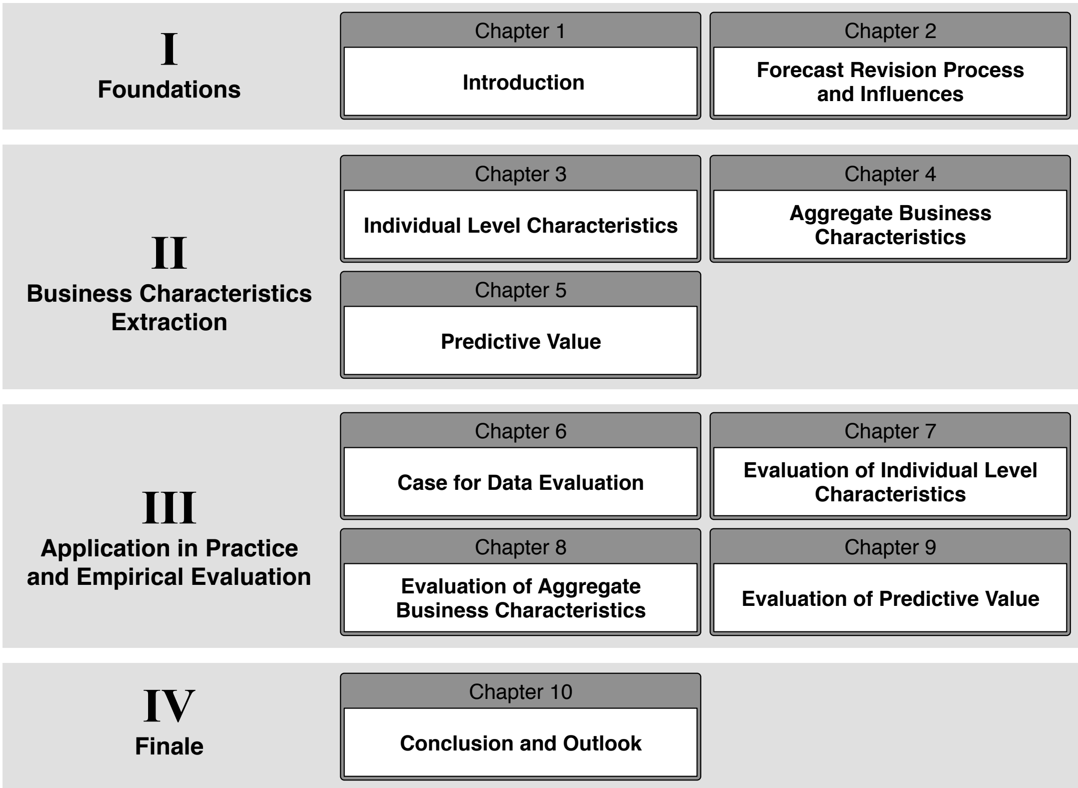

Figure 1.1: The thesis is structured into four parts. The first part provides an introduction and motivation to the thesis and introduces important foundations on related work. The second part focuses on analyzing individual and aggregate forecast characteristics, as well as model based improvement of judgmental and statistical forecasts, which are then applied and evaluated in the third part. The final part concludes, gives implications, and an outlook of future work.

Chapter 2

Forecast Revision Processes and Influences

2.1 Forecast and Revision Process

Globally operating enterprises that strongly depend on the quality of the finance department's forecasts, as they provide the data base for their decisions in management activities, typically store such forecasts in a financial information system. To improve these financial forecasts these fixed events such as accounted cash flow realizations (henceforth "actuals") are usually not forecasted only once, but the initial submitted forecasts are then adjusted and revised over time before the actual cash flow's realization date to reflect novel information and changed expectation. Therefore, based on that information the accuracy of revised forecasts is typically significantly higher than for unrevised ones (Lim and O'Connor, 1996). The sequence of an initial forecast and the revised forecasts is referred to as *forecasting process*, while the sequence of revisions is usually referred to as *revisioning process* or simply *revisioning*.

As noted before, the revision of forecasts can change the forecast quality over time. As a consequence, forecasting processes are analyzed and measurement of forecast processes uses some error measures to describe the quality of these forecasts. These measures provide information about the forecasts and their revisions to specify in terms of forecast accuracy how good the forecast is at a specific time.

However, the feature engineering of such metrics, and i.e., their aggregation, selection, and representation requires a solid understanding and modeling of business and organizational structures, which generally received scant attention in the literature so far (Gordon and Miller, 1976; Fildes et al., 2006; Han et al., 2011). Once the accuracy of forecasts can be characterized by such metrics, measures can be taken to describe efficiency and improve accuracy.

2.2 Forecast Efficiency

Forecast processes often lead to observable patterns and one research branch to analyze the systematic behavior is the *efficiency theory*. As an example for efficiency theory, let me refer to the seminal paper of Fama (1970) on market price expectations. This theory suggests forecasting processes that consider all information available when a forecast is generated or revised should not exhibit internal structures or dependencies.

Several streams investigate forecast efficiency, but decades ago Working (1934) has already shown for artificial random number series that random walks are partly not that common, and correlations can occur. Moreover, one of the most widely used adaptions of efficiency on forecasting processes has been proposed by Nordhaus (1987), who promoted the concepts of strong form and weak form efficiency. Forecasts are termed strong form efficient when they take all relevant information available at the time the forecast is generated into account. Due to the practical limitations of testing strong form efficiency, weak form efficiency is usually tested instead.

Weak form efficiency relaxes strong efficiency by declaring that forecasts efficiently incorporate information about past forecasts only – rather than all relevant available information. The tests of Nordhaus (1987) requires for weak form efficient forecast processes solely that forecast revisions and errors show no correlation with past revisions. Therefore, the revisions should describe a random walk with zero correlation among revisions or between revision and error. The intuition from a statistical perspective is that, otherwise, existing correlation structures hint that not all available information is incorporated into revisions. This would suggest that information (about correlation) could be incorporated into revisions and revisions (and errors) could be anticipated to some extent from past data.

The tests outlined in Nordhaus (1987) are very popular and particularly useful for evaluating forecasts because they involve observable phenomena, namely forecast errors and forecast revisions. Hence, the theory of weak forecast efficiency has been applied frequently, especially in the macroeconomic domain (e.g., Clements, 1995; Ashiya, 2006; Clements et al., 2007; Dovern and Weisser, 2011; Deschamps and Ioannidis, 2013). Many empirical and experimental studies find forecasts in datasets to be inefficient, i.e. reject the hypothesis of zero correlation between current revision and error, and previous revisions. Isiklar et al. (2006) provide evidence on the inefficiency of real gross domestic product (GDP) growth forecasts for 10 countries. They have found high serial correlations between forecast revisions. Inefficiencies in forecasting processes have been also reported in empirical and experimental studies (e.g., Bessler and Brandt, 1992; Lawrence and O'Connor, 2000; Ashiya, 2003), and inefficiencies have generally been associated with lower accuracy.

Dovern and Weisser (2011) analyze forecasts for four different macroeconomic variables for the G7 countries, concluding that revisions of all variables exhibit inefficiencies and that a sizable fraction of forecasters seem to smooth their GDP forecasts significantly. Similarly, Deschamps and Ioannidis (2013) find evidence for inefficient revisions and smoothing of GDP forecasts. They also note that forecasters underreact more when large forecast revisions are indicative of low forecast ability and they use this finding to explain smoothing of GDP forecasts as a result of forecasters aiming to increase their perceived ability. Another explanation for smoothing is put forward by Clements et al. (2007), who analyze the Federal Reserve Greenbook forecasts of real GDP, inflation, and unemployment for the period 1974-1997 and find weak-form forecast inefficiency and systematic bias in all revisions. The authors suggest that forecast smoothing indicates the existence of anchoring and adjustment heuristics, which in their study explain inefficiencies in inflation forecasts very well.

Further, the study of Timmermann and Granger (2004) outlines for efficient markets that a model which exploit trading opportunities (and remove biases) will lead to markets where the bias is unlikely to persist afterwards. This might be reasonable as non–random walks are expected to lead to higher error levels for reasons of statistical insufficiency due to individual cognitive biases.

2.3 Forecast Correction

The improvement of insufficient forecasts accuracy is typically considered as forecast correction. In many fields, forecast accuracy is an important topic for success, and several examples show that the use of forecasts can have beneficial effects on corporations but is challenging as well. For instance, inappropriate forecasts can have negative effects, leading to the formations of financial bubbles (Frankel and Froot, 1991) or high losses due to wrong demand assumptions (Berinato, 2001). The difficulty of having inaccurate forecasts can motivate forecast correction that can be applied rigorously for analytical purposes. Goodwin (1996) examined the use of forecast correction methods on sales forecast and found that costs could have been reduced by 46 %. The authors of Syntetos et al. (2009) show that judgmental adjusted forecasts of demand can improve stock control performance.

Improving biased forecasts is possible with forecast correction techniques that analyze and change the human prediction with statistical models (Han et al., 2011; James et al., 2013). When forecasts are corrected, the combination of judgmental forecasts that base on contextual knowledge, rather than statistical knowledge, can be beneficial (Sanders and Ritzman, 1995). Therefore, correction of forecasts in risk management based on insights into biases has a high potential to improve the performance of accounting departments in corporations.

Generally, the approaches used for forecast correction employ purely statistical approaches to identify patterns in the forecasting processes, but do not include important business dependencies like organizational prerequisites. More often, they utilize more general information such as seasonality of forecast processes. For instance, the paper of Mendoza and de Alba (2006) analyzed short time series within the year and used a Bayesian method to account for sub-seasonal information with a seasonal–based correction. In contrast to their setting, some corporation's forecast series are even shorter (e.g., five reference points instead of twelve) and (Knöll and Shapoval, 2018) applied linear regression models (instead of Bayesian models) that account for one single information that focuses on the use of a margin target at the end of year (instead of the entire sub-annual pattern).

This approach is comprehensible, as the authors of (Brighton and Gigerenzer, 2015) promote. In marketing and finance simple models sometimes predict more accurately than complex models. The authors argue that "the benefits of simplicity are often overlooked because the importance of the bias component of prediction error is inflated, and the variance component of prediction error (based on oversensitivity to different samples) is neglected". Regarding seasonality, Yelland (2006) concludes that a simple stable seasonal pattern model can perform surprisingly well, given that they are "theory-free" descriptions of booking processes. His findings are in resonance to the theme that simple empirically-based models perform frequently better than complex ones.

2.4 Individual Influences

In the search for possible causes for these inefficiencies and correction potentials, a number of studies have suggested that violations of Nordhaus's efficiency test can be explained by individual influences. Cognitive reasons, behavioristic factors, and a multitude of further boundary conditions and other reasons may have an biasing influence (*bias*) on how humans make their forecasts.

Research from various domains suggests that individual cognitive biases, such as anchoring and adjustment, cause these inefficiencies. Such biases translate to observable patterns and often lead to reduced forecast accuracy (see, among others, Bromiley 1987 and Easterwood and Nutt 1999). Hence, individual biases could explain why the accuracy of forecasts violating weak form efficiency is supposed to be lower. However, most of today's forecasting processes are the result of human judgment (Sanders and Manrodt, 2003). The latter is often prone to individual biases and studies suggest that latent human influences must not be underrated, as they affect corporations' forecasting and planning in many ways (Hogarth and Makridakis, 1981). Several studies provide evidence of the behavioral aspects that play a significant role in judgmental forecasting.

Lawrence et al. (2006) provides a comprehensive literature research to the subject of how humans adjust forecasts based on cognitive and behavioral biases, while further studies in Leitner and Leopold-Wildburger (2011, pp. 465–466) suggest that these biases can lead to important information being ignored and result in increased forecasts errors.

2.4.1 Anchoring and Adjustment

The question of how individuals are influenced through cognitive biases has received scant attention in the research community. One of these cognitive biases is the anchoring and adjustment effect, which is described in Tversky and Kahneman (1975). Anchoring and adjustment (A&A) denotes the phenomenon of already occurred values influencing humans in determining new ones, like in negotiations or forecast processes. The publication of Tversky and Kahneman (1975) is followed by studies of anchoring and adjustment in different fields, like task motivation (Switzer and Sniezek, 1991), consumers' purchasing decisions (Wansink et al., 1998), or in the financial market (Haigh and List, 2005).

Northcraft and Neale (1987) let amateurs estimate the value of houses with an given anchor value. The results indicate that at least 17 % of the variance can be explained through the anchor value. In the research of Jacowitz and Kahneman (1995) students are asked to estimate different values like the height of the Mount Everest. The estimation of the students was in average 40 % closer to a presented anchor value in comparison to the benchmark groups.

A&A transferred to time series implies that forecasters can use their past forecasts as numerical anchors, which can results in under-adjustment of revisions, i.e., not revising forecasts sufficiently to reflect new information. There exist several studies showing that human experts in financial forecast processes are influenced by anchoring and adjustment effects (Dalrymple, 1987; Mentzer and Cox, 1984; Phillips, 1984). This line of argument is followed by a number of empirical and experimental studies (e.g., Lawrence and Makridakis, 1989; Lawrence and O'Connor, 1993). Lawrence and O'Connor (1993) for instance, analyzed the anchoring by cognitive framing in a experimental study for time series forecasting. Their result implies that scale and variability influencing the prediction intervals of human forecasters.

In one of the earliest studies, Bromiley (1987) examined the relationships among potential anchors, forecasts, and actuals, suggesting that anchoring effects are present when the mean difference from forecast to anchor is smaller than the mean difference from forecast to actual. His result indicates the presence of anchors in steel-mill data sets. In a more recent study of Meub and Proeger (2016), the authors investigate the relationship between anchoring and accuracy experimentally. Their study finds that the share of weak form efficient forecasts dropped significantly in the anchor's presence, and inefficient forecasts were less accurate.

However, in the field of forecast processes, the detection of anchoring and adjustment effects offers the chance to improve forecast accuracy by means of removing distortions through A&A effects. To remove these distortion one must first identify existing anchoring and adjustment, and for many biases, there is the possibility of proving their existence and influence by means of tests. The analyses of several authors use forecasts and their revisions to identify anchoring and adjustment, also in relation to the forecast error in short forecast series (Bromiley, 1987; Harvey et al., 1994; Lawrence and O'Connor, 1992; Amir and Ganzach, 1998). These models can indicate the probability of A&A influencing specific forecast series.

The paper of Knöll and Roßbach (2018b) relates these usually applied anchoring and adjustment models to several error metrics and analyzes the performance to identify anchoring and adjustment patterns of those models in comparison to the performance of two new models in synthetic forecast processes. These two new models do outperform all the state of the art models and the paper shows that depending on the time series characteristics the previous models were not able to identify some A&A patterns correctly. The models for A&A patterns relate to specific error metrics, which suggests that the model's performance to identify these biases will anticipate forecast errors.

Additionally, in the paper of Knöll and Roßbach (2018a) two models were applied in a case of cash flow forecasts, stating that in real world forecast processes the "Logarithmic Bandwidth Model" and "Empirical Bandwidth Model" can be used to account for the reliability of forecasts in terms of forecast accuracy.

2.4.2 Optimism, Pessimism and Overreaction, Underreaction

Distinction of individual influences was suggested by Amir and Ganzach (1998), which examined the effect of three heuristics (representativeness, anchoring and adjustment, leniency) on forecasting processes. They derive the revision patterns "overreaction / underreaction" and "optimism / pessimism" as observable indicators for biased forecasting and develop tests for each of these four patterns. Their results indicate that overreaction and underreaction operate concurrently with optimism and pessimism, depending on whether revisions are positive or negative. They found less overreaction for negative than for positive revisions. Underreaction to negative information tended to be stronger than overreaction to positive information.

Easterwood and Nutt (1999) and Abarbanell and Lehavy (2003) provide further research analyses for overreaction and underreaction. Easterwood and Nutt (1999) inspected analysts' earnings forecasts with the result that analysts underreact to negative information, but overreact to positive information. Further, Abarbanell and Lehavy (2003) identify an empirical link between firms' recognition of unexpected accruals and the presence of the two asymmetries in the distributions of forecast errors. They suggest that incentive and behavioral theories should be inspected (and are not sufficiently developed) to build dependencies between optimistic, pessimistic behavior and forecast errors.

2.4.3 Revision Concentration

The accuracy of individual forecasts usually increases with decreasing lead time, as forecasts are adjusted to reflect new information and changes in expectations (McNees, 1975; Mathews and Diamantopoulous, 1990; McNees, 1990; Lim and O'Connor, 1995; Nikolopoulos et al., 2005). However, it has been found that the extent of the improvements is often related to the way forecasts are revised. For instance, Fildes et al. (2009) state that the size of forecast adjustment relates to forecast accuracy.

Further investigation of this subject is provided by the paper of Knöll et al. (2016) that analyzes how revisions relate to forecast accuracy and how patterns in revision processes can be quantified and leveraged to reduce prediction errors in forecasts of foreign exchange exposure. The authors suggest novel metrics to determine patterns in revision processes related to the concentration of revision volume. The paper shows that these measures have higher explanatory power with regard to how forecast error is related to timing and magnitude of cash flow forecast revisions than previously used measures, which rely on correlations among revisions and error. The results suggest that accounting for these patterns (point in time, volume, and direction) improve the accuracy of foreign exchange exposure forecasts. Especially, their results indicate that early revision adjustments in forecast processes lead to higher accuracy, except for one time adjustments of revision that are beneficial in the late stage of the forecast process. Overall, the paper states that timing, magnitude and trend in revision processes are playing an important role in case of over- and underestimation.

2.5 Organizational Influences

Besides individual influences organizational structures and prerequisites can exist (in a corporation or a subsidiary), which can define a framework (for each forecaster with e.g., planned targets) that affect realizations as well as forecasts, their adjustments and introduce "*organizational biases*".

At this point, the extent to which the organization's objectives have an overriding influence on the experts' forecasts must be examined. Such objectives can represent the awareness of activities (e.g., accountant's earnings management or personal financial incentives), or annual targets (e.g., percentage return targets). For instance, the sources of information for forecasters inside subsidiaries are often heterogeneous, providing differing perspectives on the internal state of a subsidiary. Fildes and Hastings (1994) discuss that insufficient information flows can result in organizational biases. Further, the experiments presented in Leitner and Leopold-Wildburger (2011) reveal that several sources of information change the way in which forecasters adjust.

Therefore, a challenge and an important goal is the distribution of relevant information. The literature shows some limitations for the implementation of this goal. The aforementioned earnings operations and planning activities might result in information asymmetry for the subsidiaries' forecasters, implying difficulty in providing the accurate prediction to the corporation. In addition, organizational biases can result in subsidiaries trying to hide bad information as shown for earnings forecasts in Penman (1980). This paper indicates that beyond the prior years' earnings further information is available in corporate earnings forecasts.

Typically, there is a need for a well-aligned management of planning, forecasting and operations in corporations to align the risk management to current and future business developments. The amount of work involved in planning, forecasting and operations often implies the separation of tasks between several managers, who might have access a different internal perspective from the subsidiary for the financial information that the corporation requires. Based on the communication within the subsidiary, a forecaster might not be aware of the preconditions of the managers in planning and operations (Fildes and Hastings, 1994).

Additionally, when organizational prerequisites motivates one manager (e.g., incentivization payment for managers in planning or operations), but not the other ones (e.g., the forecaster), the subsidiaries view might be organizationally biased by provided targets. These biases can result from the concealment of information – when managers with the different tasks do not have access to the same information (McCarthy et al., 2006).

These organizational biases, organizational structures, and incentives can introduce further biases if the aforementioned are imperfectly aligned with personal goals (Healy, 1985; Abarbanell and Lehavy, 2003; Schweitzer et al., 2004; Noval, 2016; Kim and Schroeder, 1990). Such organizational biases may affect forecast accuracy in addition to individual biases.

Furthermore, organizational structures that affect forecast accuracy can be expected to dominate and aggravate the diagnosis of individual forecast bias. That is because, e.g., cash flow actuals are uniquely controllable by the organization and cash flow-related targets are eminently important for external assessments of the organization (e.g., by shareholders and investors) as well as for managerial incentives.

Such important organizational biases are expected to influence the experts' revision behavior, and, therefore forecast adjustments are entangled by business key figures that are measured with KPIs. Some important KPIs can be found in Marr (2012). As of the importance of these KPIs, when reaching planned KPI thresholds is incentivized, it is reasonable to assume that human business operations is entangled by those KPIs. Even more, the specific KPI thresholds itself might provide an organizational bias that influences operations and forecasts (Daniel et al., 2008). The importance of such indicators can be seen in Dechow (1994), where the author associates the companies' performance measured in stock returns with realized cash flows, while the association depends on the magnitude of aggregated accruals.

In other words, operational business probably limits the predictability of cash flows with activities such as earnings management and managerial planning incentivization. However, interlinking organizational structures and personal incentives to corporate goals might be especially prone when the subsidiaries are independent of the holding corporation. If corporations are unaware of these dependencies that affect the forecasts, inaccurate risk management may result. This might require additional effort and costs (John, 1993), at the latest when forecasts are hedged.

While researchers mostly are aware of the challenges, there is practically no research available that empirically analyzes corporate internal forecasts in relation to the diverse managerial aspects (and biases) of planning, operations, and forecasting. As internal corporation data are difficult to acquire, this would explain, why there has not been any comprehensive analysis of corporate cash flow forecasts and of how their revisions relate to these organizational biases to date. Thus, corporate financial departments have little guidance on how to assess the quality of their heterogeneous forecasts and how to reduce dependencies in order to improve forecasting processes.

2.5.1 Earnings Management

In the case of business forecasts, an organizational bias might be introduced by earnings being managed (by shifting actuals) to ensure that KPIs and planned annual targets are met. A good overview in reference to the actors, the reasons, and the implications of earnings management can be found in Dechow et al. (2010). For instance, an interesting example is given in Petrovits (2006), where the author associates the topic of corporate philanthropy programs with earnings management. However, in cases where annual return is expected to be too low, accountant's earnings management may result in shifts of cash outflow realizations – within the term of credit – forward to the next fiscal year to meet the appointed targets, limiting the predictability of cash flows based on operational business developments. Such tendencies can be found in (Burgstahler and Eames, 2006; Degeorge et al., 1999), where the authors expect cash flow management is the result of operations made to ensure meeting specified targets in organizations.

When humans try to achieve personal objectives (e.g., bonus payments by financial incentives) of predefined targets that rely on KPI figures, such as *Earnings Before Interest and Taxes* (EBIT), those can motivate to alter forecasts and their adjustments to maximize the personal profit (Guidry et al., 1999). Therefore, this thesis argues that the incentives for earnings management as a personal objective introduces an organizational bias.

The looming failure to meet earnings targets (which might reduce manager's bonus payments) provides a strong incentive to hold back payments of invoices received within the terms of credit. Alternatively, managers can trigger invoices issued earlier or might change payment terms in order to align annual cash results with targets. Conversely, the opportunity that earnings targets will be met ahead of time or have already been met provides an incentive to postpone the issuing of invoices until the next year in order to increase the likelihood of achieving next year's targets. When the volumes are shifted the forecast errors can be expected to exhibit a systematic bias.

The earnings management of cash flow volumes are influenced by the considerations and motivations of various business functions; in particular, actuals are often shifted according to earnings management policies (Burgstahler and Dichev, 1997), earnings management in dependence of the fiscal year (Jacob and Jorgensen, 2007), and management incentives (Holthausen et al., 1995). Such shifting of actuals can practically lead to smoothing, which is why cash flow accounting can even impair the market valuation of company growth (Ball and Watts, 1972), and hints to unawareness of underlying dependencies.

However, when forecasters are unaware of how earnings management is affecting actuals, their forecast errors may be less attributable to individual biases than individual level analysis suggests and originally unbiased forecasts can look biased and vice versa. However, when cash flow forecasting, planning, and (operational) accounting are interlinked to some extent, pursuing annual return targets can systematically influence both actual and forecast adjustments. I.e., if forecasters are aware of earnings management targets and activities, this awareness may determine how actuals as well as forecasts will be adjusted over time, in which case the presence of non-random revision patterns may be associated with improved forecast accuracy. As a consequence, an organizational bias can substantially distort diagnosis of individual biases and make isolated analysis of individual bias and its relation to accuracy ambiguous and even misleading, as the paper Knöll et al. (2018) shows.

2.5.2 Earnings Target

Company targets and organizational prerequisites can alter the forecaster's opinion on the future outcome. Studies in business analytics suggest that detectable forecasting patterns occur, if these organizational biases are present.

For instance, subsidiaries can tend to align figures according to corporate planning (Kudla, 1976). The subsidiaries' operating managers try to reach planning figures, as most subsidiaries provide incentivization on a financial level (e.g., bonus payments). In particular, it has been found that meeting firm's earnings targets and human incentives is important enough to organizationally bias management activities. The results in (Daniel et al., 2008) indicate that organizational structures of firms entail the managers' earnings management and can indicate cuts in dividend payments, since managers regard dividend levels as thresholds.

Another organizational bias is the profitability of a company. For instance, the target of companies to avoid annual losses can be reflected in various measures. Roychowdhury (2006)'s paper shows evidence that managers manipulate real activities to avoid annual losses in companies. The author examines the real world activities of companies, such as price discounts to temporarily increase sales, overproduction to report lower cost of goods sold, and reduction of discretionary expenditures to improve reported margins. The analyses revealed that these manipulations depend on influences such as the presence of sophisticated investors or the stock of inventories and receivables.

Avoidance of losses is an important baseline, but in addition to this specific target, one of the primary KPI for corporate performance is the *Earnings Before Interest, Taxes, Depreciation, and Amortization* (EBITDA) (Marr, 2012), which is important for this thesis as it is one of the primary proxies for a company's current operating profitability.

Empirical analyses of judgmental cash flow forecasts over many companies in a business corporation support the hypothesis that forecasting the realizations of cash flow figures is subject to an organizational bias introduced by percentage return margins. In Knöll et al. (2018) subsidiary's forecasts made by human individuals are reported to be biased by organizational targets. Concealment of information goes along with this bias, alters forecast revisions, and has a substantial impact on the forecasting process (Knöll, 2018). Furthermore, the author shows that sometimes a bias does not only distort forecast revisions, but – depending on the importance level of the bias – the forecasters' bias becomes their goal of forecasting. This organizational bias changes the forecasting process with the goal of producing accurate forecasts into forecasting of the bias.

Therefore, incorporation of the findings into future organizational arrangements, organizational understanding, and accounting information systems is necessary. With KPIs being measurable, or at least with proxies assessable, the information of possible detectable biases can be used to be integrated into forecast correction to entail highly accurate forecasts (Knöll and Shapoval, 2018). In this paper they utilized a proxy for EBITDA margin target figures for a corrective model that reduces the human forecast error by up to 60 % for all forecasts of a month. Finally, the authors of Knöll and Simko (2017) show that forecasts correction methods can use organizational information to improve forecasts efficiency. Particularly, statistical information on revisions in combination with information on organizational biases (percentage return targets) are indeed beneficial for the correction of weak forecast efficiency in whole forecast processes.

Part II

Business Characteristics Extraction

Chapter 3

Individual Level Characteristics

This chapter introduces the notation used in this thesis, along with the analyses for the concepts of "forecast efficiency", "anchoring and adjustment", "optimism, pessimism and overreaction, underreaction", and "revision concentration".

The notation presented in this section is commonly used in current literature on Nordhaus (1987). Denoting the *actual* (realization) of cash flow item i as $A(i)$, the *lead time* t of a *forecast* ${}_tF(i)$ for $A(i)$ refers to the number of revision periods (i.e., in terms of a quarter of the year) until the actual date ($t = 0$). For instance, with an initial forecast at $t = 5$ the earliest forecast ${}_5F(i)$ is delivered with a lead time of five periods and is revised four times until the last one–period–ahead forecast ${}_1F(i)$ is generated. The notation ${}_te(i)$ refers to the forecast *error* of ${}_tF(i)$, computed as ${}_tF(i) - A(i)$. Figure 3.1 visualizes the temporal structure of a forecasting process in five steps for an actual $A(i)$.

Subscripts m, y, and s denote the realization month, realization year, and the ID of the corresponding subsidiary of the actual, respectively. Superscript g denotes the type of the actual ($g \in \{\text{invoice issued (II), invoice received (IR)}\}$) and superscript c denotes the standardized three letter currency code (USD, EUR, etc.)[1]. Therefore, the maximum indexing for an actual is $A^{g,c}_{s,y,m}(i)$. If certain information of an index is irrelevant or obvious in the context, the respective index is omitted for reasons of brevity. Hence, $A_{s=12}$ refers to the set of all cash flow realizations of legal entity 12, and ${}_1F_{s=12}$ to the set of all one-period ahead forecasts (lead time $t = 1$) of this entity.

To assess the accuracy of a group of forecasts (e.g., the long-term forecasts of a particular subsidiary), usually researchers calculate mean error as the sum of all individual errors divided by the number of forecasts (Armstrong and Collopy, 1992; Shugan and Mitra, 2009). Error-differences in groups, however, are difficult to interpret when item volumes vary substantially within the groups of forecasts

[1] International Organization for Standardization: Codes for the representation of currencies (https://www.iso.org/standard/64758.html).

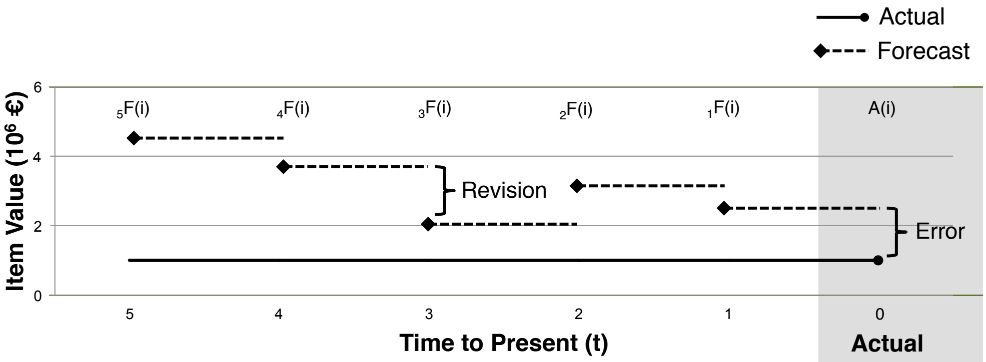

Figure 3.1: Temporal structure of cash flow forecasts ${}_t$F(i) with the corresponding actual cash flow A(i) for an example five step forecasting process.

to be compared. In such cases, it is preferable to compare *percentage error* (*pe*) – the errors of forecasts in relation to their associated actual volumes.

$$_tpe = \frac{_tF(i) - A(i)}{|A(i)|} \tag{3.1}$$

As with *e* and *pe* individual positive and negative deviations from the actual value neutralize each other, metrics such as mean percentage error can be small even if forecasts are inaccurate. To avoid such random nettings, researchers usually use *mean absolute percentage error* (*mape*). The metric *mape* penalizes each forecast-actual deviation in absolute terms (Equation 3.2). In the research, *mape* is the primary quality measure, while median(ape) is considered where needed.

$$mape = mean\left\{\frac{|F(i) - A(i)|}{|A(i)|}\right\} \tag{3.2}$$

Quality metrics that can typically be applied to single forecast processes, such as the *mean absolute percentage error (mape)*, the *mean squared error (mse)*, and the *root mean squared error (rmse)*, are shown in Table 3.1.

mape	mse	rmse
$\frac{\sum_{t=1}^{n} \lvert\frac{(_tF - A)}{A}\rvert}{n}$	$\frac{\sum_{t=1}^{n} (_tF - A)^2}{n}$	$\sqrt{\frac{\sum_{t=1}^{n} (_tF - A)^2}{n}}$

Table 3.1: Common error functions for forecast processes.

Further, let ${}_{t}r^{V}(i) = {}_{t}F(i) - {}_{t+1}F(i)$ denote the directed *revision-volume* of the t-th last adjustment of the forecasts for $A(i)$. Hence, the last revision for item i will be referred to as ${}_{1}r^{V}(i)$, the second-to-last revision as ${}_{2}r^{V}(i)$, and so forth. Since the items vary with respect to their volume levels, the analyses use the *relative revision* ${}_{t}r(i)$, computed as shown in Equation 3.3, which indicates the revision in relation to the absolute volume of the previous forecast.

$$ {}_{t}r(i) = \frac{{}_{t}F(i) - {}_{(t+1)}F(i)}{|{}_{(t+1)}F(i)|} \tag{3.3} $$

Table 3.2 gives a brief overview of the defined notation and metrics.

Notation:	Metric:
i	Cash flow item
$A(i)$	Actual realization
$F(i)$	Forecast
t	Lead time
m	Month
y	Year
s	Subsidiary ID, Entity ID
g	Type of cash flow
c	Currency
$e(i)$	Error
$pe(i)$	Percentage error
$r^{V}(i)$	Revision volume
$r(i)$	Revision (relative)
mape	Mean absolute percentage error
mse	Mean squared percentage error
rmse	Root mean percentage error
median(ape)	Median absolute percentage error

Table 3.2: Notation used for the individual characteristics.

3.1 Forecast Efficiency

Based on the efficiency theory, Nordhaus (1987) proposed tests for the structure of forecasting processes in terms of correlations amongst revisions and between revisions and errors. Forecast processes that show no correlation structures (with significant p-values) are coined weak form efficient.

While $t \in \mathbb{N}_0^+$ denotes the lead time to the realization of an actual (at $t = 0$), Nordhaus (1987) suggests testing for weak form efficiency using the Propositions (P1) and (P2).

Proposition 1 (P1). *Forecast error at t is independent of all revisions up to* $(t + 1)$.

Proposition 2 (P2). *Forecast revision at t is independent of all revisions up to* $(t + 1)$.

The test in the thesis for weak form efficiency violations uses Spearman correlations in a straightforward fashion for the Propositions 1 and 2. The test for Proposition 1 determines whether forecast errors ${}_te$ are correlated with revision ${}_jr$ at any previous position in forecast processes ($t \leq j$). Proposition 2 is tested by computing correlations within revisions ${}_tr$ with different lead time t. Expectation is that the Propositions 1 and 2 are supported, stating weak forecast efficiency.

3.1.1 Forecast Efficiency: Lead Time

The concept of efficiency is possible to examine in another way, which is more aligned to market efficiency (in reference to Fama, 1970). This thesis suggests analysis that will base on the lead time of forecasts and accuracy. When information is efficiently integrated into forecast processes, the forecasts represent accumulation of all information available. Integration of all information (that are relevant for the forecasting of an actual) results in forecasts with lower lead time to contain at least all relevant information of previous forecasts. For instance, the last forecast should contain all information relevant for forecasting of the actual and therefore exhibit the highest accuracy. If forecasting processes do not integrate new, available information into the forecasts or even do miss to integrate information that previous forecasts did integrate, a pattern should be identifiable. The pattern will result in forecasts with lower lead time being associated with higher errors, as the beneficial information is missed or even available for integration. This intention behind this association is proposed within (P3):

Proposition 3 (P3). *The decrease of lead time is associated with higher forecast accuracy.*

The thesis's Proposition (P3) is tested by comparison of accuracy over groups of forecasts with different lead times. Explicitly, the *mape* is expected to decrease within each set of forecasts with lower lead time t.

3.1.2 Forecast Efficiency Hypothesis: Increased Accuracy

It is argueable that the identification of correlations according to Propositions (P1) and (P2) – maybe at some aggregation levels or after the transformation of the raw forecast and actual items – has potentials to anticipate future adjustments. This is a consequence of existing structures hinting to information that could be incorporated into revisions because revisions are predictable, which might allow accuracy improvements at longer forecast horizons. The existence of these improvement potentials for longer forecast horizons require that the forecast processes do not integrate information according to Proposition (P3).

A violation of these three propositions opens the following three questions: (1) Violation of Proposition (P3) questions if timely efficient integration of information is beneficial for forecast accuracy? (2) Can information entail forecast processes in a way that inefficient forecasting (concerning P1 and P2) is beneficial for forecast accuracy? (3) Prediction of future adjustments due to inefficiencies requires that inefficiency must relate to forecast accuracy. Therefore, is efficiency truly associated to accuracy?

Analysis of these questions should be stated empirically. Since the answers to the first two questions become obsolete by answering the third question with regard to forecast prediction, I intend to analyze the latter one.

Exhibiting the implications of the further analysis clearly requires some theoretical introduction. The last question breaks down to the general question of "efficiency hypothesis". Efficiency hypothesis (Fama, 1970) requires forecasts to follow Equation 3.4, which means that the expected value of an asset j at time $t+1$ under information set Φ_t equals the value p of an asset at time t adding the one-period percentage return r.

$$\text{Expected Return Theory:} \quad E(\tilde{p}_{j,t+1}|\Phi_t) = \left[1 + E(\tilde{r}_{j,t+1}|\Phi_t)\right] p_{j,t} \tag{3.4}$$

The efficiency hypothesis, understood as the theory of efficient markets, states that if forecasts contain all available information, they will not reveal any trading opportunities. As a result of Equation 3.4 when all information Φ_t is integrated, the overall expected return will be zero. Equation 3.5 shows the return and Equation 3.6 shows the expected return. In other words the forecast errors $x_{j,t+1}$ must solely depend on the information Φ_t being integrated into the forecasts $p_{j,t+1}$.

The error may have low or even zero dependency on the integrated information that is unimportant. However, integrated important information must reduce the error and result in a negative dependency of integrated important information to the error, while inefficiencies should have positive dependency to forecast error. That is because otherwise a forecaster omitting such information would give rise to trading opportunities, which violates the efficiency hypothesis.

$$\text{Return:} \quad x_{j,t+1} = p_{j,t+1} - E(p_{j,t+1}|\Phi_t) \tag{3.5}$$

$$\text{Expectation of Return:} \quad E(\tilde{x}_{j,t+1}|\Phi_t) = 0 \tag{3.6}$$

The efficiency hypothesis received high attention in the research community and lead to several tests that state different stages of efficiency: strong form, semi-strong form, and weak form. The details of each stage are omitted with reference to the "expected return theory" based efficiency in Fama (1970). But, important to note here is that evidence for violation of weak form efficiency will lead to the rejection of the strong form efficiency.

Carried out tests for weak form efficiency (such as in Nordhaus, 1987) over a wide range of research papers revealed that the respective empirical analyses suggest both, inefficiency and rejection of inefficiency. With efficiency and inefficiency being stated, the understandable and intriguing substance of the efficiency hypothesis seems to be widely accepted by the research communities as a fact.

However, despite the persuasiveness of the efficiency hypothesis with a hypothesized dependency of efficiency and accuracy (by information being aggregated into forecasts) there is a lack of research empiricism[2], nor a specific and suitable testing framework is provided to state the efficiency hypothesis. My scientific surprise led to the Hypothesis 1.

Hypothesis 1 (Validity of the Efficiency Hypothesis)**.** *In general, efficiency and accuracy is not required to relate to each other (in corporate forecast processes).*

The hypothesis does not question the existence of efficient and inefficient forecasting (and markets). Explicitly, this hypothesis questions the validity of the efficiency hypothesis itself, with it's assumption of efficiency and accuracy being related.

[2]The research of Lawrence and O'Connor (2000); Dovern and Weisser (2011); Meub and Proeger (2016) (and with limitations: Nordhaus 1987; Bessler and Brandt 1992; Ashiya 2003, 2006) give an indication of the dependence between accuracy and weak efficiency, but are not empirically conclusively supported. None of these studies analyzes and tests the dependency directly and even if one relates the experiments to this question, the sample size ≤ 10 is too small for each individual experiment.

The further intention of this paragraph is to provide a test that is able to state the Hypothesis 1, and can be applied on empirical data later on. Weak form efficiency being a requirement for strong form efficiency, wherefore the constructed test base on the analysis of the relation of weak form efficiency with accuracy. Following the efficiency hypothesis that violations of Propositions (P1) and (P2) are related to lower accuracy, I explicitly formulate the Proposition (P4).

Proposition 4 (P4)**.** *Violations of (P1) and (P2) are associated with lower forecast accuracy.*

The evaluation framework for Proposition (P4) in this thesis bases on absolute correlation values, because the interest is in the association of accuracy to the general strength of inefficiency. To avoid random netting effects the *mape* is taken for accuracy measure, leading to Equations 3.7 and 3.8 (with $a \geq b$) for testing the Proposition (P4).

$$mape({}_1F(i)) = \beta_0 + \beta_1(|Cor({}_ar, {}_bpe)|) + \epsilon \tag{3.7}$$

$$mape({}_1F(i)) = \beta_0 + \beta_1(|Cor({}_ar, {}_br)|) + \epsilon \tag{3.8}$$

Without current research that questions the validity of Hypothesis 1, the expectation for a valid efficiency hypothesis leads to positive β_1 estimates. If negative estimates are found, the efficiency hypothesis must be rejected and Hypothesis 1 is supported.

3.2 Anchoring and Adjustment

The question what might cause inefficiencies led to the common anchor of last years realizations. To determine whether forecasters use the previous year's actuals as anchors, the tests are proceeded as proposed in Bromiley (1987). The author suggests that "on average the difference between the anchor and the forecast should be less than the difference between the anchor and the actual" (Bromiley, 1987, p. 202). This results in the two inequations (see Equation 3.9), where the forecast should be typically located between the actual and the anchor κ. Logic transformation results in the equation for Δ (as computed in Equation 3.10). Negative values of Δ indicate the presence of an anchor, while positive values reject the thesis of anchors.

The intuition is that over a fiscal year the anchoring results can differ for subsamples based on monthly forecasting groups. For these groups of forecasts a t-test is used to determine whether anchors are present.

$$\kappa < F < A \quad or \quad \kappa > F > A \tag{3.9}$$

$$\Delta = |\kappa - F| - |\kappa - A| \tag{3.10}$$

Improving the Identification of A&A Patterns

Typically, A&A models focus on the direction of past revisions and assign values with low consideration concerning the strength of the revisions. The Bandwidth Model (BWM) focuses on the strength of the revisions and assigns a positive value to a positive revision and a negative one to a negative revision. The BWM assigns a revision to the *Up*-Group if it is above a certain threshold α and to the *Down*-Group if it is below $-\alpha$. Otherwise it is assigned to the *Const*-Group as shown in Equation 3.11.

$$\begin{aligned} & {}_t r \in Up \Leftrightarrow_t r > \alpha \\ \textbf{or } & {}_t r \in Down \Leftrightarrow_t r < -\alpha \\ \textbf{or } & {}_t r \in Const \Leftrightarrow |{}_t r| \leqslant \alpha \end{aligned} \tag{3.11}$$

This model can be influenced through more parameters than for example Harvey's model and is on the other side not vulnerable for small changes in forecasts. The limitation is, that a forecast can only be assigned to three different classes. The results are highly depending on the chosen α, so a second model will be introduced. This model is inspired by the BWM, supplemented by an assigning function. The assigning functions needs to fulfill the Equations 3.12 – 3.14.

$$f^{+}(0) = 0 \tag{3.12}$$

$$f^{+}(max\ {}_t r) = 1 \tag{3.13}$$

$$f^{+\prime}({}_t r) \geq 0, \forall\ {}_t r \in {}_t r^{+} \tag{3.14}$$

The function should assign a value of 0 to a revision where no adjustment has taken place. The largest revision should further be assigned to 100% to the *Up*-Group. The function should monotonically increase as the assigned weight should not lower for higher revisions. As an assigning function that can fulfill these conditions, the logistic growth function will be used. This function offers a sigmoid process assigning small values for revisions near 0 a value near 1 for large revisions and a steady transition near the threshold α. The revisions will be assigned to a positive and a negative group. The logarithmic growth function will be modified so that a weight on every revision can be assigned. The original logarithmic growth function shown in Equation 3.15 is influenced through the saturation limit G, a parameter k influencing the strength of the growth, the functions values for revisions of size 0, and the exponential function *exp*.

$$f_x = \frac{G}{1 + exp^{(-kGx)}(\frac{G}{f(0)} - 1)} \tag{3.15}$$

This function is transformed to fulfill the Equations 3.12–3.14. First of all the functions value for revisions of 0 should be 0. The function can only convert to 0, for this reason a parameter μ is introduced. The function should convert to this parameter, therefore the parameter should be arbitrary close to 0. The maximal revision should be valued as 1, the saturation limit G is therefore set to 1. Additionally the turning point should be 0.5. In a next step the function is shifted with the value of α so that the values in Equation 3.16 are reached.

$$f(0) = 0.5 \textbf{ and } f(-\alpha) = \mu \tag{3.16}$$

The parameter k can be predicted in dependency of μ and α, as shown in Equation 3.17, where *ln* is the logarithmic function.

$$k = \frac{\ln(\frac{1}{\mu} - 1)}{\alpha} \tag{3.17}$$

Re-shifting this function with $-\alpha$ is resulting in Equation 3.18 and Equation 3.19 that differentiate between positive and negative revisions. These equations are showing the functions for the *Logistic Bandwidth Model (LBWM)*, where negative revisions are handled in the same way as positive revisions, except for changing the sign of the revision.

$$f^{+}_{log}({}_t r) = \frac{1}{1 + exp\left(\frac{\frac{\ln(\frac{1}{\mu} - 1)}{\alpha}}{(-{}_t r + \alpha)}\right)} \tag{3.18}$$

$$f^{-}_{log}({}_t r) = \frac{1}{1 + exp\left(\frac{\frac{\ln(\frac{1}{\mu} - 1)}{\alpha}}{({}_t r + \alpha)}\right)} \tag{3.19}$$

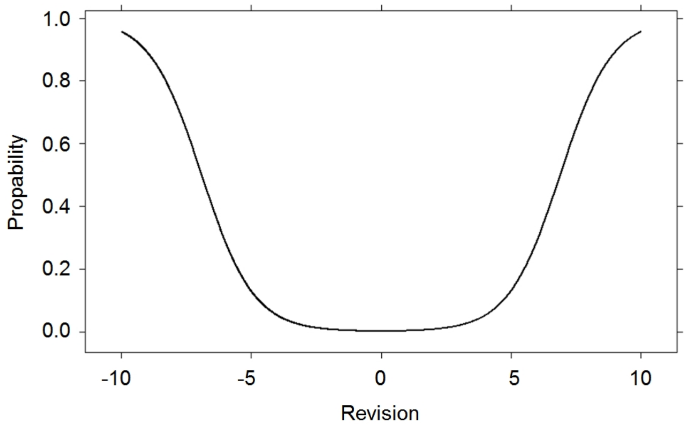

Figure 3.2: Logistic assigning function for anchoring probability of forecasts with positive and negative revisions.

Finally this results in two different new models for detection of $A\&A$ effects. The Bandwidth Model classifies all forecast in three different groups, assigning three different values on them. The Logistic Bandwidth Model classifies the forecasts in two different groups complemented by a weight for $A\&A$ effects. Based on the two provided models the Propositions 5 and 6 will be evaluated.

Proposition 5. *Bandwidth Models can provide beneficial information to identify anchoring and adjustment effects that relate to forecast accuracy.*

Proposition 6. *The relation of the Bandwidth Models to other anchoring and adjustment models depend on the forecast series.*

The evaluation uses five synthetic forecast series and three loss functions for the comparison of the two Bandwidth Models BWM and LBWM with common $A\&A$ models (Bromiley, 1987; Harvey et al., 1994; Lawrence and O'Connor, 1992; Amir and Ganzach, 1998). Each of the mentioned models detects $A\&A$ effects in a different way, which will be adjusted to the synthetic series as in (Knöll and Roßbach, 2018b). In real world forecast series it is difficult to relate forecast series to one unique $A\&A$ pattern and to identify dependencies between the pattern and the models. Therefore, synthetic forecast series were generated with specific kind of $A\&A$ pattern influencing the forecast series. The synthetic series allow a comparison of the identification performance of the different models, as a control for the underlying pattern is feasible. The different forecast series are expected to relate to (or even occur in) real world forecasts.

Three of the five series base on a normal distribution with no or only low trend: *independent (Ind)*, *random walk without trend (RW-1)*, and *random walk with trend*

(RW-T). Two series are used to simulate a stronger growth component: *logarithmic growth (LogG)*, and *exponential growth (ExpG)*. Each type of forecast series consists of 1000 observations. The independent series consists of normal distributed series with an expected value (μ) of 1000 and a standard deviation (σ) of 1. The random walk series are based on normal distributed steps, $x_0 = 1000$, a μ of 0, and a σ of 1. The random walk series with trend are defined through normal distributed steps, a starting value of $x_0 = -1000$, a μ of 2, and a σ of 1. The logarithmic growth series consists of logarithmic growing forecasts, with a uniform distribution of the basis between 0.1 % and 3.0 % starting by x_0 of 100. Last of all, the exponential growth series will consist of forecasts with exponential growth with growth rates uniform distributed between -100 % and 100 % starting by x_0 of 1000. For example, the random walk series were generated with Equation 3.20.

$$x_n = x_0 + \sum_{t=1}^{6} \mathcal{N}(\mu, \sigma^2) \tag{3.20}$$

For each synthetic forecast process in each forecast series, all the different models calculate the probability value ν of an anchor and adjustment pattern. The probability in each forecast process is determined by the absolute mean probability of anchoring $|mean(\nu)|$ of all revisions within the process. Explicitly, the forecast processes have a maximum lead time $t = 5$ (based on real forecast processes), which results in four probability values: $\nu_f({}_t r)$ with $t \in \{1, 2, 3, 4\}$. The model BWM indicates $\nu_{f=\text{BWM}}({}_t r)$ with percentage values of 100 %, 0 %, or -100 % (according to the classes: *Up*, *Const*, *Down*), whereby positive and negative values cancel each other out. The LBWM provides continuous probabilities for $\nu_{f=\text{LBWM}}({}_t r)$ with percentage values in the interval $[100\,\%, \ldots, -100\,\%]$. I.e., the BWM assigns an anchor probability of 50 % to a forecast process with three revisions of the *Up*-Group and one revision of the *Down*-Group.

Finally, for each set of forecast series the probability of the models are Pearson correlated with the *mse*, *rmse*, and *mape* error measures (see Table 3.1) to analyze Proposition 5. Further, the evaluation will analyze the correlations between the models in order to support Proposition 6.

3.3 Optimism, Pessimism and Overreaction, Underreaction

In order to determine whether the bias-related patterns “optimism, pessimism” and “overreaction, underreaction” are present in the forecasts, the test design is followed as proposed by Amir and Ganzach (1998). From their analysis of forecasts, the authors conclude that overreaction and underreaction operate concurrently with optimism and pessimism.

Optimism refers to cases where the last forecast exceeds the actual (${}_1F > A$). *Pessimism* refers to cases where the last forecast lies below the actual (${}_1F < A$). *Overreaction* describes the case of revisions being greater than required (e.g., for $t = 1$: ${}_1r > 0 > {}_1pe$; revision and error have different directions). *Underreaction* describes the case of revisions being too small (e.g., for $t = 1$: ${}_1r$ and ${}_1pe$ have the same sign).

The results reported by Amir and Ganzach (1998) indicate that the strength of these patterns decreases with lead time. This finding makes sense intuitively, since more reliable information becomes available as one approaches the actual date, leaving less room for speculation and strongly diverging expectations.

Following the methodology of Amir and Ganzach (1998, pp. 339–341), the test measures the strength of optimism, pessimism, overreaction or underreaction with the parameters learned in the regression shown in Equation 3.21. In contrast to Amir and Ganzach the tests use standardized revisions on the basis of forecasts with subsequent lead times and standardized errors on the basis of actuals. Positive α's indicate optimism, negative α's pessimism. Positive β's indicate overreaction, negative β's underreaction.

$$ {}_tpe = \alpha(t) + \beta(t)_t r + \epsilon \tag{3.21} $$

3.4 Revision Concentration

Anchors that influence forecasts could not only have an influence on the error, but could also show divergent effects for the error at different points in time. This argument refers to the work of Knöll et al. (2016). The work studies whether specific structures (in contrast to random walks) in forecast processes are observable, whether these are related to accuracy, and how knowledge on such patterns can be used to statistically correct the forecast in order to reduce error in the exposure prediction.

Geometric Center

To test whether structures (in contrast to randomness) in revisions relate to concentration, this paragraph proposes to determine the geometric center of a revision process. The geometric center of a revision process is computed as follows. First, each revision is set into relation to the first forecast, and normalized by the sum of all revisions relative to the first forecast, as shown in Equations 3.22 and 3.23. The coordinates for the geometric center are computed with Equations 3.24 – 3.26.

$$ {}^{1}_{t}r(i) = \frac{{}_{t}F(i) - {}_{t+1}F(i)}{|{}_{1}F(i)|} \tag{3.22} $$

$$ {}^{x}_{t}r(i) = \frac{{}^{1}_{t}r(i)}{\Sigma_t|{}^{1}_{t}r(i)|} \tag{3.23} $$

$$ x_i = -2 \cdot |{}^{x}_{t+3}r(i)| - 1 \cdot |{}^{x}_{t+2}r(i)| + 1 \cdot |{}^{x}_{t+1}r(i)| + 2 \cdot |{}^{x}_{t+2}r(i)| \tag{3.24} $$

$$ y_i = \frac{\Sigma_t {}^{x}_{t}r(i)^2 - 0.25}{(1.0 - 0.25)} \tag{3.25} $$

$$ z_i = \frac{\Sigma_t {}^{x}_{t}r(i)}{4} \tag{3.26} $$

If revisions follow a random walk without drift, a mean center (x_0,y_0,z_0) in a subsample of processes will be observed. A value of $x < x_0$ indicates that larger adjustments are made earlier in a revision process (timing). Larger y (compared to y_0) indicate a higher concentration of adjustments at a specific revision in a forecast process (volume). Positive z indicate that, overall, revisions are positive, i.e. the extent of upward revisions during the process is greater than of downward revisions (direction).

Take, for instance, a revision process with ${}_{1}r(i) = 1$ and ${}_{2}r(i) = 0$ and ${}_{3}r(i) = 0$ and ${}_{4}r(i) = 0$, i.e., the forecast is revised only once at the end of the revision process. The coordinates for this process are then (x_i,y_i,z_i) = (2,1,0.25), indicating that revisions were concentrated at the end of the revision process, more specifically: in one revision, and that this revision was positive. With $p(i)$ as the forecast revision process for item i and P as a set of forecast revision processes for different items i, the following Proposition 7 is formulated.

Proposition 7. *The average geometric center of a set of forecast revision processes P must not deviate significantly from (x_0,y_0,z_0).*

The test of Proposition 7 uses Wilcoxon rank sum tests on mean differences of forecast processes for x,y and z measures.

Change in Error Level

Now the question is turned on whether the concentration measures provide explanation value for the error term, which is required to correct forecasts by using concentration measures. The analyses will measure the change between the error level of the first and last forecasts (${}_5F$ and ${}_1F$) in terms of ape, described in Equation 3.27.

$$\textit{change in error level}: \qquad \Delta_{5,1} = |{}_5pe| - |{}_1pe| \tag{3.27}$$

Considerable error rates are particularly important in this analysis of the data, which is why the data is reduced to forecasting processes where the *ape* of ${}_5F$ is greater than 5 %. The analysis of $\Delta_{5,1}$ will base on the explanation value of the concentration measure in comparison to metrics required for inefficiency. For this purpose the linear regression model bases on Equation 3.28 and 3.29. The test will compare explanation values with the R^2-value of both regression models. It is important to note that the regression will be evaluated for different set of forecast processes split by the sign of error *pe* (positive, negative), wherefore the results are independent from absolute forecast numbers (such as ${}_1F$).

$$\begin{aligned} \Delta_{5,1} = \beta_0 + \beta_1({}_4r^V) + \beta_2({}_3r^V) + \beta_3({}_2r^V) + \beta_4({}_1r^V) + \beta_5(g) + \\ \beta_6(\textit{Division}) + \beta_7(\textit{Sign change (none)}) + \beta_8(\textit{Sign (positive)}) + \epsilon \end{aligned} \tag{3.28}$$

$$\Delta_{5,1} = \beta_0 + \beta_1(x_i) \times \beta_2(y_i) \times \beta_3(z_i) \times \beta_4(g) + \epsilon \tag{3.29}$$

The final descriptive analyses will examine the Y metric (volume concentration), which is interesting in particular with regard to the empirically unsupported statement in Leitner and Leopold-Wildburger (2011, p. 466) that "large adjustments of forecasts improve accuracy most, and small adjustments harm it". This statement is questioned in Hypothesis 2.

Hypothesis 2. *Revision processes might be harmed by small forecast adjustments, reducing forecast accuracy.*

The distribution of revision volume is expected to indicate at which time the integration hint to important information, most likely to exceed random noise[3]. Therefore the analysis of the Y concentration measures will provide detailed information for different types of revision processes and how the metrics interact with each other. The analyses will base on how the Y metric interact with X

[3]For example, adjustments of 1 Euro are considered unimportant (to the forecast process) when the forecast volume is 1 million Euro and typical revisions amount to ten percent of this figure. Such unimportant adjustments could be framed as random noise in forecast processes generated by forecasters to indicate their active involvement.

(timing concentration) and Z (direction concentration) with regard to the error level $\Delta_{5,1}$. The first part will analyze $\Delta_{5,1}$ of the data based on Y and Z measures in dependency to item type (g) and over-/underestimation. The second part will analyze $\Delta_{5,1}$ of the data in dependency to Y and X measure.

Chapter 4

Aggregate Level Business Characteristics

This thesis argues that some useful structures in revisioning might only be found at particular transformation and aggregation levels of the data, requiring the engineering of features from the data. The engineering of features, i.e., their aggregation, selection, and representation, requires a solid understanding and modeling of business and organizational structures.

4.1 Ratio Metric

Because the planning for the fulfillment of the corporation's targets is determined on an aggregate level the cash flow forecasts are accumulated up to this level. For the return–related analyses at the organizational level, the abstraction has the form of an aggregated perspective of cash inflows and cash outflows for actuals (and for forecasts).

4.1.1 Construction Process

As a proxy for percentage return margin within a fiscal year for a specific subsidiary, the computation of the entity's *ratio R* uses aggregated revenues (invoice issued) and expenses (invoice received).

Definition 1 (Ratio). *The ratio for an specific subsidiary ($s = S$) in the M-th month of a year Y and the K months ($K < M$) before M is computed as:*

$$R^K_{s=S,y=Y,m=M}(A) = \frac{\sum_{1 \leq j \leq K} A^{g=II}_{s=S,y=Y,m=M-j}}{\sum_{1 \leq j \leq K} A^{g=IR}_{s=S,y=Y,m=M-j}}$$

while:

$$
\begin{aligned}
Y = &\quad \textit{specific year}\\
M = &\quad \textit{specific month}\\
K = &\quad \textit{aggregated number of months}\\
S = &\quad \textit{specific subsidiary}
\end{aligned}
$$

As with individual actuals and forecasts, the use of lead time $t > 0$ refers to ratios computed over forecasts ($_tF$) noted as $_tR$; the ratios over individual actuals (A) noted as $_0R$.

For instance, $_tR^3_{2010,11}$ refers to the ratio with lead time t of all cash flows from September to November 2010. The notation $_tR^K_{Y,M}$ omits the superscript K, if $K = M - 1$, and is an aggregation of all realized cash flows in year $y = Y$ up to (and including) month $m = M$. The usage of the indices (s, c) specifies particular data sets for $\langle$subsidiary, currency$\rangle$-tuples. A ratio above one indicates the appearance of more revenues than expenses (positive return).

Since ratios are specific for each subsidiary s, for reasons of comparability, this thesis focuses on normalized ratios R^n (Definition 2). For the readers convenience, if not specifically relevant for differentiation, the notation $_tR$ refers to the normalized ratio instead of the entity specific ratio ($_tR_{s=S} := {_tR^n_{s=S}}$).

Definition 2 (Normalized Ratio)**.** *Normalized ratio is obtained by subtracting the minimum ratio within an entity from R and dividing by the difference of its maximum and minimum ratio. The values are always between zero and one per entity.*

$$
{_tR^n}_{s=S,y=Y,m=M} = \frac{{_tR}_{s=S,y=Y,m=M} - min(\bigcup R)}{max(\bigcup R) - min(\bigcup R)}
$$

while:

$$
\bigcup R = \{{_tR}_{s,date} : s = S \wedge date < (Y, M)\}
$$

The proxy for the suggested annual return target (*target ratio*) for an entity $s = S$ is defined as $T(_0R)_y$ in year y. As subsidiaries' targets are unknown (to me), but business development measured with EBITDA margin figures seems to be rather stable over the years, the target is calculated on the basis of Definition 3.

Definition 3 (Target)**.** *The target ratio in year $y = Y$ is estimated by averaging the December actual ratios of the three preceding years. It is formally defined as:*

$$
T(_0R)_{y=Y} = mean(_0R_{y=Y-j,m=12}),\ with\ j \in \{1, 2, 3\}
$$

Alternatively, one could use the EBITDA margin figures provided in the official annual reports to retain a proxy for target margins. But, since this thesis analyzes predictive purposes too, and numbers of the annual report are expected to contain several business adjustments, the aforementioned data-driven approach is chosen.

Definition 4 (Target Difference)**.** *The difference from target is defined as:*

$$TargetDiff = T({}_0R) - {}_1R$$

Definition 5 (Revision)**.** *The revision of ratios describes the adjustment from the second to last forecast before the actual. It is formally defined as:*

$${}_{12}R = {}_1R - {}_2R$$

This thesis uses the last revision because generally the latest judgmental forecast incorporates the most information and is the most accurate (McNees, 1990).

Definition 6 (Ratio Error)**.** *Finally, the error of forecast ratios is defined by:*

$${}_1E = {}_0R - {}_1R$$

For reasons of clarity: Ratios and revisions are not stored in the database, but derived from the aggregation of invoice items as shown in Definition (1). Table 4.1 gives a brief overview of the defined metrics.

Notation:	Metric:	
${}_0R$	Actual Ratio (normalized)	Definition 1 for $A(i)$
${}_tR$	Forecast Ratio (normalized)	Definition 1 for ${}_tF(i)$
$T({}_0R)$	Target (normalized)	Definition 3
TargetDiff	Target Difference	Definition 4
${}_{12}R$	Revision	Definition 5
${}_tE$	Error	Definition 6

Table 4.1: Notation used for the aggregate characteristics.

Denoting the actual of cash flow margin ratio as ${}_0R$, the lead time $t > 0$ of a forecast ${}_tR$ for ${}_0R$ refers to discrete process steps until the actual date ($t = 0$). Figure 4.1 visualizes the temporal structure of an example forecasting process in five steps for an actual ${}_0R$. The initial forecast ratio ${}_5R$ is delivered with a lead time of five periods and is revised four times until the last one–period–ahead forecast ratio ${}_1R$ is generated.

Analyses at the ratio level are important as they are supposed to be directly related to foreign exchange exposure, which strictly relates to the accumulated

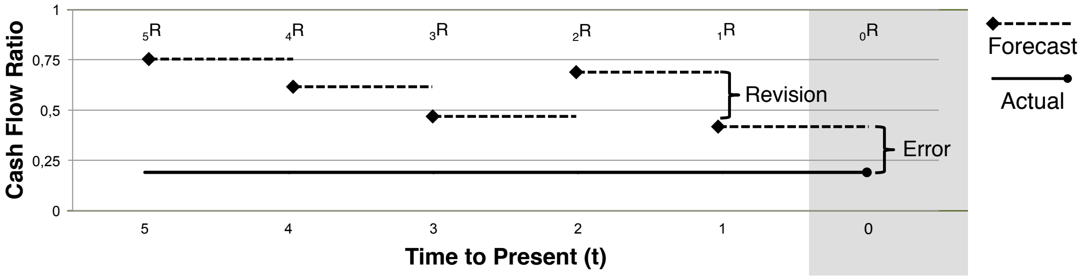

Figure 4.1: Temporal structure of margin ratio forecasts ${}_t$R ($t > 0$) for the corresponding actual margin ratio ${}_0$R. The figure shows the ratios for an example five step forecasting process.

ratio of cash inflows and cash outflows. Therefore, improving the ratio error is expected to allow an improvement of the overall exposure forecasts to reduce in the future either unhedged risks or hedging-costs.

4.1.2 Ratio Metric: Validity

The number of individual cash flow items increases continuously in the ratio with the month m, which might also lead to a stabilizing effect for the ratios, reducing the standard deviation. The following hypothesis argues that the stabilizing effect is of minor impact:

Hypothesis 3 (Minor Stabilizing Effect)**.** *The aggregation to the ratio level on a monthly level exhibits no indication for a strong impact of the stabilizing effect.*

To support the hypothesis, the analyses will examine the standard deviation of the unnormalized ratio under the influence of time lags to analyze if the standard deviation of actual ratio over the months is not predefined by the metric itself. The lag of l months is added to the date of the invoices, to calculate the ratio with a different beginning than January. After reaching December the values of the following year are taken. The approach is therefore called lag-shifted ratio calculation. For instance, using lag $l = 1$ results in the first month February in year Y, where the ratio only includes II and IR of this February. This lag results in the last month January of the subsequent year Y+1 for the aggregation, where the II and IR of all other months between are integrated (including February in year Y and January in year Y+1). This approach allows an analysis for a different setting than the calendar year.

In the analysis the standard deviation of unnormalized accumulated ratios for all subsidiaries and years for each month with increasing number of items is calculated, based on the different allocation of lags with ($0 \leq l \leq 11$). The expected result, if the stabilizing effect exists, is that standard deviation does reduce continuously from the month on that the aggregation started (framed as “1st Month”) to the last month (framed as “12th Month”). If the standard deviation does not decrease in general until the last month, the analysis will refuse a strong stabilizing effect and support Hypothesis 3 to state the validity of the ratio construction.

4.1.3 Ratio Metric: Earnings Target Existence

EBITDA Figures

Before describing the design for this section of the empirical study, this section will briefly review the intuition of the design.

EBITDA figures are a primary KPI for corporate performance, and many corporations incentivize their managers to meet such prearranged KPI targets. The overall intuition is that meeting prearranged EBITDA targets is well incentivized and should therefore predefine the way on how aggregated actuals will develop over a year, and, as a consequence, how cash flow forecasts will (have to be) adjusted. The feature that this thesis considers is the subsidiary’s ratio of cash inflows and cash outflows accumulated over a fiscal year – a figure tightly related to a KPI such as EBITDA.

For the hypotheses, it is therefore assumed that the derived target ratios are linked to the percentage EBITDA margin figures of the company. This assumption seems to be plausible for two reasons. (1) Realized revenues (through invoices issued) and expenses (through invoices received) will later result to the derived EBITDA margins. (2) This assumption would be underpinned by the reported percentage EBITDA margin figures published in the annual report, if they are in line with the ranks of division ratios for December values.

The fulfillment of the second reason allows to advocate the retainment of a substitute for percentage EBITDA margins with ratios on a monthly basis.

Decrease of Standard Deviation

The assumption of the margin targets should be underpinned statistically. If margin targets are present, the 12th month should have decreased standard deviation compared to the 1st month. An indication that targets possibly exists and might be met early, would be provided if the standard deviation reaches its minimum before the 12th month.

The constructed test will analyze the standard deviation of normalized ratios, for specific lags where Hypothesis 3 is supported, i.e. in the fiscal year, to consider numerical differences between subsidiaries.

Ratio End of Year Drifts

Further support for the existence of the target will be provided by a median ratio analysis over time for the subsidiaries, which will be grouped into the associated divisions. The analysis will study whether the ratio feature will drift towards the end-of-year ratios of the preceding years. The examination focuses whether there are regular and strong shifts of aggregated cash-in/cash-out volumes in the ratios towards the end and beginning of the fiscal year. In the absence of earnings management, ratios could stabilize over the course of a fiscal year as actuals accumulate, but there should be no discernible pattern in the changes of ratios between December and January.

4.1.4 Ratio Metric: Subsidiary Specific Revision

First analysis for the revision questions if the normalization helps to identify specific pattern of the subsidiaries' adjustments in ratio. The test will analyze the revision of all subsidiaries being made with regard to the error, based on unnormalized and normalized ratio figures. Indication of the importance of the normalization will be provided by visualization of ${}_{12}R$ and ${}_{1}E$.

4.2 Efficiency at Aggregate Level

Weak forecast efficiency can be tested by using Propositions 1 and 2. The intention is that efficiency can differ for different aggregation levels, and biases that might matter at the individual level might be of no concern at an aggregate level. For instance, an organizational bias on the aggregate level might distort individual forecast, but with regard to the aggregate level the influence of individual biases might vanish. Therefore, the following paragraphs proposes a theoretical framework to unite findings of both levels – individual and aggregate level – before analyzing the efficiency at the aggregate level further.

4.2.1 Reasoning Beneficial Inefficiency in Individual Forecasts

Thesis suggests that organizational biases need to be analyzed together with or before individual biases. Otherwise, the results from analyzing individual biases may be confounded, which ought to result in violations of Proposition (P4). For instance, organizational biases such as earnings targets can trigger earnings management activities, which results in shifts of cash flows into the next month or to the previous ones – depending on item type of expense or income. Upcoming actual values that are shifted in a subsidiary might differ structurally from the actual item values of the subsidiaries with no shifts. These actual shifts result in errors that a uninformed forecaster can not account for at all. The resulting individual level errors and seemingly individual level biases might be questioned for such a confounding influence. In other words, if inefficient forecasts are associated with *higher* forecast accuracy, organizational biases may be at play, which is formulated in Proposition (P8).

Proposition 8 (P8)**.** *Organizational bias generates violation of (P4).*

Support of the Proposition 8 should be provided with an explanation framework that associates the organizational biases with the violation of Proposition (P4). This means that the information available on a case-by-case basis, which is determined among other things, from the examined biases, should be brought in line with the efficiency perspective. Using the results from the test of the validity of the efficiency hypothesis (Equations 3.7 and 3.8), this work on corporate forecasts focuses to offer a consolidating perspective. The confounding influence is considered to be found if the explanation of the differences between violations and non-violations can conclusively base upon the association of the organizational biases.

4.2.2 Testing Aggregate Level Efficiency

On the aggregate level the efficiency of the corporate data will be tested, using Propositions 1 and 2. The efficiency test analyzes Spearman correlation of revisions ${}_{t,t+1}R$ with previous revisions ${}_{j,j+1}R$ ($j < t$), and correlation of revisions ${}_{t,t+1}R$ with errors ${}_{j}E$ ($j \leq t$). Expectation is that on the aggregate level efficiency is not given, indicating the existence of organizational biases.

4.3 Organizational Relations

Experts might be not fully aware of targets and earnings management activities. A further challenge is that there are no direct observations of earnings management or other potentially bias-related activities. With such information available, it would become much easier to disentangle the effects of different biases on forecasting processes.

When earnings management takes place and the exact figures for cash transfers are unavailable, which is usually the case, the organizational target might reveal pattern in which way incentives alter forecasts and accuracy. Such found pattern can lead to automated correction of longer–term forecasts by anticipation upcoming revisions and errors. Research results from other domains (such as in earnings forecasts) are transferred to proxies of return margins to apply findings to the domain of cash flow forecasting.

This paragraph provides the following contributions to the literature: First, analyses cover the dependency between target and error to identify if knowledge for the target extends traditional knowledge and to uncover possible correction opportunities. Second, it is argued that pursuing annual return targets introduces an organizational bias, the pattern of concealed information (introduced later), which systematically influences the forecast revisions. The section analyzes the ratio to provide evidence that forecast and their revisions provided probably do not reflect the entire internal view of a subsidiary. Third, analyses quantify dependencies of the assumed organizational bias on the purpose of forecasting processes. Here, the intention of the analyses is to reveal that managed cash flow earnings and pursued targets distort forecast revisions, thus undermining the corporate original goal of the forecasting process – to receive an accurate representation of upcoming cash flows. The subsequent sections explain and present the test design for the hypotheses.

4.3.1 Error Dependencies on Earnings Target

In order to investigate further the case of organizational biases induced by planned targets and earnings management, this section conducts the analyses on the organizational level. In particular, this section designs the analyses whether regular patterns in the subsidiaries' revision process made by the managers' cash flow forecasts can be exploited to improve the forecast accuracy by considering proxies of key figures.

As noted before, reaching margin targets is an important organizational goal. The expectation with regard to the importance is that a statistical model has a higher explanatory power when additional key figures of planning and operations are provided, namely the *Target* listed in Table 4.1, which motivates the following hypothesis:

Hypothesis 4 (Incorporation Beneficial for Explanatory Power)**.** *Incorporation of key figures (that organizationally biases forecasts) has a beneficial influence on the explanatory power of forecast correction models.*

The influence of the integration of such a key figures can be measured in three ways: by the R^2-value of the model (explanatory power), by a meaningful estimate for the variable of the key figure, and finally by out-of-sample tests (covered in Chapter 5).

The support for the Hypothesis 4 will be provided by the following analysis conducted on the empirical study. Two linear models are regressed on the ratio errors ${}_1E$ (difference between the actual ratio and the forecast ratio, computed over the final forecasts) using given data. The first linear model only uses statistical information: a constant for regression intercept, last forecast ratio ${}_1R$, and last revision ${}_{12}R$. In order to examine whether high ratio errors are associated with high differences between forecast and target ratio, the second linear regression model uses a regression intercept, last forecast ${}_1R$, last revision ${}_{12}R$, and additionally the information of business key figures, difference from target *DiffTarg*. The two regression models are shown the Definitions (7) and (8).

Definition 7 (Basic statistic model M_{Basic})**.**

$${}_1E = \beta_0 + \beta_1({}_1R) + \beta_2({}_{12}R) + \epsilon$$

Definition 8 (Organizational model M_{Orga})**.**

$${}_1E = \beta_0 + \beta_1({}_1R) + \beta_2({}_{12}R) + \beta_3(\mathit{TargetDiff}) + \epsilon$$

Explanatory Power in Analytic Correction Models

The influence on the explanatory power of additional information can be shown, by using R^2-values that describes the part of variance being explained by the model. The effect of increasing the R^2-value is an important indicator for the beneficial information added, measured by the additional amount of variance explained. For the linear regression models the R^2-values will be compared within an in-sample training period. The R^2-value of the model using the business key figures (*TargetDiff*) must be greater than the model without that information in order to support Hypothesis 4.

Significant Influence of the Estimate

The second analysis examines whether ratio errors ${}_1E$ increase with the difference between the forecast and the assumed target ratio (*TargetDiff*). The expectation is an estimate of $\mathit{TargetDiff} > 0$, in particular towards the end of a fiscal year. The significance of the estimate will provide support that the business key figure has a non-random influence.

If forecasters have at least partial foreknowledge whether targets have been met and earnings will be managed, they can integrate this knowledge into their earlier forecasts. As a result, one would expect to observe only a weak relationship between forecasts ${}_2R$ and ${}_1R$, and *last revision* ${}_{12}R$ would seem independent from *ratio error* (insignificant estimate of ≈ 0) at the end of the year.

The test will analyze the regression estimates for the full year in comparison to the regression estimates for a models based on December actuals. Further, the test will analyze the December model to a model based on January actuals.

4.3.2 Dependencies on Revision

This section designs the analyses to determine whether regular patterns in the subsidiaries' aggregate level revisioning process, which result from the cash flow forecasts of the forecasters, can be exploited by anticipating subsequent adjustments.

Revision: Direction and Strength Influenced by Targets

Suggesting an accountant within a legal subsidiary to aim at achieving a predefined EBITDA margin, the magnitude of changes in ratio as a result of cash flow revisioning should increase with the distance to a presumed target. As it is assumed that the target ratio has to be met at the end-of-year, the difference from target should decline over the months of the year. Therefore, the predefined corporate planning figures of EBITDA margins motivate the following hypothesis:

Hypothesis 5 (Predefined Revisioning)**.** *Corporate planning can pave the way for revision adjustments in decentralized forecasting processes (as an organizational bias).*

Explicitly, expectation is a dependency of the target ratio ($T({}_0R)$) and revision (${}_{12}R$), together with a decrease of adjustments over time when the current forecast ratio approaches the suggested target. A schematic illustration of the expected relationships is shown in Figure 4.2. In order to support Hypothesis 5 this thesis conducts several analyses to test this relationship:

(1) The regression analyzes the magnitude of ${}_{12}R$ on strength of *TargetDiff* together with the actual month within a fiscal year (*Month*), using Definition 9.

(2) In order to operationalize these dependencies to improve cash flow prediction, information is required for the direction of the final change in the forecast ratio. Therefore, revision ${}_{12}R$ is regressed on the strength of *TargetDiff* and *Month*, using Definition 10.

(3) However, the interpretation of the regression outcomes when a forecast ratio is already above the suggested target is challenging. Therefore, analysis covers how forecast ratios are revised when suggested targets are already reached with

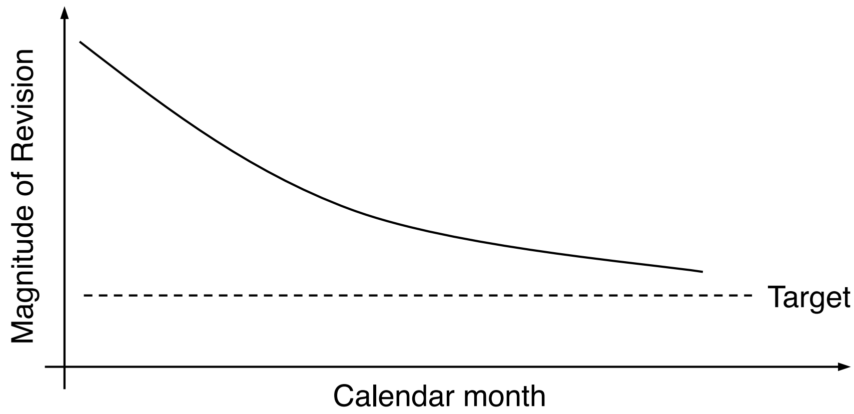

Figure 4.2: Hypothesized relationship between the magnitude of revision and target within the fiscal year. Assuming an accountant within a legal subsidiary aims at achieving a pre-defined EBITDA target, the magnitude of change in ratio as a result of cash flow revisioning is expected to increase with the distance to the target. As the target ratio is expected to be met at the end-of-year, the difference from target should decline over the months of the year.

the forecast compared to forecasts that are below target. With $Sign(TargetDiff)$ as binary variable indicating whether ${}_1R$ is above or below the suggested target $T({}_0R)$, the model regresses the final revision ${}_{12}R$ on $Sign(TargetDiff)$ in Definition 11.

Definition 9.

$$|{}_{12}R| = \beta_0 + \beta_1(|TargetDiff|) + \beta_2(Month) + \epsilon$$

Definition 10.

$${}_{12}R = \beta_0 + \beta_1(|TargetDiff|) + \beta_2(Month) + \epsilon$$

Definition 11.

$${}_{12}R = Sign(TargetDiff) + \epsilon$$

Revision: Information Concealment by Targets

In this section, the theoretical background for the hypotheses and additional assumptions are discussed, before the new hypothesis follows.

Aligning risk management with planning of future business activities can induce organizational biases that manifest themselves in a pattern of concealed information. The theoretical background bases on Burgstahler and Eames (2006), where the authors analyzed published cash flow forecasts and actuals of firms as a function the expectations of market analysts. While Burgstahler and Eames focus the management of cash flows on the outer shell of firms, the proposed analysis cover the internal forecasts and actuals within the sample corporation. In contrast to Burgstahler and Eames (2006), the following hypothesis should be considered as an extension by referring the shifts of earnings management to a specific reason based on empirical data. Further, the data will cover the internal forecasts and actuals of the corporation, from which official market reports are derived later on.

The difficulty for corporations lies in their need for a well–aligned management of planning, forecasting, and operations. To align the management to recent, current, and future business development, the corporation requires information from the subsidiaries. Information is usually provided through managers (and information systems) that have the possibility to access a perspective on the internal state of the subsidiary, which often requires preprocessing information to a view required by the corporation. The amount of work involved in planning, forecasting, and operations often implies sharing of tasks by several managers. When organizational structure motivates one manager (e.g. with incentivization payment), but not the other ones, an organizational biased view might occur for some of the information–giving managers. As a result, organizational biased forecasters might provide a view that incorporates inaccuracies in the forecast data. These inaccuracies originate partly from the concealment of information—when managers with the different tasks are not well aligned and one side is hiding information (unintentionally). Hence, the following hypothesis is made:

Hypothesis 6 (Information Concealment)**.** *Organizational biases can result in forecasting that follows a pattern defined as the "concealment of information".*

As noted before, reaching planned targets is an important organizational goal. If forecasts are adjusted to follow these targets, a pattern of concealing information inside the subsidiary may occur. The resulting pattern for Hypothesis 6 will drive adjustments differently for revisions regarding their current position. The pattern is an indication of the prevention of bad news. Here, the performance above the target is perceived as good current state. In order to conceal bad news, adjustments should increase more strongly when the performance is bad (or not as good as required) and should decrease with a good performance – but not as fast as bad news. As a result, some of the good news can be held back for worse times of the subsidiary.

The expectation on Hypothesis 6 with regard to end of year targets (in alignment to Hypothesis 5) leads to a decrease of adjustments over time, as the current forecast ratio approaches to the target. A schematic diagram of the expected adjustments is given in Figure 4.3.

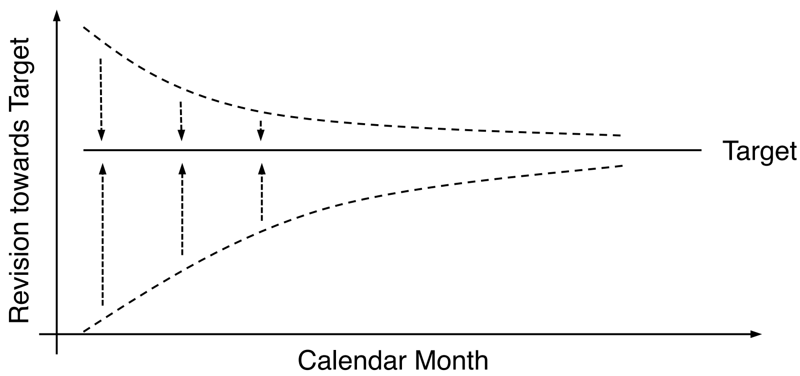

Figure 4.3: Required pattern that adjustments follow to conceal bad news. Current performance below the target increases the revision upward and performance above the target decreases the revision. The magnitude of revisions for performance below the target should be much higher compared to a performance above the target.

To test the relationship, the regression for ${}_{12}R$ uses one boolean variables for the relation between target and forecast ratio (TargetDiff$_{(+)}$), while the other state of the boolean variable is indicated by the intercept. Therefore, the intercept is renamed to "TargetDiff$_{(-)}$". Further the regression uses the month and interaction effects of month and TargetDiff$_{(+)}$. The linear regression is modeled with the Definition 12.

Definition 12 (Information Concealment)**.**

$$
\begin{aligned}
{}_{12}R = \beta_0(\mathit{TargetDiff}_{(+)}) + \beta_1(\mathit{TargetDiff}_{(-)}) + \beta_2(\mathit{Month}) + \\
\beta_3(\mathit{TargetDiff}_{(+)} \times \mathit{Month}) + \epsilon
\end{aligned}
$$

while:

$$
\begin{aligned}
\mathit{TargetDiff}_{(+)} &= \textit{true (equals one) indicates a forecast below the target,} \\
\mathit{TargetDiff}_{(-)} &= \textit{true (equals one) indicates a forecast above the target,} \\
\mathit{Month} &= \textit{the number of the month in the fiscal year, and} \\
\mathit{TargetDiff}_{(+)} \times \mathit{Month} &= \textit{interaction of the target relation and the month of the} \\
&\quad \textit{fiscal year, stating that the forecast is below the target.}
\end{aligned}
$$

4.3.3 Impact on Organizational Goals

The subsequent analyses in this paragraph are proposed to alter the corporation's understanding of the meaning of "the goal of forecasting" in forecasting processes. After the analysis of organizational biases in subsidiaries (target influence, revisions predefined, and concealment of information), it will be analyzed whether corporate operations are well aligned to the goal of accurate forecasting. Structures in organizational operations might alter the realizations (e.g., with earnings management) that are compared to the forecasting figures. These changes can have serious implications on forecast error measures. Therefore, Proposition 8 and Hypothesis 6 motivate the Hypotheses 7 and 8. These new hypotheses aim at disentangling the "goal of forecasting" for corporations from the managerial "goal of forecasting", as organizational influences are to be expected to alter the former goal.

The intention behind the corporation's "goal of forecasting" is that forecasters should provide perspectives for future expectations and should try to minimize the forecast error, which can be understood as an organizational bias itself on forecast processes. The assumption is that forecasting process might have a random baseline, but more importantly, to underline the foretold intention, in a forecast process the forecasting adjustments should depend on actual realizations. This leads to the following Hypothesis 7.

Hypothesis 7 (Distorted Forecast Processes)**.** *Structures in organizations (as a bias) can alter or distort forecasting processes.*

When the tasks of planning, forecasting, and accounting are interlinked to some extent, the pursuit of planned annual return targets can systematically influence both actual and forecast adjustments, which requires a comprehensive perspective. Tasks of forecasting, planning, accounting operations can be assigned to different managers. Forecasters who actually focus to intentionally give purposeful forecasts can, however, provide organizationally biased forecasts – in relation to Hypothesis 6 – suggesting a trade-off between the internal view they have, planned figures, and the operational view. This trade-off becomes even more rigid when the dedicated forecaster is also involved in planning and operating tasks within the subsidiary (and these additional tasks can provide incentives). For example, a forecaster tries to integrate known planning figures, previous and upcoming earnings management, with own expectations. But, however, this forecaster might give more credit to the expected annual return targets than to the internal state of the subsidiary. Depending on the impact of these influences, the combination of organizational biases could substantially distort the overall goal and change the forecasting process from an accurate forecasting to a forecasting of ambiguous and even misleading organizational influences (Hypothesis 8).

Hypothesis 8 (Goal of Forecasting). *The goal for forecasters can change or be distorted in dependence of organizational biases.*

Forecast adjustments that are strongly influenced by organizational biases, giving rise to the question what influences would justify the revisions of the expert with regard to the Hypotheses 7 and 8. The intention is to analyze what influences a model considers to be essential for revisions. For this purpose, the manager's revisioning is regressed with a model that can access actuals, and another model that can additionally access suggested earnings targets.

First, Hypothesis 7 requires that accurate forecasting (the goal of forecasting for corporations) relates to revisions. This relation incidentally is a precondition for the analysis of Hypothesis 8, requiring two competing goals. Thus, the first regression analyzes the dependency of revisions on the difference from the actual ratio and is modeled with Definition 13.

Definition 13.

$$_{12}R = \beta_0 + \beta_1({}_1E) + \epsilon$$

Revision $_{12}R$ is expected to be dependent on the actual error $_1E$ (minimization of "$_0R - {}_1R$" symbolizes the corporation's goal of forecasting) and to be independent of the *Constant* (symbolizes indistinguishable biases in forecasting, including target focus and operational earnings management). In the resulting model, *Constant* should have a small estimate and low significance, while $_1E$ should have a significant influence. If $_1E$ has an insignificant estimate, this would suggest that the revision is not influenced by the corporation's goal of forecasting (rejection of Hypothesis 7.

Second, Hypothesis 8 requires a comprehensive perspective on dependencies. Integrating the organizational bias of Hypothesis 5 (planned earnings targets) into Definition 13 leads to the disentanglement of the effect *TargetDiff* from the *Constant*, resulting in the Definition 14.

Definition 14.

$$_{12}R = \beta_0 + \beta_1({}_1E) + \beta_2(\mathit{TargetDiff}) + \epsilon$$

The expectation according to the Hypothesis 8 requires *TargetDiff* to play a significant role in the regression model. The revision's dependency on *TargetDiff* should imply a significant estimate with a higher magnitude in comparison to the other variables ($_1E$ and *Constant*).

Overall, as simple as it may seem, Definition 14 can result in wide-ranging implications. First, the regression model might state that the forecast process is distorted from the corporation's original goal of forecasting (assuming that full knowledge of the error would be given in advance). If forecast processes (intentionally or unintentionally) dependent on another organizational bias than error minimization, some actions should be taken. Second, as the organizational bias of error minimization might not be the primary goal, the forecast should be corrected. With detailed knowledge for the reason behind, the integration of the considered organizational bias of planning targets might be used to improve forecast correction.

Chapter 5

Predictive Value

Financial services within corporations usually are part of an information system on which many business functions depend, such as decision support systems for judgmental forecasts. As of the importance of forecast quality for financial services, means of forecast accuracy improvement, such as data-driven statistical prediction techniques and forecast correction, have been subject to forecast research for decades.

The evaluation of the predictive value for forecast correction techniques applies the following framework: Expert forecasts will be compared to model forecasts that apply statistical prediction techniques on individual and aggregate level. It is expected that the models provide forecasts with higher accuracy than the uncorrected ones. Therefore, it is expected that models provide reliable recommendations to managers where differences between model forecasting and experts are most pronounced. Studies on improving forecast accuracy usually apply correction techniques such as linear regressions for analysis and correction of biases. With no regard for further improvements the thesis applies linear regression techniques as reasoned by (Brighton and Gigerenzer, 2015), and provides a initial approach to the model correction of forecasts. Assumed that the descriptive statistics provide evidence that a regression model at the individual or aggregate level can partially explain dependencies (e. g. an organizational model compared to a statistical base model), it is justified to assume that more advanced models (e. g. random forests or neural networks) can also use this information.

All model forecast are based on regressions that are trained with sample data from the training period covering the years from 2008 up to 2012. The evaluation analyses are based on the out-of-sample data with a test period that covers the subsequent year 2013. Evaluation uses recalculation with month-end rates to retrieve Euro-equivalent volumes for items in different currencies than Euro. The model notation uses $M_{\text{Def. \#}}$ or $M_{\text{Equ. \#}}$ to refer to the specific definition or equation, while $M_{\varnothing}$ refers to the experts' forecasting. If an element of the forecast processes has a subscript with a model it indicates that the element refers to the model corrected forecast. For instance, the notation ${}_1F_{\{M_{\text{New}}\}}$ refers to the forecast of model "New" with lead time $t = 1$. The dependent variable of most interest for corporate controllers is the error of the last forecast, when the revision process is completed and biases can be detected based on a full dataset of forecasts and revisions. Therefore, the evaluation of the predictive value will base on the error of the last forecast for models and experts. The following section will explain the analyses in detail.

5.1 Predictions on Individual Level

5.1.1 Correction: Anchoring and Adjustment

The correction approach for the reduction of individual level biases of A&A applies to two trained regressions, one for negative and one for positive revisions. These regressions utilize Equation 5.1 with lead time $t = 1$.

$$ {}_tpe = \alpha + \beta({}_tr) + \epsilon \tag{5.1} $$

After training the models the out-of-sample errors are predicted. One percent of these predicted errors are then removed from the expert forecasts ${}_1F$ to account for the "bias bias" (Brighton and Gigerenzer, 2015). For the model-corrected forecasts (${}_1F_{\{M_{\text{Equ. 5.1}}\}}$) and the original expert forecasts (${}_1F_{\{M_\varnothing\}}$) the forecast errors of the models are computed for the out-of-sample period (year 2013), which are later aggregated by date (each month of 2013) and currency. This aggregation uses absolute volumes for each $\langle$month, currency$\rangle$-pair to provide error volumes of net foreign exchange exposures. As, for reasons of confidentiality, absolute volumes are not reported. Instead, the percentage error reduction of the correction model (*Improvement*) for each month is calculated (see Equation 5.2).

$$ \textit{Improvement (in \%)} = \frac{\sum |{}_1pe_{\{M_\varnothing\}}| - \sum |{}_1pe_{\{M_{\text{Equ. 5.1}}\}}|}{\sum |{}_1pe_{\{M_\varnothing\}}|} \cdot 100\ \% \tag{5.2} $$

5.1.2 Correction: Concentration Measures

Focus is now turned to the question how the results – specifically, the revision patterns described by the concentration measures (X_i, Y_i, Z_i) – can be leveraged to improve forecast accuracy, and the judgmental forecasts of the net foreign exchange exposure. The results compares a benchmark model, as shown in Equation 5.3, with the full model as specified in Equation 5.4.

$$_{1}e = \beta_1(c) \times \beta_2(m) + \beta_3(g) \times \beta_4(Division) \times \beta_5({}_{1}F) + \epsilon \tag{5.3}$$

$$\begin{aligned} {}_{1}e = \beta_1(c) \times \beta_2(m) + \beta_3(g) \times \beta_4(Division)\times \\ \beta_5(X_i) \times \beta_6(Y_i) \times \beta_7(Z_i)\times \\ \beta_8(Sign) \times \beta_9(Sign\ change) \times \beta_{10}({}_{1}F) + \epsilon \end{aligned} \tag{5.4}$$

After predicting the error volumes with both models, the error prediction is removed from the expert forecast to receive the model forecasts of ${}_{1}F_{\{M_{\text{Equ. 5.3}}, M_{\text{Equ. 5.4}}\}}$ and the R^2-values. Based on the absolute model errors $|{}_{1}e|$ the aggregated net exposure improvement in the test period is calculated and compared to one another to evaluate the potential of forecast improvement.

5.2 Predictions on Aggregate Level

This section explains the motivation and development of predictions on the aggregate level of business characteristics. In particular, question is how the correction of forecasts on the aggregate ratios of subsidiaries can improve corporate business. A financial department might have interest to achieve two objectives: reducing costs and reducing workload. As foretold, forecast inaccuracies can translate into costs increase (for instance in hedging activities). Further, when managers manually inspect the validity of specific forecasts the workload will increase with numbers of issued forecasts.

Implications by Aggregate Level

The aggregation of the forecasts to a subsidiary-specific ratio level provides several implications:

First, accurate recommendation techniques on aggregates result in fewer issues recommended for manual review, and therefore fewer workload for managers. Compared to the validation of thousands of issues for individual forecasts, reducing the number of data points to inspect upon the important core, improves both quality of the forecast in terms of random noise and total number of issues. This is important for corporations as human workload is a vital topic and costly.

Second, organizational biases can inflict the accuracy of many underlying forecasts in different ways (e.g., earnings management often affects a set of items), but at the aggregate level the biases can directly relate to a specific forecast. Utilizing the information at the aggregate level can provide beneficial insights to better identify the concerning issues at a level where meaningful decisions are made – the business level. And, as these issues concern the business level the solved issues can improve forecast accuracy. For corporations with tasks in risk management, obtaining an accurate forecasting basis is important as it can help to reduce the costs by avoiding unnecessary currency hedges.

Third, forecast correction techniques on an aggregate level can easily integrate key figures for these biases, providing more reliable predictions. When verification of individual level forecasts is determined in a forecasting support systems, correction approaches could take into account statistical information relevant at all levels of the organization to provide a more accurate determination of manual verification issues. While business organizations and scientific communities are aware of various biases, it seems that little effort was put into the combination of correction techniques and organizational biases to improve decision support.

Finally, by identifying the meaningful issues the accuracy and reliability of model predictions become more important as the aggregates combine many forecasts. Otherwise, based on a biased model forecast, falsely predicted issues potentially increase workload as it leads the managerial attention on unimportant work scopes. An improved predictive value for forecast support systems can help to reduce the workload of forecast inspections.

Models on Aggregate Level

When the information retrieval processes can not be changed (the way subsidiaries gather and transfer the forecast data to the corporation), the subsidiaries' forecasts need to be enhanced with information of planning and operations to overcome organizational biases. However, current forecast correction techniques usually build models that employ solely statistical information of basic features based on historical data – neglecting the important business information of organizational biases for forecast correction approaches. An example of a basic statistic model can be found in Definition 7 (M_{Basic}). Here, the forecast error ${}_1E$ is regressed using basic variables such as regression intercept, ratio ${}_1R$, and revision ${}_{12}R$. Theoretically valid, this model optimizes the error based on the human forecasting and revisioning behavior. But the accuracy of these forecasts is most likely reduced by biases of the organizational structure. In case of aggregated cash flows in accounting, the forecasts are expected to highly depend on KPIs, such as return margins. Therefore, the thesis argues that correction approaches should also incorporate such important organizational information. As noted before, reaching predefined target KPIs is an important corporate goal and the distance to such organizational prerequisites should be measured and take into consideration. That is why Definition 8 integrates the information of *TargetDiff* into the regression model M_{Orga}.

Support for the subsequent hypotheses is evaluated based on the two regression models (M_{Basic}, M_{Orga}), utilizing the results of Hypothesis 4. Considering the seasonality in the business data, both models are trained for each month of the year independently. Therefore, the data is split into 12 monthly subsets that are accessed to train one specific instance of the model for each month (resulting in 2×12 models for $\{M_{Basic}, M_{Orga}\}$ in total). To show the benefit of the organizational information empirically, the model prediction of the error ${}_1E$ requires to add the original forecast ${}_1R_{\{M_\varnothing\}}$ to derive the model predictions ${}_1R_{\{M_{Basic}, M_{Orga}\}}$ of the actual ratio ${}_0R$.

Forecast evaluation utilizes the results (${}_1R_{\{M_\varnothing, M_{Basic}, M_{Orga}\}}$) for comparison in the test period. These model predictions in the empirical study will then be analyzed in comparison to the original forecasts and with each other in terms of forecast correction (and forecast efficiency in Section 5.3). The baseline for comparison is the forecast based on $M_\varnothing$, which will be evaluated first. For reasons of clarity, the model forecast substitutes the original forecast, which leads to three possible forecast processes $\langle {}_5R, {}_4R, {}_3R, {}_2R, {}_1R_{\{M_\varnothing, M_{Basic}, M_{Orga}\}}, {}_0R \rangle$ with changed revision and error measures for ${}_{12}R$ and ${}_1E$ depending on the selected model. Understandably, the evaluation focuses on these changed measurements only.

Test Design for Forecast Correction

The hypothesis is that re-adjustment of the subsidiaries' forecasts, utilizing the previously defined model, will provide meaningful accuracy improvement within the correction process.

Hypothesis 9 (Business Information Improves Predictive Results)**.** *Utilization of a proxy for business key figures in a forecast correction model can improve the predictive results.*

In order to evaluate the correction of predictions, a comparison of the errors for future predictions should be striven for. To support Hypothesis 9, the monthly predictions of the models will be compared to the expert forecasts in terms of absolute error ratio, shown in Equation 5.5. In addition, Equation 5.6 measures the percentage improvement of the model error in comparison to the expert error, which is analyzed for each month separately. To show empirically that percentage differences between the models are significant, the results on the improvements are validated with a t-test. Further, evaluation will analyze error distributions of forecast corrections to provide the quantiles, maximum, minimum, mean, and median descriptives for the errors ${}_1E_{\{M_\varnothing, M_{Basic}, M_{Orga}\}}$.

$$\textit{Forecast Error} = \sum |{}_1E_{\{M_\varnothing, M_{Basic}, M_{Orga}\}}| \tag{5.5}$$

$$\textit{Improvement (in \%)} = \frac{\sum |{}_1E_{\{M_\varnothing\}}| - \sum |{}_1E_{\{M_{Basic}, M_{Orga}\}}|}{\sum |{}_1E_{\{M_\varnothing\}}|} \cdot 100\ \% \tag{5.6}$$

5.3 Improvement of Aggregate Efficiency

Empirical analyses on weak forecast efficiency or on biases in cash flows is a major topic for specific research communities and therefore easy to find in the literature. These efficiency tests usually provide confirmation or rejection of efficiency from a statistical perspective, but, they can also provide further qualitative information about the objects to be examined. Such forecast research for the assessment of the corrected predictions that evaluates forecast based on efficiency, does not receive the attention it deserves.

Correction techniques usually evaluate their results with some error metric, such as error (deviation), absolute error, percentage error, absolute percentage error, and so on. Slightly different use cases can favor a specific error measure as most of them have known flaws that suit one case but not others. The research presented in the next analyses tries to be independent of those restrictions that would make comparison of scientific results difficult. For this purpose the subsequent analyses use forecast efficiency to provide statistical information, which results in a model comparison evaluated in an error metric independent way – the forecast efficiency of corrections. As a result, the most diverse error metrics, which in the specific case are more or less justified but block the comparability of the approaches, are then not as relevant anymore.

In forecast processes, basic correction techniques with linear models (such as in Definition 7) regress the targeted variable with basic statistical information. As a result, these basic statistics as input information deliver no information about forecast process dependencies to the correction model. I.e. organizational biases that result in dependencies between forecast processes will not be taken into account. Models that miss such dependencies can hardly optimize entire forecast processes while correcting the target variable. One could compare these forecasting models, which focuses only the target variable, is as if blindly walking through a forest, trying to avoid bad "symptoms" (e.g., walking into trees). Guiding the model's forecasting with relevant information about the inherent dependencies of the forecast process changes this circumstance[1]. A corrective model enhanced with such forecast process information might be able to produce forecasts that are aligned with the forecast process[2]. The resulting model forecast can be understood as optimized for the forecast process's "causes" that result in the symptoms (such as errors). Therefore, enhancing basic statistical approaches with information for organizational debiasing seems beneficial. Combining the argumentation for organizational debiasing and efficiency, the following hypotheses are proposed:

Hypothesis 10. *Disregarding the organizational information in forecast correction mostly decreases the efficiency of forecast processes.*

Hypothesis 11. *Forecast correction that incorporates organizational information (that organizationally biases forecasts) is beneficial to efficiency of forecast processes.*

Hypothesis 12. *Organizational forecast correction is superior to solely statistical approaches in terms of weak forecast efficiency.*

5.3.1 Weak Forecast Efficiency Analysis

The subsequent analyses are expected to show that organizational information is beneficial to forecast correction techniques in terms of forecast efficiency. The model predictions are the same as those given in Section 5.2 (Models at Aggregate Level). The three hypotheses will be stated in terms of forecast efficiency on the aggregate ratio level, analyzing the Spearman correlations between ${}_1E_{\{M_\varnothing, M_{Basic}, M_{Orga}\}}$ with ${}_{12}R_{\{M_\varnothing, M_{Basic}, M_{Orga}\}}$, ${}_{23}R$, ${}_{34}R$, and ${}_{45}R$ (Proposition 1 in Nordhaus, 1987). Further, changes of correlations will be analyzed for ${}_{12}R_{\{M_\varnothing, M_{Basic}, M_{Orga}\}}$ with ${}_{23}R$, ${}_{34}R$, and ${}_{45}R$ (Proposition 2 in Nordhaus, 1987).

[1] Aspects of random noise for organizational correction techniques in terms of forecast efficiency: Considering that adding big random values with correction approaches means forecast processes are perfectly efficient afterwards. E.g. an approach might generate a bias feature randomly, which would make revisions and errors appear independent from each other. Such an approach has the following consequence: the resulting forecast error should increase – if random walks are not the best option. But, the sensitivity of most correction approaches to a random noise of extreme values will result in an insignificant influence to change the error term. Thus, a correction model would hardly use these provided values (based on the error distribution) for a corrective model. Corrective model in general are not entailed by this concern, since the models would not utilize these random metrics. Therefore, this matter is no limitation for (organizational) debiasing techniques and result in the validity of correction model in terms of efficiency.

[2] And with regard to the targeted variable as "symptom"-free.

Expectation for Hypothesis 10 suggests the result that correlations of M_{Basic} in comparison to $M_{\varnothing}$ might increase, except for $Cor({}_1E, {}_{12}R)$ as both models targeted to optimize the variable ${}_1E$. Expectation for Hypothesis 11 hints to results that correlations could decrease for M_{Orga} in comparison to M_{Basic}, except for $Cor({}_1E, {}_{12}R)$. Finally, Hypothesis 12 leads to the expectation that the model M_{Orga} offers higher efficiency of the forecast processes in comparison to M_{Basic}. Further, it leads to the expectation that the model M_{Orga} will produce forecasts that align the revision to the organizational information. This alignment is expected to result in adjustment of ${}_1R$ with slight changes for ${}_1E$.

Evaluation of Hypotheses 10 and 11 uses the Models $M_{\varnothing}, M_{Basic}, M_{Orga}$ to calculate the percentage difference on absolute correlation values of one model M_{New} in comparison to the other model $M_{Baseline}$ as shown in Equation 5.7. The evaluation of Hypothesis 12 (which might be partially stated within the evaluation of Hypothesis 11) will base on the analysis of the statistics for correlation and distribution of ${}_1E$ and ${}_{12}R$.

$$\textit{Efficiency Improvement (in \%)} = \frac{|\text{Eff.}(M_{Baseline})| - |\text{Eff.}(M_{New})|}{|\text{Eff.}(M_{Baseline})|} \cdot 100\ \% \tag{5.7}$$

5.3.2 Extended Weak Forecast Efficiency Analysis

Based on the previous hypotheses on forecasting efficiency, this thesis questions what further insights are possible with the theory of weak efficiency. Forecast efficiency theory could provide an alternative approach to understand the value of specific information within forecast correction (compared to other approaches such as entropy or information gain). It suggests itself therefore to extend the often adapted efficiency test and to demonstrate the increase of theoretical understanding for forecasts and their corrections. Therefore, this section introduces the concept of the "extended weak forecast efficiency" and the design of the research analyses with this concept.

Concept of Extended Weak Forecast Efficiency

The extended weak forecast efficiency proposes a concept that aligns the Propositions 1 and 2 (as proposed in Nordhaus, 1987) with the following two Propositions 9 and 10.

Proposition 9 (Timing). *Forecast error at t is dependent of all subsequent revisions until* $(t-1)$.

Proposition 10 (Impact)**.** *Forecast error at t is independent of all preceding errors until* $(t+1)$.

The concept of extended forecast efficiency refers to the weak efficiency theory Propositions 1 as "*Purpose* (1)", and Proposition 2 as "*Revision* (2)" , while the new extending parts of the concept focus on Propositions 9 as "*Timing* (3)", and Propositions 10 as "*Impact* (4)" of forecast processes. A graphical representation of the concept that groups the dependencies with regard of lead times t is depicted in Figure 5.1.

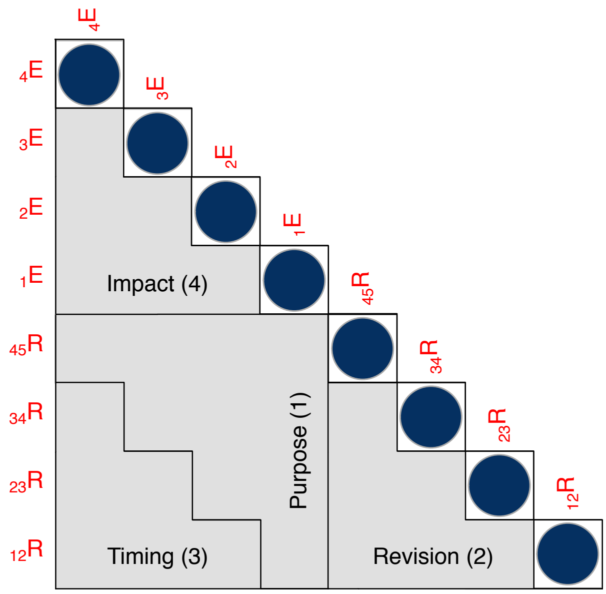

Figure 5.1: The concept of the "extended weak forecast efficiency" analysis as a graphical representation. All dependencies that are calculable between revisions and errors are grouped into four distinct parts, while blue bullets represent self-dependencies with values of 100 % dependency. These four parts cover *Purpose (1)*, *Revision (2)*, *Timing (3)*, and *Impact (4)* of the forecast process. Based on at least two different approaches of forecast correction, the comparison of the resulting values of the forecast processes can provide insights for these parts of efficiency of the different behavior shown by the correction approaches. For convenience of the reader that are common with the Nordhaus analyses that cover elements of (1) and (2), it is noted that the most left side column for dependencies with error ${}_5E$ is dismissed in the figure.

The concept utilizes all possible dependencies between revisions and errors. At this point the different groups of dependencies are explained with regard to forecast processes, the comparison of different forecast processes, and forecast corrections.

1. The *Purpose (1)* group shows dependencies of the errors with previous revisions. As the revision should give no indication for subsequent errors low values are beneficial. Forecast processes that show low or insignificant dependency are considered as weak efficient. The comparison of different forecast processes on behalf of these dependencies can help to indicate which specific forecast process has the better progresses in integrating information into forecasts. This comparison is ought to show which processes serving the purpose of efficient forecast processes to receive a adequate representation of the actual value (and to minimize errors), or at which point the forecast processes require improvements. Comparing different forecast corrections, which usually change the last forecast to optimize the forecast error, one should favor the correction with lower dependency.
2. The *Revision (2)* group shows dependencies of revisions with previous revisions. Revisions should give no indication of subsequent revisions. Otherwise anticipation of this information into revisions could make the aforementioned revision partially obsolete. Therefore, low dependency is beneficial. Forecast processes that show low or insignificant dependency are considered as weak efficient. Comparison of different forecast processes can indicate at which point the forecast process is improvable. Forecast corrections that change the last forecast should be favored if the correction result in lower dependency to previous revisions, as the revisions will show a random walk behavior, where information is efficiently integrated.
3. The *Timing (3)* group shows dependencies of revisions with previous errors. The intuition is that subsequent revisioning should reduce the forecast error at previous points in time. Otherwise, at the point in time when errors would require change of forecast no adjustment would be made. High dependency is considered as beneficial for forecast processes. Forecast processes should show high and significant dependencies stating that the forecast process considers the errors made over time. Favorable among different forecast processes are those that constantly improve over time showing high dependencies, while low dependencies can indicate that the integration of information does partially not serve the error reduction. Preferred are forecast corrections that show the highest dependencies to the last revision of the corrected forecast. Corrections that increase the dependency indicate that information that is present in the early stages of the forecasting process but has not yet been fully taken into consideration is now integrated in the corrected forecast. Depending on the information utilized by the specific correction algorithm, dependency states the relevance of these information for specific earlier stages of the forecast process.

4. The *Impact (4)* group shows dependencies of errors with previous errors[3]. The intuition for this group is that a forecast processes should integrate as much information as possible in an efficient way, resulting in a constant change of forecasts. Such forecast processes will have a high impact on the forecasts being made. Forecasts that integrate irrelevant or few information will not exhibit high changes, resulting in a high probability that forecast errors stay the same. Forecast processes should exhibit low dependencies. Low dependencies state that forecasts change over the forecast processes, indicating that the information used influences forecast errors. A high dependency between errors would state that errors being made will propagate through the forecast process untouched. Among different forecast processes the ones with the lowest dependency are preferable, since high dependency suggests useful information that could be integrated – regardless of whether or not the possibility to extract exists at all. Forecast correction that aims to reduce the error should have the lowest dependency possible, showing that the correction approach has a low dependence to previous forecasts within the forecast process (that might serve as input) to produce the corrected output. Otherwise, the impact of the correction would be marginal, producing high forecast errors when errors were already high and producing low errors when errors were already low.

This concept is applicable to domains, where exploratory data analysis, evaluating specific information, and forecast correction play an important role in time series forecasting.The resulting empirical analyses derived by the concept of extended weak forecast efficiency should help to understand forecast correction approaches better, leading to Hypothesis 13.

Hypothesis 13. *The concept of extended forecast efficiency can help to understand the inherent adjustments made by different correction approaches.*

Summary of Extended Weak Forecast Efficiency Concept

The provided insights cover important details for the correction with models, which is summarized as: *Purpose (1)* states that the process does what it should do (increasing accuracy). *Revision (2)* questions if all information is integrated. *Timing (3)* detects the duration of the corrected pattern (since when it existed), and *Impact (4)* measures the integration of information (magnitude of adjustments) for the forecasting process. The information of what is targeted for the dependency

[3]This group might be considered as an converse group of the *Revision (2)* group – oriented on the error output instead of revisions.

values of a forecast processes is summarized as follows: Low dependencies for the groups of *Purpose (1)* and *Revision (2)* qualifies weak efficient forecast processes, which is beneficial. It is helpful to notice that in the case of the *Timing (3)* group a higher dependency does mean that forecast processes are beneficial. For the *Impact (4)* group lower dependency is beneficial.

Test Design for Extended Weak Forecast Efficiency

Hypothesis 13 claims that the extended weak efficiency analysis provides a statistical tool to evaluate different correction approaches. The analysis of efficiency figures can provide insights for the differences of models' predictions. The extended efficiency analyses will be used on accounting cash flows to underline the validity of the hypothesis. Further, the analysis will contribute to the current research as the concept extended forecast efficiency could show that including specific information (of organizational dependencies) into correction models is key for further improvements in correction techniques.

The evaluation is based on the comparison of forecast efficiency for different forecast processes with the models $M_{\varnothing}$, M_{Basic}, M_{Orga}. The model predictions are the same as those given in Section 5.2 (Models at Aggregate Level). The applied forecast correction with M_{Basic}, M_{Orga} is expected to change the specific forecast (${}_1R$), wherefore the extended weak forecast efficiency analyses cover Spearman correlations of the revision (${}_{12}R$) or error (${}_1E$) with all other existing revisions (${}_{t,t+1}R$) and errors (${}_{\tau}E$) for $\tau \geq 1$. For instance, a forecast process with five forecasts result in changes of four correlations in the *Purpose (1)* group, four correlations in the *Revision (2)* group (with the self-correlation of ${}_{12}R$), four correlations in the *Timing (3)* group, and four correlations in the *Impact (4)* group. These four groups of correlations are analyzed to identify changes for the different models.

Differences in the correlations of the models (for the 4 groups) are considered as support for Hypothesis 13 if specific model differences are discernible from the correlations and the information used. The results are also expected to provide further support to the Hypothesis 12. Expectation for the empirical outcomes of these organizational models in comparison to the purely statistical models is that both models reduce the error, but the disregard of organizational information in the purely statistical approach does crucially harm the efficiency. Expectation is that the organizational information changes the extended weak forecast efficiency in different ways and the integration of this information can be related to specific benefits being identified, answering how does efficiency for organizational correction differ from basic statistical approaches.

Part III

Application in Practice and Empirical Evaluation

Chapter 6

Case for Data Evaluation

The empirical dataset used in the thesis stem from the confidential, unique record of real-world cash flow forecasts and corresponding realizations within the financial system of a large multinational corporation. The corporation is headquartered in Germany but has worldwide operating subsidiaries in different countries. With over 100,000 employees, the company generates annual revenues in the medium double-digit billion Euro range and is one of the largest corporations registered in Germany.

The corporation has more than 300 separate legal entities, including the subsidiaries. The subsidiaries are grouped into three large distinct business divisions, based on their fundamentally different business portfolios: "Agricultural products" (AP), "health and pharmaceuticals" (HP), and "industrial materials" (IM). Entities with business portfolios (products) belonging to more than one division are summarized under a fourth artificial division, "diverse" (DV). Companies in AP produce a broad spectrum of agricultural supplies and therefore largely depend on agricultural cycles, i.e., a yearly cycle of seeding, and harvesting. Companies in IM develop and produce industrial materials, depending on orders of manufacturing companies that again depend on macro-economic uncertainties. HP researches and produces health-related products and pharmaceuticals, which mostly only weakly depend on the economy or annual cycles.

Processes in today's business of corporations often rely on qualitative and quantitative expectations about future events – commonly known as forecasts. In the case of a globally active corporation, business results usually in invoices and cash flows in various currencies. Financial risk management is centralized, with local financial managers at the subsidiaries reporting cash flows and invoices to the corporation's central finance department, where these data serve as the basis for further actions in corporate finance. One important task of the finance department is the management of financial risks, in particular future foreign exchange risks.

The experts in the corporation's subsidiaries generate judgmental cash flow forecasts of accounts receivable and accounts payable in a decentralized fashion for the corporate finance department[1], in the individual subset of currencies in which each of the subsidiary issues and receives cash flows. Accounts receivable result mainly from sales invoices expected to be issued, accounts payable from invoices expected to be received from suppliers and other counterparts.

After the realization date, the corporation receives the accountants' cash flow and invoice figures for realizations (hence, "actuals") of the subsidiary every month. The forecasts and actual data available for the analyses cover item-types of invoices issued (*II*) and invoices received (*IR*) in the corporate information system. Delivered by the subsidiaries on a quarterly basis, the forecasts cover monthly intervals with differing forecast horizons of up to 15 months (five quarters).

Each (revised) forecast has a specific time horizon depending on the month in which it is delivered. Forecasts are only delivered in the months of March, June, September and November and remain unchanged between forecast deliveries. Table 6.1 shows schematically the temporal structure of forecast deliveries for actual cash flows realized between January and March 2012: the months in which a forecast is delivered are labeled F, and the month in which the corresponding cash flow is realized is labeled A. The first forecast will have been delivered in November 2010, and the corresponding revised forecasts in March 2011 (with a horizon of four quarters), June 2011 (three quarter horizon), and so on. Hence, revised forecasts for January 2012 will have been delivered 10, 7, 4, and 2 months before. Therefore, the lead time refers to quarters of the year before the actual realization. An exemplary revision process for a whole short actual time series is shown in the Appendix B, Table B.1.

The dataset for actual invoices ranges from January 2008 to December 2013. The corresponding forecasts were delivered from November 2007 to September 2013 and cover the actuals' period.

[1]Taken literally, accounts receivable and accounts payable are accruals rather than cash flows. Forecasts of accounts receivable and accounts payable are used in the empirical analysis rather than cash flows, because there is no access to detailed historical data for realized (actual) cash flows. As in most companies, the partner company's reporting systems were traditionally designed to meet the requirements of financial and tax reporting, i.e., they were oriented towards revenues (and other income) and expenses, not to cash in–flows and out–flows. For all practical purposes, the forecasts of accounts receivable and accounts payable are comparable to forecasts of cash in flows and out flows. The results of the empirical analyses are thus generalizable to cash flow forecasts. For the sake of simplicity, this thesis continues to refer to the forecasts used in the empirical analyses as cash flow forecasts.

Horizon	2010			2011												2012		
	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3
5 Quarters		F														A	A	A
4 Quarters						F										A	A	A
3 Quarters									F							A	A	A
2 Quarters												F				A	A	A
1 Quarter														F		A	A	A

Table 6.1: Temporal structure of expert forecast deliveries for the first quarter of cash flows and invoices in 2012 with the months of actual cash flows (A) and delivery of the corresponding forecasts (F) for different forecast horizons.

6.1 Information System: Landscape and Workload

The subsidiaries forecast figures provide main inputs for the financial information system, which are further processed to support acquisition, data preparation, and representation of the relevant information. A forecast support system attached to the information system will validate these inputs with subsequent debiasing techniques for decision support. The forecast support system will provide aggregate views on a corporate level, upon the managers give recommendations for hedging activities. The Figure 6.1 depicts the components and connections of the technical landscape implemented for the forecast support system.

As corporate managers expect that biases may affect the corporation's cash flows and much effort is spent on identification and handling of biases in cash flows. Therefore, the corporation aims to reduce forecast error and to enhance corporate forecast support system with automated validations and also with validations that employ model driven support.

The validation process starts when the forecasts are transferred by the subsidiary into the corporate information system, after which the forecast support system provides validations on the syntax and the semantic for each single forecast item. The current set of validations also checks if a specific forecast is in line with the predictions of correction algorithms. The algorithms cover time-series and behavioral analysis, such as identification of anchoring pattern. The predictions of the algorithms are fed into a decision support system, which recommends the inspection of specific forecasts (*issue*) to the corporate managers, who then contact the subsidiary's responsible to review the situation. After the manual review, the corporate managers finalize the forecast process, or the subsidiary's responsible may be asked to update the forecasts with a new forecast

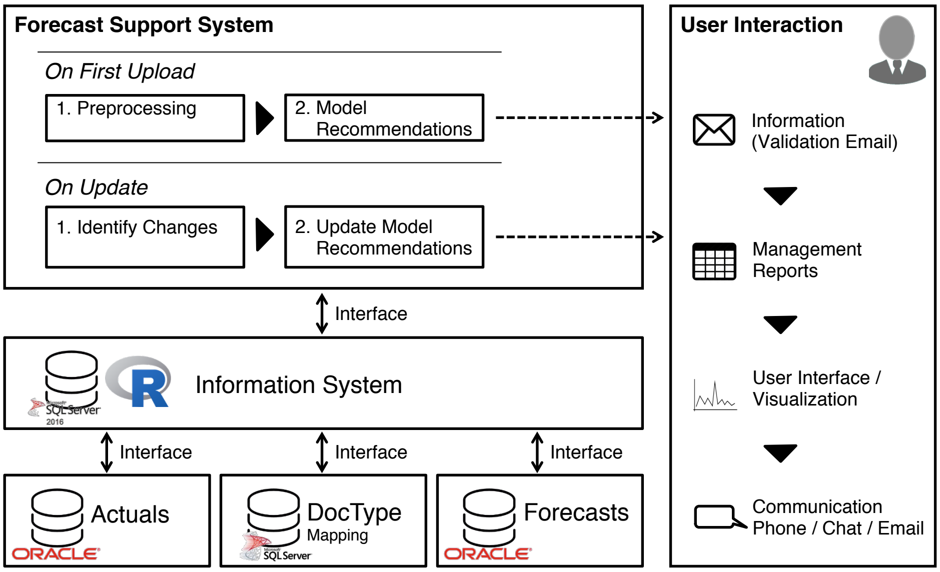

Figure 6.1: The technical landscape of the corporate forecast support system shows the underlying databases that are connected to the central information system. The forecast support system connects to the information system and provides recommendations to the subsidiaries' user. These users receive information about the process status (validation email). Based on management reports and user interface visualizations the corporate managers communicate with the users to solve the recommended issues.

transfer and thus initializing a new iteration of the forecast validation. Figure 6.2 depicts the process. While different algorithms can provide multiple issues for one forecast, the workload for the managers increases with the number of issues to be inspected. Also, managerial understanding of each specific issue is required, which further increases the workload. Overall, for thousands of forecasts, with potentially one or more issues each, the effort in cooperation with the subsidiaries is enormous.

6.2 Corporate Reporting Structure

Each subsidiary operates officially independently of the corporation, while there are some organizational dependencies. (1) The figures of corporate planning are defined in agreement with the subsidiaries. Based on the set of local plans, the corporation re–adjusts the planning to an overall view and defines the requirements for local operations being rated as "successful" subsidiaries. These requirements are split and communicated by division mangers to each subsidiary. (2) In the corporation the fiscal year ends in December and the subsidiaries' focus on

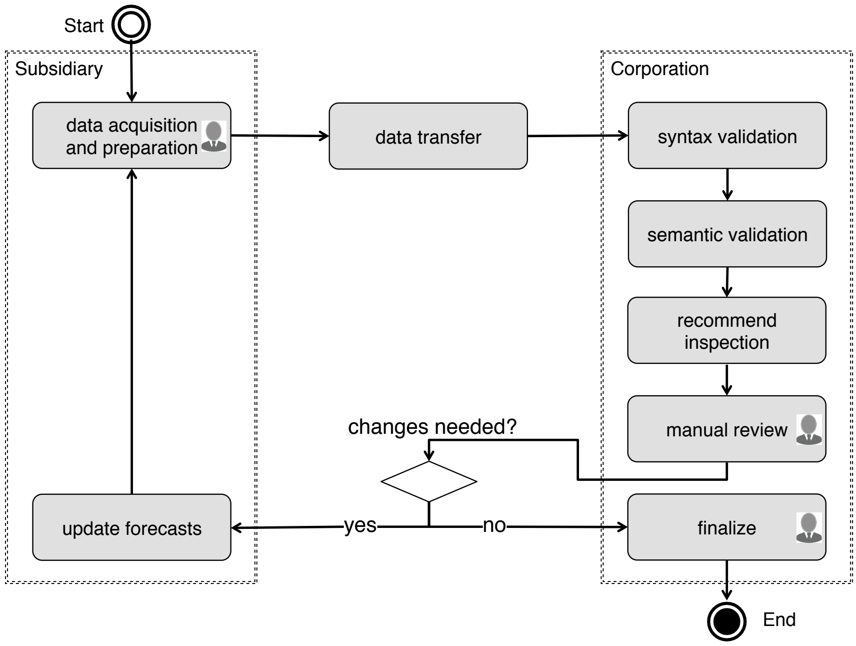

Figure 6.2: The validation process for the delivered forecast data of the subsidiary. The process is starts with the initialize data acquisition preparation of the subsidiary. After the data transfer the data is processed within the information and forecast support system that validates the data and recommends specific forecasts for inspection. Corporate managers manually review the forecast data and can iterate a new forecast update or can finalize the process.

meeting targets is assumed to be most pronounced at the end of the year. (3) In every subsidiary, a manager dedicated to forecasting should provide accurate forecasts to the best of his knowledge for the corporation. The corporation does not incentivize the managers for these tasks. (4) Full time employees in the subsidiaries are expected to work on a mix of different tasks, if the workload in planning, forecasting, or operations enables resource shifts. (5) As the subsidiaries operate independently, they have their own financial system and a heterogeneous payment structure (e.g., incentivization bonuses), and they have to ensure liquidity for their operations (e.g., with earnings management processes). (6) Each subsidiary that is participating in the forecasting process –mostly large-volume entities– enters their expectations on future cash flow in a digital, corporate–based forecasting system. Forecasts accessible are aggregated for corporate risk management to apply hedging measures and further instruments later on.

Figure 6.3 depicts the interactions between the corporation and a subsidiary. Planning figures, forecasts, and realization volumes are needed to be communicated, but the responsible managers (planner, forecaster, and earnings manager) have mostly restricted access (as a personal view) to the internal state of the subsidiary.

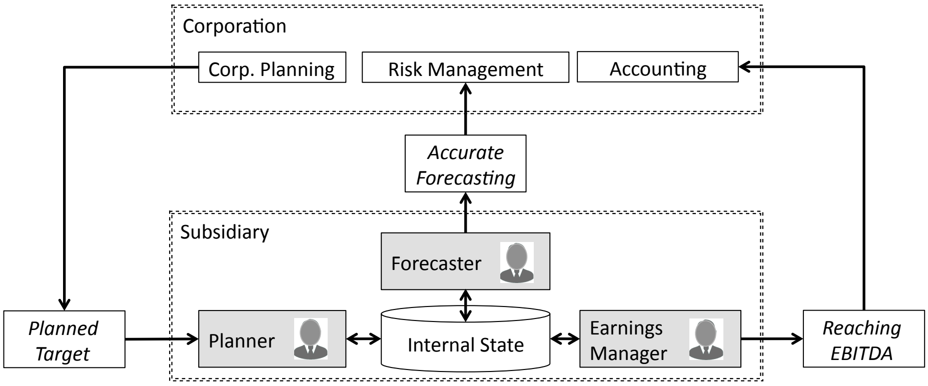

Figure 6.3: Dependencies of reporting units in the corporate structure. The figure shows three directed dependencies of the units inside of one exemplary subsidiary to the corporation. Target planning, forecasting processes and operative earnings management stay next to each other, but do not need to be interlinked if the managers in the subsidiary have a restricted perspectives.

6.3 The Business Importance of Forecasting

The corporation, which is a Euro-led one, records its earnings in the same currency. These invoices and cash flows are so crucial to the solvency of a company that the performance of the exchange rate of a currency in which the invoices are submitted represents a risk to the company. For instance, the risk of a currency rate drop is ubiquitous, so that earnings cannot be fully entered. A look at the history of different currency pairs confirms the importance, for example during the year 2014, when the combination of the Euro/Dollar rate experienced a long-term collapse of about 24 %. For an assumed invoice volume of 10 million Euros, this drop would create a loss of 2.4 million Euros, which might be considered on the company side for future purchases.

In order to minimize this loss risk, so-called currency options (currency hedging) are purchased. This produces costs in dependence of the volume and currency pair, but makes the foreign exchange risk (exposure) calculable at all. In order to specify this volume in concrete terms, forecasts are required. The forecast volume to be hedged should be specified as accurately as possible to prevent costly hedging errors and to avoid that remaining risks are left unsecured (which can lead to losses of profits). This is the motivating basis for the corporation, which strives for accurate forecasts to improve risk assessment or reduce costs.

6.4 Domain Expert Knowledge

In reconciliation with the management of the sample corporation, I used a data driven approach to identify several issues for the data base. The approach led to identification of issues that are explainable and covered by expert's domain knowledge, and those issues that required interaction with the subsidiaries. These aforementioned issues cover the following topics:

Issues covered by Expert Knowledge

(1) Very few samples of a testing entity are inside of the database. These samples must be removed as they exhibit irrelevant data of forecasts and actuals. (2) Due to the system requirements, data samples of the holding corporation is contained inside of the database. The data is required to be removed. (3) Data samples of entities that are from Argentina encounter political import and export restrictions. The data samples are required to be removed. (4) Subsidiaries can switch invoice currencies due to business decisions. As the human forecaster does or does not know about this situation, the forecasts can entail very high errors. A currency switch can occur in one step or over a longer period of time with partial adjustments for invoice items. For instance, switching the realization currency completely from the symbolic old currency A to the new currency B in one step can result in forecasts being unaligned to this matter. This results in all forecasts of one specific invoice item having no actual counterpart in currency A and up to five forecasts entail a percentage error of -100.0 % when the forecasts are revised. Additionally, the second currency B misses the forecasts which results in five additional forecast errors. This will result in a high percentage error in dependence to the other invoice volumes in that currency B. Currency switches usually apply in more than one single month. These currency switches starts at a specific point in time and items are issued and received with the new currency in the period after. This may result in up to 15 forecast series being associated to the wrong currency, depending on the time the forecaster receives information for the currency switch. In total, each single currency switch can have a massive impact on error metrics for up to 150 forecasts. Possible solutions are to remove or recalculate the respective items. In reconciliation with the sample company, the items in both currencies are recalculated in the EUR currency, for both forecasts and actuals. This enables identification of overalls-errors for forecasts. But, as a result, the specific items must be recalculated to the original currencies when hedging measures are applied. (5) Usually the standardized three letter currency code should be provided for forecasts and actuals. But, the currencies of items

were not standardized in the beginning working period of the information system. Data items with misspelled currencies and currency codes like "097" do occur. Data samples of these issues have to be removed, as an allocation is not possible. (6) For the American subsidiaries five so called reference entities exist. These entities provide aggregate forecasts of the other subsidiaries in the USA with regard to the different business divisions. The actuals of each subsidiary in USA are provided separately. But, some subsidiaries do not deliver actual realization volumes – mostly small entities. In reconciliation with the management of the sample corporation, the data samples should be removed. (7) As realization entries are made by humans, sometimes false booking entries for actuals do exist. The mistaken entries are corrected with a second booking for that item with the inverse signed volume. As these mistakes are recognized mostly in the same month there is nearly no effect. Very few corrections have a delay that result in corrections being shifted in the next, or later months. These correction entries are easy to identify based on the exact volume and inverse sign and should be removed. (8) Subsidiaries exist that are not fully registered in the corporate database. This issue results in missing information for local currencies in which the subsidiary operates, preventing hedging operations. These data samples should be removed. (9) For twenty-one subsidiaries no technical interface does exist to provide actual realization volumes to the database. For these forecasts no actual counterpart exists. To prevent percentage errors of -100.0 % these data samples must be removed.

Issues Requiring Subsidiary Knowledge

For each forecasting subsidiary, a local database provides actual realization volumes for invoices. These booking systems of the subsidiaries have different labels for document types, a two letter alphanumeric code system. These codes have developed over the years and their meaning depends on the subsidiaries. Thus, the same document code can provide different meanings for different subsidiaries. Furthermore, the subsidiary's document codes depend in few special cases on currencies, partner subsidiary, and time of the invoice.

Based on these attributes, I developed a classification system that allocates the specific invoice type by a combination of attribute characteristics (classification tuple). If the classification does not allocate an item type, the item is dismissed in the further analyses and the classification frames the item type as "unknown". The classification tuple is described in Equation 6.1.

$$\text{ItemType} = (\text{Document Type}, \text{Subsidiary}, \text{Partner}, \text{Currency}, \text{Date}) \tag{6.1}$$

The specific characteristics that determine a item type are stored in a central database within the forecast support system. After my implementation of the classification system, the corporate manager reconciled with the subsidiaries to determine the meaning of specific document types, reducing the existing unknown items to a minimum (in volume and number). The specific attribute characteristics were updated in the database to provide knowledge for future data deliveries. Continuous improvement processes were implemented to ensure the validity of the classification system.

6.5 Data Preprocessing in Practice

The CRISP-DM reference model (Chapman et al., 1999, p. 10) describes the typical stages of a data mining process, upon which the data mining process was build on. In practice, the preprocessing of the data mining process for development of the forecast support system in the sample corporation requires data acquisition, data understanding, and the identification of foretold data artifacts. Further work is required for the classification system, establishing continuous improvement processes, and in acquisition a comprehensive business understanding. The data acquisition, data understanding, and preprocessing is widely known to take up to 80 % of the total workload for data mining processes (Mannila, 1996). The amount of work in my project with the corporation did take about 3.0 years for these steps and around 75 % of the initial workload. This workload does not cover the software implementation of the data classification and continuous improvement processes. The data cleaning process covers the applied steps of "Preprocessing Content Cleaning" and "Preprocessing Ratio Cleaning", to provide high quality input for the scientific analyses. The section "Preprocessing Overview" provides an overview on the metrics for different stages of data preprocessing.

Preprocessing Content Cleaning

The data cleaning covers the following preprocessing steps: (1) Integration of all considerable and known issues retrieved by expert knowledge and subsidiary knowledge. The data samples are removed or recalculated as exhibited previously. (2) Removing samples that contain false sign of invoice type. For instance, items of type "invoice received" that have a forecast or actual above zero states a false direction of invoice flow. (3) Samples with an actual monthly volume below 100,000 EUR equivalent will to be removed due to a high expected percentage error. (4) Removing samples that exhibit a percentage error of more than 1,500.0 %.

Preprocessing Ratio Cleaning

After the cleaning based on expert and content knowledge, further preprocessing based on ratio insights is applied. These steps of preprocessing cover: (1) Samples that miss one item type of invoices in forecasts or actuals are removed, as a ratio can not be obtained without the complement of item type. (2) Subsidiaries that permanently have a ratio level of zero are removed, as these result mostly from selling-only subsidiaries. In such cases a normalization is not possible. (3) Removing samples that have a ratio above five, as these result mostly from selling-only subsidiaries. (4) Samples that have a history of less then four years are removed to ensure both target calculation over three years and out-of-sample evaluation of one year. (5) Ratios of currencies that do not achieve a correlation over 0.8 to the overall ratio of a subsidiary are filtered. The intention is that currencies without high correlation to the subsidiaries ratio can hardly provide hedging opportunities without further correction, which would require an approach based on the split of invoice received and issued depending on all entity specific currency.

Preprocessing Overview

Table 6.2 shows the different stages of preprocessing. Mean percentage error for the whole data set (second column) is reduced from nearly 80,000.0 % down to 51.4 % for the content cleaning and down to 28.5 % for ratio cleaning. Median percentage errors are reduced too. Obviously, these numbers state that cleaning is essential for data analyses and predictive purposes. With poorly preprocessed or unprocessed data the predictive models and analyses will render unreliable.

Metric	Data Sample						
ape	All	AP	HP	IM	DV	EUR	USD
				Pseudo Actuals (Data #0)			
mean	58.7 %	84.2 %	44.4 %	55.3 %	90.2 %	—	542.2 %
median	—	—	—	—	—	—	—
				Uncleaned (Data #1)			
mean	79237.8 %	414.0 %	1900.5 %	8316.7 %	186399.6 %	1465.3 %	2696.1 %
median	84.8 %	98.8 %	58.6 %	100.0 %	100.0 %	60.3 %	77.9 %
				Content Cleaned (Data #2)			
mean	51.4 %	55.8 %	44.3 %	47.7 %	44.0 %	42.6 %	58.4 %
median	26.1 %	33.8 %	24.5 %	26.8 %	24.5 %	19.0 %	29.9 %
				Ratio Cleaned (Data #3)			
mean	28.5 %	44.7 %	27.2 %	21.5 %	24.4 %	14.4 %	35.2 %
median	12.8 %	17.8 %	9.2 %	12.6 %	12.5 %	8.7 %	19.3 %

Table 6.2: Importance of data cleaning: Comparison of ape metric for different stages of uncleaned and cleaned data. First column notates if mean and median of the ape metric taken. The other columns cover numbers for the whole dataset, all divisions, and selected currencies. Data #0 show numbers as reported in (Martin, 2012), but just covers deliveries of 06/2009 to 11/2010 and does not cover median metric and EUR. His numbers do not cover ape based on real actuals, instead pseudo-actuals are taken (pseudo-actuals replace actuals $A(i)$ by forecasts ${}_1F(i)$ and use the second to last forecasts instead of the last ones (${}_1F(i) := {}_2F(i)$). Data #1 is the raw, uncleaned data. Data #2 is derived from Data #1 and applies preprocessing for content cleaning – the data is used in the individual analyses of this thesis. Data #3 additionally applies preprocessing for ratio cleaning. The resulting data is used in the ratio analyses of this thesis.

The focus to analyze empirical data of existing forecasting processes, avoids biases that might be inherent to management surveys with additional workload for participants. It is important to note that the corporation's privacy policy ensures the anonymity of the subsidiary managers and make surveys impossible in any case.

6.6 Individual Level Business Descriptives

Based on the finest data granularity usable, a subset of the whole corporate record can be grouped into forecast/actual, division, subsidiary, currency, date and item-type. In the Appendix B, Table B.2 exhibits the data structure of a data sample. Country information of each subsidiary can be retrieved, but is not used in the further analyses. Also, the specific partner entities to which each of the subsidiary issues and receives are abstracted, as the current data analyses and models for the invoices aggregate underlying invoice items.

In total, actuals and forecasts in the information system are available for the 99 largest subsidiaries, while the generated forecasts of a subsidiary cover the individual subset of currencies in which it issues and receives invoices—resulting in 44 different currencies for the dataset. Actuals grouped by division, subsidiary, currency and item-type result in 484 actual time series. Overall, the dataset consists of 20,472 monthly invoice actuals, with five associated forecasts each. Table 6.3 gives a brief summary of the dataset.

Divisions	Subsidiaries	Currencies	Actual Time Series	Actuals	Forecasts
AP	12	16	70	3,402	17,010
HP	19	26	146	5,814	29,070
IM	13	8	52	2,692	13,460
DV	53	37	216	8,564	42,820
All	99	44	484	20,472	102,360

Table 6.3: The summary of available individual invoice data in the sample company. Characteristics of analyzed invoice data grouped by divisions and over all divisions.

6.7 Aggregate Level Business Descriptives

In order to evaluate possible operational measures and provide further information for KPI figures such as percentage return ratio the forecasts and actuals are aggregated for the corporate risk management. As a proxy for the percentage return margin within a fiscal year, the entity's *ratio* of aggregated revenues (II) and expenses (IR) is calculated. The aggregated dataset used in the analysis covers forecasts and actual for the entities' ratios.

In total, actuals and forecasts are available for the 67 largest subsidiaries resulting in 25 different currencies for the dataset. Actuals grouped by division, subsidiary, currency and item-type result in 72 actual time series. Overall, the dataset consists of 3,087 monthly invoice actuals, with five associated forecasts each. The underlying raw dataset of non-aggregated forecasts cover 102,360 items. Table 6.4 gives a brief summary of the ratio dataset.

Divisions	Subsidiaries	Currencies	Actual Time Series	Actuals	Forecasts
AP	10	7	11	618	3,090
HP	13	8	15	608	3,040
IM	6	4	7	420	2,100
DV	38	20	39	1,441	7,205
All	67	25	72	3,087	15,435

Table 6.4: The summary of available aggregate invoice data in the sample company. Characteristics of analyzed invoice ratio data grouped by divisions and over all divisions.

Additionally, partial data from the official corporation's annual report are used for testing the hypotheses. In the annual report 2010 the EBITDA margins listed are 19.0 % (AP), 26.0 % (HP), and 13.4 % (IM). Official figures for division DV were not reported separately. In 2011, the figures were: 22.8 % (AP), 27.4 % (HP), and 10.8 % (IM). In 2012, the figures were: 24.0 % (AP), 27.2 % (HP), and 10.9 % (IM). The figures in 2013 were comparable in magnitude, namely, 25.5 % (AP), 28.2 % (HP), and 9.5 % (IM).

6.8 Framework for Data Evaluation

These analyses for the data evaluation uses several techniques to retain the empirical results. These analyses consist of methods, such as correlation analysis for efficiency, linear regression analysis, in particular revision and error analysis, analysis of the out-of-sample results, and t-test evaluation. For the analyses and hypothesis testing the experiments use the programming language R and tools provided by (R Core Team, 2013) and the libraries `corrplot` (Wei and Simko, 2016), `data.table` (Dowle et al., 2015), and `ggplot2` (Wickham et al., 2016).

Chapter 7

Evaluation of Individual Level Characteristics

The following sections analyze the sample data set (see Table 6.3) for individual level forecasts and present the empirical results of the analyses from Chapter 3. These results cover efficiency analyses, testing of the efficiency hypothesis, and the analyses of individual level biases. The results are followed by the interpretation and a final summary.

7.1 Forecasting Efficiency

The Propositions (P1) and (P2) for weak forecast efficiency are tested by examining correlations between forecast errors and revisions as well as between revisions. The first four columns of Table 7.1 show Spearman correlations between relative revisions and percentage errors. The last three columns of Table 7.1 show Spearman correlations between relative revisions. Significance levels of the p-values are given after the correlation value.

	Proposition 1				Proposition 2		
	${}_4pe$	${}_3pe$	${}_2pe$	${}_1pe$	${}_3r$	${}_2r$	${}_1r$
${}_4r$	-0.04 ***	-0.04 ***	-0.06 ***	-0.05 ***	0.07 ***	0.08 ***	-0.03 **
${}_3r$		-0.01	-0.04 ***	-0.07 ***		0.11 ***	0.09 ***
${}_2r$			-0.03 **	-0.03 **			0.04 ***
${}_1r$				-0.08 ***			

Note: *p<0.1; **p<0.05; ***p<0.01

Table 7.1: Spearman correlations and significance levels of percentage error and relative revision. The correlations are grouped based on Nordhaus Propositions 1 & 2. Significant correlations indicate inefficient individual level forecasting. The results show that revisions (${}_tr$) are inefficient for errors ${}_\tau pe$ (Proposition 1) and revisions ${}_\tau r$ (Proposition 2) at all times.

All but one of the correlations are significant with p-values below 0.05. With estimated correlation coefficients between -8 % and -1 %, all correlations between forecast errors and revisions are negative and relatively small. Correlations between revisions are positive except for the correlation between revisions ${}_1r$ and ${}_4r$. The results indicate violation of both Propositions. The revisions ${}_1r$ and ${}_4r$ comprise forecasts of different years (${}_1F$ and ${}_5F$), wherefore their negative correlation might exhibit a interesting conjunction to the year in which the forecast are made. This suggests that the corporation's forecasting processes are not weak efficient.

7.1.1 Forecast Efficiency: Lead Time

Next, the analyses focuses on how inefficiencies are related to forecast accuracy. Proposition (P3) suggests that forecasts are less accurate when they are inefficient. In other words, Proposition (P3) leads to the expectation that forecast accuracy lessens with the strength of inefficiency patterns – in the revision setting, as lead times shorten. Analysis covers forecast groups separated by division and for different lead times.

Results in Tables 7.2 and 7.3 show *mape* values by lead time and division for all months (Table 7.2) and for December actuals only (Table 7.3). Taking all months together, it's observable that *mape* generally decreases with lead time. The exception is an increase between ${}_4F$ and ${}_3F$ in division AP. Taking December forecasts only, increasing *mape* is observable between ${}_2F$ and ${}_1F$ for divisions AP and IM, and between ${}_3F$ and ${}_2F$ for DV and IM.

Division	Lead time (in Quarters)				
	t = 5	t = 4	t = 3	t = 2	t = 1
AP	0.655	0.582	0.594	0.566	0.558
HP	0.543	0.490	0.477	0.472	0.443
IM	0.579	0.530	0.517	0.493	0.477
DV	0.570	0.486	0.466	0.457	0.440

Table 7.2: Mean absolute percentage error (*mape*) by division for all months. Most divisions have decreasing errors for decreasing lead time and are aligned to theory, except for division AP (from lead time t = 4 to t = 3).

The findings show that a decrease of the lead time is not associated with a reduction of the error. This provides the first indication that some influences are at play and Proposition (P4) may not hold.

Division	Lead time (in Quarters)				
	t = 5	t = 4	t = 3	t = 2	t = 1
AP	0.784	0.723	0.699	0.675	0.724
HP	0.603	0.562	0.553	0.543	0.526
IM	0.649	0.542	0.503	0.523	0.559
DV	0.639	0.549	0.508	0.524	0.503

Table 7.3: Mean absolute percentage error ($mape$) by division for December. Divisions have decreasing errors, except in divisions AP (from lead time t = 2 to t = 1), in division IM (from lead time t = 3 to t = 2, to t = 1), and in division DV (from lead time t = 3 to t = 2), where the $mape$ increases for these forecast revisions. The results for these three divisions are contrary to theory.

7.1.2 Forecast Efficiency Hypothesis: Increased Accuracy

For Proposition 4 the analyses cover the relation of $mape({}_1F)$ to the absolute correlation values $|Cor(x,y)|$ of all Nordhaus's correlations that are derived on an entity–currency level. Table 7.4 shows the results of bivariate correlation tests on $mape({}_1F)$ and absolute correlations between revisions and percentage errors ($|Cor({}_tr, {}_\tau pe)|$), and on $mape({}_1F)$ and absolute correlations between revisions ($|Cor({}_tr, {}_\tau r)|$). The first ten rows in Table 7.4 show the correlations between $mape$ and absolute correlations between revisions and percentage errors. Proposition (P4) holds for one case ($|Cor({}_3r, {}_1pe)|$). In two cases, $|Cor({}_1r, {}_1pe)|$ and $|Cor({}_3r, {}_3pe)|$, inefficiency patterns are associated with higher forecast accuracy (rejection of Proposition (P4)). The next six rows in Table 7.4 show correlations between $mape$ and absolute correlations between revisions. Proposition (P4) again holds for one case ($|Cor({}_4r, {}_3r)|$). In two cases, $|Cor({}_2r, {}_1r)|$ and $|Cor({}_3r, {}_1r)|$, inefficiency patterns are associated with higher accuracy. For each single estimate more than 1,400 absolute correlation values $|Cor(x,y)|$ were accessed, which underlines the significance of the results.

In summary, obtained results are mixed for Proposition (P4). Two correlations show that efficient forecasting is associated with lower error levels – while four correlations show contrary results. I conclude that inefficient forecasts are not necessarily associated with lower forecast accuracy – counter-intuitively, some inefficiency patterns are even associated with higher accuracy. This thesis complements the literature with a study where revision patterns are associated with higher forecast accuracy, that is why Proposition (P4) is not supported. Therefore, the validity of the efficiency hypothesis must be refused for the analyzed data of corporate internal forecasts, which supports Hypothesis 1.

	Variable	Estimate	Alpha
Proposition 1	$\lvert \mathrm{Cor}({}_1r, {}_1pe) \rvert$	-0.481^{*}	0.922^{***}
	$\lvert \mathrm{Cor}({}_2r, {}_1pe) \rvert$	0.009	0.581^{***}
	$\lvert \mathrm{Cor}({}_3r, {}_1pe) \rvert$	0.618^{**}	0.207
	$\lvert \mathrm{Cor}({}_4r, {}_1pe) \rvert$	2.363	-0.291
	$\lvert \mathrm{Cor}({}_2r, {}_2pe) \rvert$	0.371	0.355^{*}
	$\lvert \mathrm{Cor}({}_3r, {}_2pe) \rvert$	0.315	0.391^{**}
	$\lvert \mathrm{Cor}({}_4r, {}_2pe) \rvert$	1.906	-0.028
	$\lvert \mathrm{Cor}({}_3r, {}_3pe) \rvert$	-0.788^{***}	1.087^{***}
	$\lvert \mathrm{Cor}({}_4r, {}_3pe) \rvert$	1.048	0.492
	$\lvert \mathrm{Cor}({}_4r, {}_4pe) \rvert$	2,379	-0.346
Proposition 2	$\lvert \mathrm{Cor}({}_2r, {}_1r) \rvert$	-0.535^{*}	0.980^{***}
	$\lvert \mathrm{Cor}({}_3r, {}_1r) \rvert$	-0.949^{***}	1.222^{***}
	$\lvert \mathrm{Cor}({}_4r, {}_1r) \rvert$	1.687	0.181
	$\lvert \mathrm{Cor}({}_3r, {}_2r) \rvert$	0.352	0.340
	$\lvert \mathrm{Cor}({}_4r, {}_2r) \rvert$	1.782	0.017
	$\lvert \mathrm{Cor}({}_4r, {}_3r) \rvert$	0.743^{***}	0.099
Observations		n > 1400	
Note: *p<0.1; **p<0.05; ***p<0.01			

Table 7.4: Bivariate correlation tests for testing the efficiency hypothesis. Each line represents a seperate bivariate correlation-test that utilizes the obtained absolute correlations as predictor for mape(${}_1F$). Negative estimates indicate that inefficient revision patterns improve forecast accuracy. The tests are grouped based on Propositions 1 & 2 and indicate that negative estimates exist. Four correlation estimates are negative and all of them are significant.

7.2 Anchoring and Adjustment

Next, analyses diagnose well-known bias-related patterns that are regularly reported in the literature to explain forecast inefficiencies: anchoring (in the case of previous year's actuals).

Table 7.5 shows the results for testing whether forecasters use the previous year's actuals as an anchor (κ) for the forecast ${}_1F$. For confidentiality reasons, absolute volumes are not shown; the mean values of Δ (Equation 3.10) divided by mean absolute anchor are reported instead. The metric of Δ-Percent is computed as shown in Equation 7.1.

$$\Delta\text{-Percent} = \frac{\mathrm{mean}(\Delta)}{\mathrm{mean}(|\kappa|)} \tag{7.1}$$

In nine months patterns are observed that fit anchoring (negative Δ-Percent). In five of those months the effect is significant to the p-value of 0.05, and it is particularly pronounced (Δ-Percent $= -0.06$, $p < 0.001$) in the last two months of a year. This intensified A&A effect at the end of the year suggests that previous year's actual is much more important for the expert's forecasts. A predetermined business objective that has to be achieved at the end of a business cycle and therefore anchors forecasts would correspond to these circumstances.

Month	1	2	3	4	5	6	7	8	9	10	11	12
Δ-Percent	−0.01	0.01	−0.09	−0.01	−0.04	−0.03	0.01	0.00	−0.01	−0.01	−0.06	−0.06
p-value	0.575	0.320	0.039	0.530	0.023	0.015	0.528	0.803	0.605	0.625	<0.001	<0.001
Obs.	1636	1637	93	1660	1660	1402	1793	1793	1536	1850	1854	1908

Table 7.5: Indication of anchoring effects on cash flow forecasts. The table indicates anchoring effects based on previous year actuals, providing mean percentage differences for each month with p-values and number of observations. Nine months of the year show a pattern consistent with anchoring and adjustment with negative Δ-Percent, while five months show significant anchoring effects ($p < 0.05$). Especially in November and December the influence of anchors seem to increase (Δ-Percent) and results have higher significance.

Improving the Identification of A&A Patterns

The up-following results focus on the analysis of synthetic revision processes with anchoring and adjustment effects. The Figure 7.1 shows an example of $A\&A$ effects with all six models measured on one type of forecast series (*RW-T*). For the forecast series all models except Lawrence's detect a high probability ν of $A\&A$. This is consistent, as Lawrence's model detects anchoring if the values tend to the mean and are not following a specific trend. Harvey's model on the other side tends to predict $A\&A$ effects for all forecasts. In this forecast series the model of Harvey can not generate an additional benefit, as the predictions state $A\&A$ patterns for all forecasts. This example shows that some models (BWM and LBWM) provide better capabilities for the identification of $A\&A$ patterns than the other models.

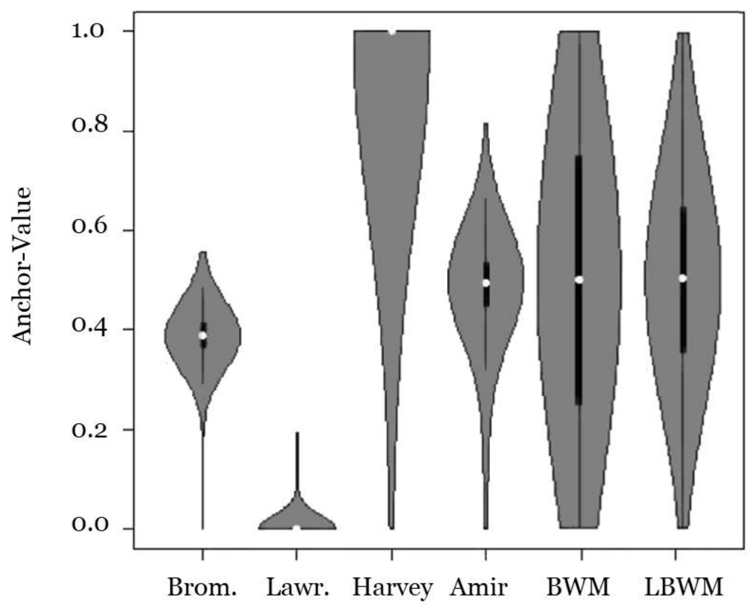

Figure 7.1: Anchor and adjustment detection for an example forecast series of type *RW-T*. The figure shows the distribution of measured A&A effects for Random Walk with normal distributed steps and $x_0 = -1000$, $\mu = 2$ and $\sigma = 1$.

The results for all forecast series with detailed correlations between the models and loss functions are shown in Table C.1, which supports Proposition 5. Explicitly, all models show a good performance for identification of $A\&A$ effects on independent series (*Ind*), as there is low baseline correlation among the models and loss functions. For both types of forecast series that follow a random walk (*RW-1* and *RW-T*) the identification of the common models is acceptable (absolute correlation values above those of *Ind*). For RW-1, all models show a correlation in dependence to the loss function between 0.22 and 0.50, while the model of Lawrence reached a value between -0.10 and -0.20. Bromiley's model performs quite good, but reached lower correlation values than both Bandwidth Models for random walk series. The Bandwidth Models identify the *A&A* pattern in a reliable way and outperform the other models by far for either loss function. This is mainly a result of the fact that both models are taking all values into account, but are not as easily influenced by small changes as the other approaches. Adding a trend (*RW-T* series) enhances all correlation values of the models further. In this series, LBWM is able to reach a correlation of 0.67 with the RMSE closely followed by BWM with 0.60 and Bromiley's model with only 0.40. In all three series the results of Lawrence's model are strictly dominated by the other models, which is reasonable as the used series do not tend to the mean. For these first three forecast series both Bandwidth Models show a good performance compared to the other models. The performance differs especially for the growth series *LogG* and *ExpG*, where correlations decrease. Detection of *A&A* effects seems to be more difficult. For strict monotone growth series the N.A.s describe that Harvey's model always detects *A&A* and Lawrence's never detects *A&A*. No correlation is be calculated for Amir's model for LogG series as it is resulting in either 1 or 0. Therefore none will be further considered for these forecast series. However, the Bandwidth Models show an good precision in detecting *A&A* effects for these series and are highly correlated with the used loss function in general. An overview of the comparison is shown in Table 7.6.

To further improve the precision of identification for these particular growth series (*LogG* and *ExpG*) one could transform the forecast series with the inverse function: the exponential function for *LogG* series and the logarithmic function for *ExpG* series. Another possibility would be to modify the model directly by a corresponding function, e. g. to use bandwidths for exponential growth instead of percentage growth in an area where BWMs perform best.

Proposition 6 suggests that the the degree of A&A identification of the models correlate with one another, in dependence to the forecast series. The Pearson correlation coefficient is used for the correlation between the different models. A low correlation for a forecast series will state that a combination of different models would be beneficial for identification of A&A effects. The correlations between the models are shown in Table C.2, which supports Proposition 6. For Bromiley's model the correlation to the other models highly depends on the kind of forecast series. For instance, in the *ExpG* series Bromiley's model and the Bandwidth Models have instead of a high positive correlation a low negative correlation of -0.1, reasoned by the separate treatment of positive and negative revi-

Model	Time Series				
	Ind	RW-1	RW-T	LogG	ExpG
Bromiley	$\surd$	$\surd$	$\surd$	$\bigcirc$	$\bigcirc$
Lawrence	$\surd$	$\surd$	$\surd$	N.A.	N.A.
Harvey	$\surd$	$\surd$	$\surd$	N.A.	N.A.
Amir	$\surd$	$\surd$	$\surd$	N.A.	$\bigcirc$
BWM	$\surd$	$\surd\surd$	$\surd\surd$	$\bigcirc$	$\bigcirc$
LBWM	$\surd$	$\surd\surd$	$\surd\surd$	$\bigcirc$	$\bigcirc$
Appropriate Use:	$\bigcirc$ with limitations, $\surd$ good, $\surd\surd$ better.				

Table 7.6: Comparison of A&A models on different time series.

sions by Bromiley's model. The approach of Lawrence focuses on the mean of the previous forecast instead of tendencies, which results in low or even negative correlations with the other approaches. The models of Lawrence and Harvey show negative correlation, but both models can not be considered for the forecast series of *LogG* and *ExpG*. Lawrence's model never detects *A&A* and Harvey's model always does. Furthermore, Harvey's and Amir's models show a high correlation, as both are considering if consecutive revisions dispose over equal signs. Amir's model is not considered for *LogG*, as the resulting values are only 0 and 1. Finally, a very high correlation was found between BWM and LBWM, consistent over all kinds of series.

Combining multiple models can be an appropriate approach if the models are highly correlated with the loss function but not with each other. For instance, Amir's model is only weak correlated with the Bandwidth Models and all of them reach a good correlation with the loss functions. Bromiley on the other side shows a considerable correlation with all metrics, in dependence to the forecast series. As a result, this would suggest that a combination of Amir's model and the LBWM can be considered beneficial for A&A identification – especially when combined with a model that accounts for the interaction of forecast series with Bromiley's model.

Interim Result

The results indicate that previous year actual provides an anchor for the subsidiary's forecasting. Especially in the end of the year (November and December) the anchor had highly significant influence on the forecasts. These results suggest that cash realizations at the end of the year may have a stronger impact than in the previous months, and a end-of-year effect may exist.

The results present the Bandwidth Models BWM and LBWM to determine $A\&A$ effects. These models are compared with the models from findings of previous papers. The two models base on the $A\&A$ influence of previous forecasts for the succeeding forecast value. The evaluation uses short, synthetic forecasts series with specific pattern. The Bandwidth Models can predict the probability of a forecast series being influenced by $A\&A$ effects with higher accuracy and outperform each analyzed $A\&A$ models in at least three types of synthetic time series. Detecting the influence of $A\&A$ on human forecasters offers high potential for forecast correction as they have a higher relation to common loss functions, which supports Proposition 5. For instance, a forecast correction model may be applied only on those forecasts that exhibit A&A behavior, or even use the information directly within the correction model to improve the forecast error.

For application of the models it is assumed that real world forecast series have similarities to the used kinds of forecast series. The performance of the $A\&A$ models is expected to partially relate to the real world time series, depending on the distribution to the patterns of the synthetic forecast series. The application on real world series requires further analysis, where the authors of (Knöll and Roßbach, 2018a) started to explore this branch of research.

7.3 Optimism, Pessimism and Overreaction, Underreaction

The following results cover the analyses for biases of optimism, pessimism, overreaction, and underreaction. Table 7.7 shows outcomes of linear regressions on the full data set, grouped by revision sign and lead time. Positive revisions are presented in the first four columns, negative revisions in the last four columns.

In accord with the findings reported by Amir and Ganzach (1998), the results indicate the presence of individual biases. For negative revisions, pessimism is observed: α's are negative, implying that the actual is, on average, greater than the last forecast. For positive revisions, optimism is observed: α's are positive, implying that the actual is, on average, smaller than the last forecast. For both positive and negative revisions, underreaction is observed: β's are negative, implying that revisions are too small. However, contrary to intuition and the findings of Amir and Ganzach (1998), it is not found that these patterns weaken consistently as the forecast horizon shortens. In fact, three of the four patterns become more pronounced; only underreaction in positive forecasts becomes somewhat weaker.

	Positive revisions				Negative revisions			
t	4	3	2	1	4	3	2	1
α	0.274^{***}	0.268^{***}	0.275^{***}	0.294^{***}	-0.219^{***}	-0.231^{***}	-0.263^{***}	-0.284^{***}
β	-0.392^{***}	-0.342^{***}	-0.431^{***}	-0.300^{***}	-0.307^{***}	-0.365^{***}	-0.395^{***}	-0.433^{***}
Obs.	13,743	13,827	13,973	14,206	10,541	10,618	10,813	11,033
R^2	0.009	0.007	0.010	0.005	0.005	0.007	0.007	0.008
Note: *p<0.1; **p<0.05; ***p<0.01								

Table 7.7: Indication of optimism, pessimism and underreaction. Forecast errors are regressed by revisions with ${}_tpe = \alpha(t) + \beta(t)_tr + \epsilon$. Data is grouped by revision sign and lead time t. Results indicate optimism for positive revisions ($\alpha > 0$), pessimism for negative revisions ($\alpha < 0$), and underreaction in both cases ($\beta < 0$).

7.4 Revision Concentration

The results for the concentration metrics were applied on a particular selection of the content cleaned data (instead of ratio cleaned data). The selection without ratio cleaning serves the purpose to generalize the application onto forecast processes without dependencies of positive and negative forecasts (item type g). But, without ratio cleaning, additional cleaning measures were required. Forecast processes were selected that exhibit an actual volume above 250,000 EUR equivalent, absolute percentage errors below 200 % for all forecasts ${}_tF$. As division-specific differences were in interest for the corporation the analyses omit the subsidiaries of division DV.

Geometric Center

The results of Table 7.8 exhibit in the first row the company-wide results (All) and in the following rows the results by division (AP, HP, IM). The table indicates that the Proposition 7 is violated and the revisions deviate in most cases significantly from the geometric center (x_0, y_0, z_0). The last column of the table shows that the forecast accuracy per division significantly differs from the average forecast accuracy. The results show that the geometric center and error measures of the revision processes differ from random forecasting processes. The results indicate early adjustments in the forecasting processes (metric $x < 0$: revisions with high lead time) with more pronounced volumes (metric $y > 0$: high adjustment volume), while only division IM exhibits a direction of adjustments (metric $z < 0$: downtrend).

Change in Error Level

The comparison or change in error level ($\Delta_{5,1}$) starts with the regression results of $M_{\text{Equ. 3.28}}$ before analyzing $M_{\text{Equ. 3.29}}$. Based on explained variance of $M_{\text{Equ. 3.28}}$ (Adj. R^2 of 12.8 %) it is concluded that efficiency does not explain the change of forecast accuracy very well. This finding is in line with the results of Section 7.1.2. Furthermore, $M_{\text{Equ. 3.29}}$ uses the concentration measures to analyze the difference between the error level of the forecasts. The results indicate that at least weak or moderate improvement terms of explained variance is achieved in cases of sign changes (Adj. R^2 between 8 % and 22 %). The regression results for forecast processes without sign changes, shown in Table 4 and 5 in Knöll et al. (2016), state that the concentration measures explain the change of error $\Delta_{5,1}$ very well (Adj. R^2 between 52 % and 66 %). Based on the concentration measures and interactions between the measures for volume, timing, and sign of revision the change

Sample	Proposition 7	median(ape)
All	$x - x_0 = -0.07^{***}$	0.244
	$y - y_0 = 0.35^{***}$	
	$z - z_0 = -0.001$	
AP	$x - x_0 = -0.09^{***}$	0.299^{***}
	$y - y_0 = 0.33^{***}$	
	$z - z_0 = 0.0008$	
HP	$x - x_0 = -0.08^{***}$	0.212^{***}
	$y - y_0 = 0.41^{***}$	
	$z - z_0 = 0.0012$	
IM	$x - x_0 = -0.003$	0.253^{***}
	$y - y_0 = 0.24^{***}$	
	$z - z_0 = -0.008^{***}$	
Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Table 7.8: Test results for dependency of concentration measures (Proposition 7) on a subselection of the data. Results cover groups of non-DV divisions and the group of all divisions.

of error $\Delta_{5,1}$ can be explained to a high degree. Providing the correct measures (in comparison to efficiency measurement) seem indeed to provide benefits for the regression models.

The final descriptive analyses on concentration measures examine interaction effects between the Y metric and the Z, respective X metrics to explain changes in forecast accuracy. The first result is retrieved for Y and Z measure. Figure 7.2 shows for extreme levels of the Z measure that the Y measure can indicate of up to 0.6 in percentage error difference (a 0.3 decrease or 0.3 increase of $\Delta_{5,1}$). In evenly distributed revisions ($Z \leq 0.4$). the effect on error change is increased when compared to more concentrated revisions ($Z \geq 0.6$). The second result in Figure 7.3 shows the interaction of volume measure Y and timing measure X. For the X measure the results show that for one division early revisions can reduce forecast error, but, however, this effect depend strongly on the volume of the revisions. In case of evenly distributed revisions (low Y values), where early revisions are beneficial (large negative X values). This result is diametrically opposed to late revisions (large positive X values) for which concentrated revisions (large Y value) are beneficial.

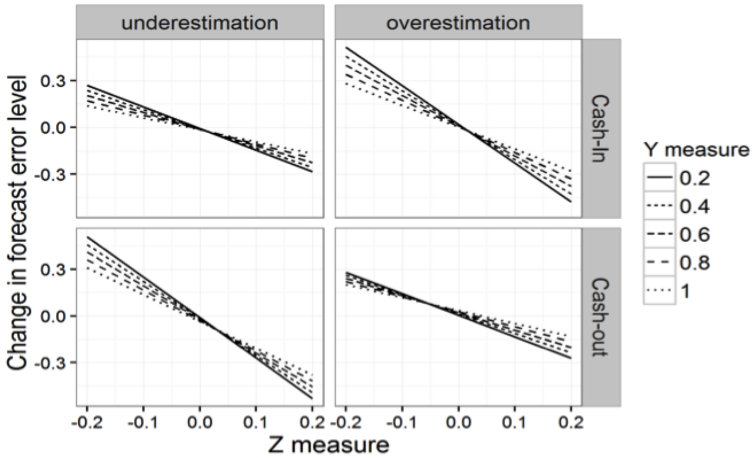

Figure 7.2: Interactions for volume (Y) and direction (Z) measures grouped by item type and under-/overestimation (no sign change). Figure from the paper (Knöll et al., 2016).

Interim Result

Summarizing the concentration measures leads to an descriptive extension for the theoretical aspect of the efficiency processes by Nordhaus, explained as follows: the Y concentration metric identifies if the adjustment is made by one or many steps. The Y metric measures therefore the degree of volume relation between revisions. As inefficient revisions show systematic behavior they naturally should exhibit a low Y measure, as the revisions tend to be more similar to each other. For instance, the value $Y = 1$ can not be reached for similar revisions – instead only with a one time peak where the entire adjustment of a forecasting process is made at once. Further, the results state that accuracy depends also on the point in time of revisions: the X concentration metric. Early, evenly distributed revisions tend to have reduced error levels – while late, evenly revisions have higher error levels. Therefore, based on the interpretation and analyzed data it is arguable: Inefficient, early revisions might have higher accuracy than efficient revisions (with peak-structure). Overall, the results clearly support Hypothesis 2.

7.5 Summary

This chapter provides the results on individual level analyses of financial forecasting processes. The empirical analysis of efficiency reveals that forecasting processes are not weak form efficient. The inefficiencies of individual level forecasts are often expected to relate to behaviors of widely established biases, such as anchoring and adjustment. Analyses that account for these biases did indicate

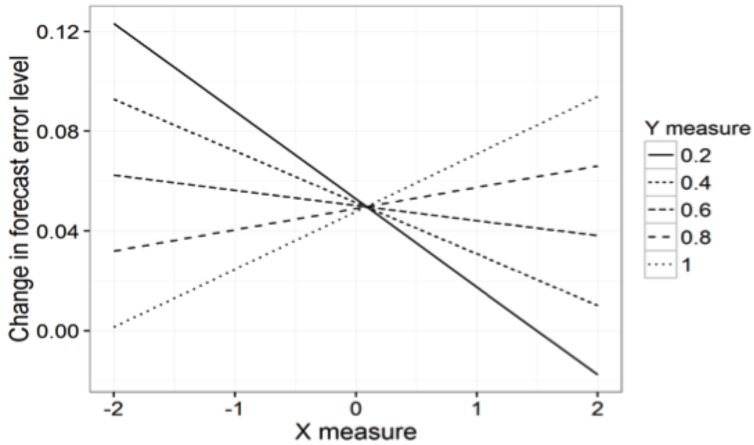

Figure 7.3: Interaction effect for timing (X) and volume (Y) measures of division HP (overestimation). Figure from the paper (Knöll et al., 2016).

that individual level biases are at play. But, detailed inspection of the analyses suggest that other underlying influences might form these behavioral aspects.

Efficiency and Efficiency Hypothesis

The analyses reveal that weak form forecast efficiency can not be stated and the reduction of lead time is not solely associated with accuracy increase, especially for December forecasts. Furthermore, the analyses reveal that weak forecast efficiency is not invariably connected to accurate forecasting – and as a consequence thereof the validity of the forecast efficiency hypothesis for the analyzed corporate internal forecasts must be rejected. However, with regard to market efficiency, it would be interesting to analyze data from the financial markets to determine whether similar effects exist there.

Behavioral Individual Level Reasoning

The analyses of A&A metrics and concentration metrics revealed interesting insights in individual level behavior of forecasting processes. First, the results indicate that the influence of the A&A effect intensifies for previous year's actuals in November and December. Second, depending on the kind of metric used for A&A biases, performance for identification is different, and metrics do correlate with error metrics in differing ways. Utilizing advanced approaches for pattern identification of A&A can improve predictive performance due to error correlation. Third, complex descriptive measurement of whole forecast processes with Bandwidth Models and concentration measures show that important information is inherent in forecast processes in their entirety. Analyses that base solely on the examination of single forecasts misses opportunities for understanding and correction, as revisions provide meaningful information based on the dimensions time, volume, and direction of adjustments.

Indication of Further Influences

However, the findings show that anchoring is most pronounced in the last two months of a year, and the strength of bias-related patterns increase as lead time decreases, in particular for actuals approaching the end of a fiscal year. These results provide further indications that other influences than individual bias are at play and suggesting reasons why Proposition (P4) does not hold. The rejection of the efficiency hypothesis for the analyzed internal corporate forecasts is an important contradiction to the common expectations in forecasting research. The distorting influence that seem to impact forecasting especially at the end of the year, provides the argumentation for the next chapter.

Chapter 8

Evaluation of Aggregate Level Business Characteristics

This chapter presents the empirical results of the aggregate level analysis. These consist of the ratio metric analysis, which supports the existence of targets at an aggregate level, the explanation framework for beneficial inefficiencies and the examination of organizational relations. The examination analyzes in particular the target, revision and organizational dependencies. The chapter concludes by a summarizing interpretation of the results.

8.1 Ratio Metric: Validity

The results for the validity analysis on lag-shifted unnormalized ratio calculation is shown in Table 8.1. The standard deviation of ratios only decreases for the fiscal year from January to December (column $l = 0$, from 3.40 to 2.08). When a different starting point than January is chosen, the aggregation results for all other alternatives in increased standard deviation of ratios instead. For instance, when starting in April as the first month of the aggregation (column $l = 3$), the standard deviation of ratio starts with 4.80, decreases for invoices that aggregate April and May to 3.63, but end up with 8.21 for the last aggregation that covers all calculated ratios based on the starting month April.

Month	Lag (in Months)											
	l=0	l=1	l=2	l=3	l=4	l=5	l=6	l=7	l=8	l=9	l=10	l=11
1st Month	3.40	1.23	4.82	4.80	4.76	4.66	3.30	3.32	2.18	2.14	2.02	1.95
2nd Month	3.78	2.42	3.73	3.63	3.61	3.55	2.81	2.79	2.06	2.03	1.94	8.57
3rd Month	3.16	2.60	4.78	4.65	4.62	4.58	3.68	3.65	2.70	2.65	1.68	5.22
4th Month	3.30	1.51	2.51	2.50	2.49	2.46	2.13	2.12	1.73	7.26	7.16	6.48
5th Month	4.28	1.35	2.10	2.11	2.10	2.08	1.87	1.86	10.57	8.95	8.87	7.82
6th Month	1.37	1.28	1.91	1.92	1.91	1.90	1.73	1.38	1.23	1.20	1.17	1.45
7th Month	1.26	1.23	1.88	1.89	1.89	1.87	1.47	1.23	1.15	1.14	1.13	1.32
8th Month	1.23	1.20	1.82	1.84	1.83	1.49	1.23	1.18	1.14	1.12	1.12	1.28
9th Month	1.23	1.18	1.57	1.59	2.56	1.80	1.16	1.13	1.13	1.12	1.12	1.25
10th Month	1.29	1.18	1.55	2.93	2.74	2.09	1.43	1.42	1.27	1.24	1.24	1.32
11th Month	2.21	1.78	12.23	11.69	11.34	10.70	5.09	5.11	2.66	2.57	2.38	2.25
12th Month	2.08	1.57	8.40	8.21	8.05	7.73	4.33	4.36	2.46	2.38	2.23	2.11

Table 8.1: Standard deviation of unnormalized ratio ${}_0R$ calculated with delay of l months. The first column refers to the specific (non-calendar) month that includes actual ratio figures (the fiscal year is shown in column $l = 0$).

The result suggests that a proxy for a end of year target only exists in the fiscal year, supporting Hypothesis 3. The further expectation that other sub-annual influences exist could explain the differences in the lagged aggregates of the other months. Also, the aggregation and lag aspect depends on the business cycle, which in the sample corporation is the calendar year. The closure of yearly accounts may vary for other corporations and in those cases the correct setting of the lag is assumed to be different. According to Section 4.1, all further analyses will base on ratios calculated with zero lag.

8.2 Ratio Metric: Earnings Target Existence

Decrease of Standard Deviation

The results for the validity of a earnings target existence on division level is shown in Table 8.2. Here, standard deviation is calculated over the aggregated ratios of entities belonging to a division. The table shows decreasing standard deviation of the ratio over time for division AP. For the other divisions its behavior is more like a martingale process, finalizing with minimum standard deviation in December. For instance, the standard deviation in January for the business division AP is 1.20, which decreases to 0.55 in December. Another example of decreased standard deviation is shown for the business division HP that reduces by 28 % (from 1.06 to 0.76). For all divisions except DV, the accumulated ratios approach their minimum values in December, when approaching the end of a fiscal year. However, division DV has decreased standard deviation at the end of the fiscal year when compared to January. The result clearly indicates a division specific converging actual ratio while approaching the end of year.

Division	Month											
	m=1	m=2	m=3	m=4	m=5	m=6	m=7	m=8	m=9	m=10	m=11	m=12
AP	1.20	1.31	0.96	0.74	0.69	0.75	0.72	0.68	0.69	0.62	0.60	0.55
HP	1.06	0.90	1.15	0.87	0.80	0.83	0.82	0.83	0.79	0.81	0.79	0.76
IM	0.83	0.82	0.97	0.85	0.95	0.97	0.88	0.86	0.89	0.83	0.82	0.80
DV	4.73	5.30	4.57	4.66	6.09	1.79	1.63	1.59	1.60	1.69	3.06	2.88

Table 8.2: Standard deviation of ratio ${}_0R$ for each division over the year. For all divisions the standard deviation in December (m=12) has decreased in comparison to January (m=1).

Ratio End of Year Drifts

Figure 8.1 shows how unnormalized mean ${}_0R$ by division (unnormalized ${}_0R$ averaged over all companies of each division) develops over time. One observes division-specific seasonal patterns, with autocorrelation coefficients of 0.38 (AP), 0.08 (HP), −0.03 (IM), and 0.18 (DV). The coefficients are significant for AP and HP. Similarities in divisions between ratios are most pronounced towards the end of a year, and the ranks of division ratios are in line with the official EBITDA margins of the corporation (as exhibited in Section 6.7). Figure 8.1 shows steep and regular shifts of ratios towards the end and beginning of a year. Division AP, for instance, exhibits a sharp drop in ratios between December and January and steeply rising ratios over the first months in the year. This pattern strongly hints at earnings management, specifically the shifting of cash outflows to the next fiscal year.

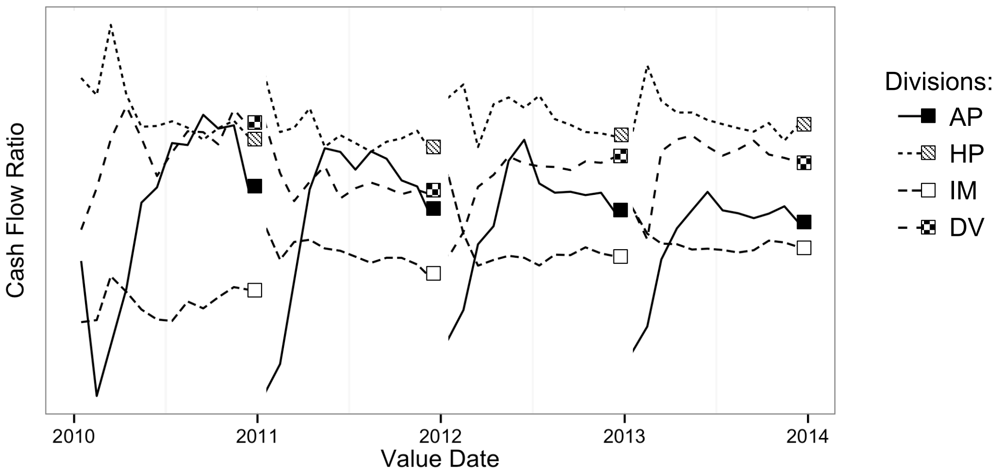

Figure 8.1: Temporal development of the median ratio for different business divisions. Ratio exhibits annual pattern and division-specific values. The end-of-year ratio of a division is in the same range every year, except for division DV in year 2010. Corporate goals seem to influence the ratio to a specific, predefined target ratio at the end of the fiscal year.

8.3 Ratio Metric: Subsidiary Specific Revision

The ratio of realizations seem to aim for a specific ratio, while the examination of revisions do not seem to follow a specific pattern. The revisions are depicted in Figure 8.2, altogether with the errors to visualize distribution and possible dependencies between these metrics. The result shows that the corporate-wide revisions hardly indicate a specific pattern. To analyze whether a pattern for the revisions exists within the entity, the revisions (and errors) are normalized based on the history of ratios. The importance of this entity specific normalization is depicted with Figures 8.2 and 8.3. Without normalization the ratio of the forecasts distributes with an center of zero error and zero revision. Instead, with normalization the relation between error and revision shows a clear negative pattern. One could argue that without normalization the forecasts seem to be "efficient" and without predictive value, while they obviously show some dependency that suggests "inefficiency" for normalized ratio revisions. For analytic and predictive purposes the entity-specific normalization is obviously beneficial, allowing to relate the errors and revisions.

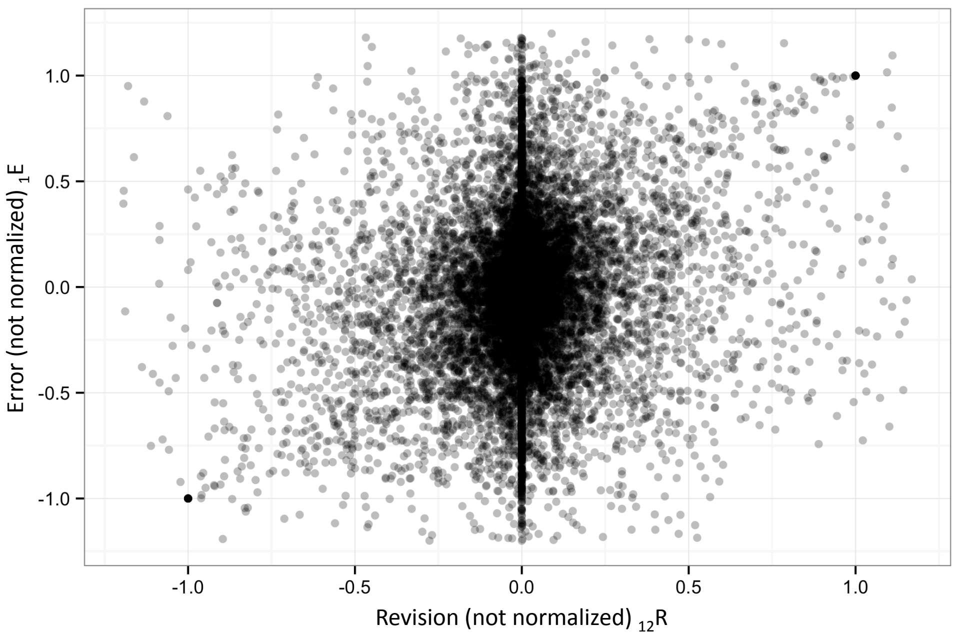

Figure 8.2: Relation between not normalized revisions and not normalized error of entities. Revisions and errors scatter, following a Gaussian normal-distribution with a center of zero revision.

8.4 Efficiency at Aggregate Level

Previous sections offers a perspective that entity specific behavior might influence the forecasting process. This motivates the following analyses for efficiency at the aggregate level, as it is assumed that forecasting processes has to differ in efficiency for the single item forecasting and the entity level forecasting. Furthermore, it is expected that influences are more pronounced at the entity level.

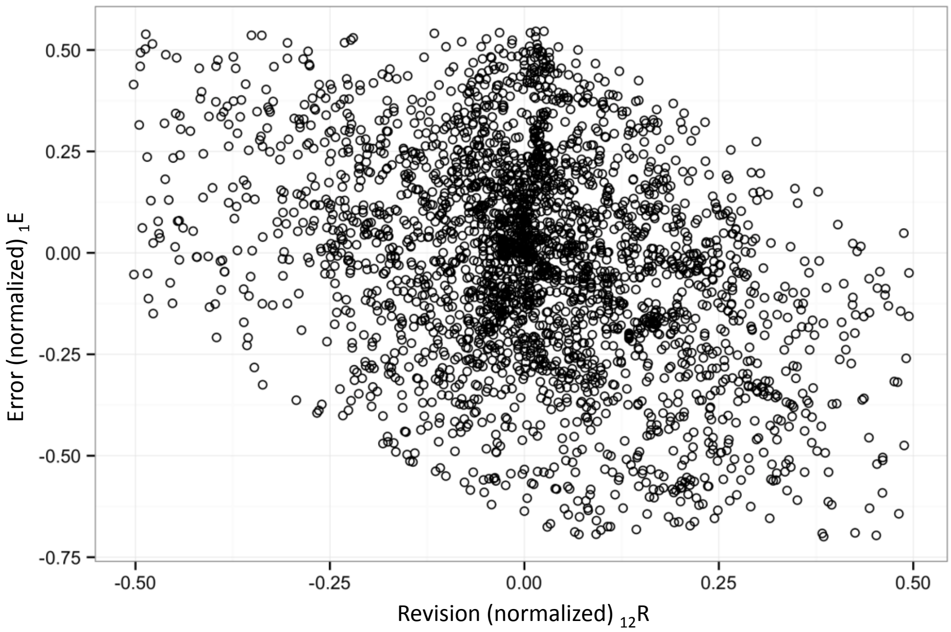

Figure 8.3: Relation between normalized revisions and normalized error of entities. Revisions and errors scatter between values of plus and minus one suggesting a negative correlation.

8.4.1 Reasoning Beneficial Inefficiency for Individual Forecasts

This section provides a conclusive theoretical explanation for the inefficiency patterns based on the considerations of earnings management activities and communication to forecasters. The section tests Proposition (P8): whether violations of Proposition (P4) are due to organizational bias introduced by earnings management, in particular whether earnings management can help explain the counterintuitive patterns in which accuracy improves with inefficiency.

Figure 8.4 schematically illustrates a forecasting process, with revision and error metrics. Further, it shows the location of the inefficiency patterns that are associated with a decreasing *mape* of the final forecast ${}_1F$ (from Section 4), namely $|Cor({}_1r, {}_1pe)|$, $|Cor({}_2r, {}_1r)|$, $|Cor({}_3r, {}_1r)|$, and $|Cor({}_3r, {}_3pe)|$. In addition, Figure 8.4 shows when two sets of information on earnings management and targets, κ_1 and κ_2, become available to forecasters. κ_1 refers to information about the previous year's actuals, including the impact of potential earnings management in the previous year. κ_2 refers to information on currently planned earnings management. The effect first turned on: what to expect to observe when forecasters are unaware versus when they integrate this information into their forecasts.

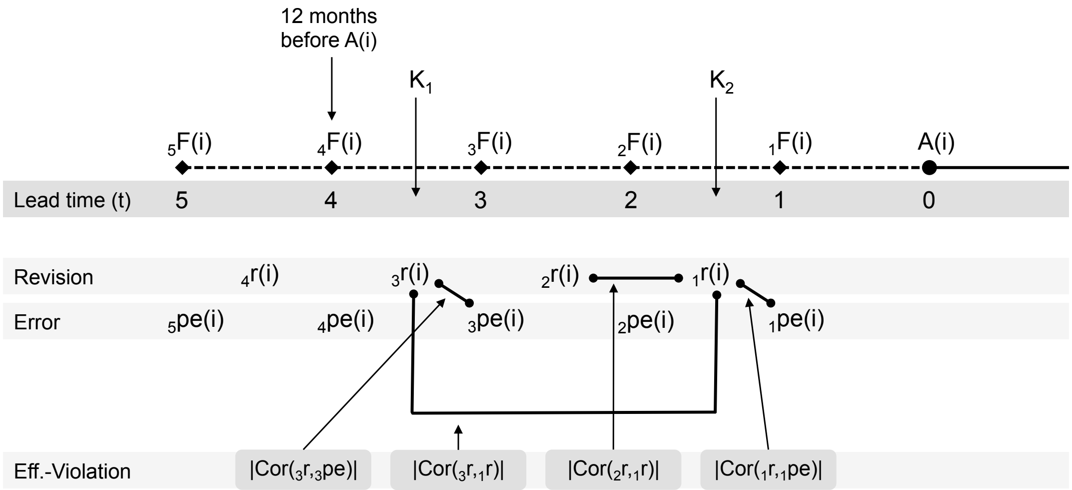

Figure 8.4: Temporal structure of cash flow forecasts ${}_tF(i)$ with the corresponding actual cash flow $A(i)$ and forecasters' (presumed) knowledge of past (κ_1) and current (κ_2) earnings management. All negative relations for efficiency and accuracy interlink to the temporal occurrence of the knowledge for earnings management.

1. Unawareness of κ_2: If forecasters are unaware of earnings management–driven adjustments of actuals (i.e., forecasting is strictly separated from planning) and base their forecasts strictly on current business developments, their forecasts may look worse than they are and wrongly suggest the presence of individual level biases. For instance, regular shifts of cash inflows to year $Y+1$ would make forecasts—in particular the final forecast ${}_1F$—look optimistic, as they would regularly exceed actuals. This is in line with findings of Buehler and Griffin (2003), where optimistic behavior is a result of narrow task focus and the neglect of useful information. This would explain why *mape* increases in Y as lead time decreases, why optimism apparently increases (Table 7.7), and why forecast errors in December are higher than the average errors over the year (Table 7.3). The question is, of course, whether forecasters have access to this kind of knowledge. In the case of the sample corporation, general policy prescribes separation of planning and forecasting. However, when these functions are performed within the same department, forecasters and planners may share information and even consult.
2. Awareness of κ_2: If forecasters are aware, to some extent, of intended earnings management (i.e., κ_2), revisions will be aligned with expected cash flow adjustments, resulting in observable inefficiency. Forecasts will be very accurate, since they are based on reliable information about actual develop-

ments. Obtaining such information, however, requires effort (e.g., meetings with managers). As Goecke et al. (2013) argue, forecasters invest this effort only if the benefits outweigh the costs. In the current setting, forecasters ought to perceive net benefits—especially towards the end of the year, when earnings management is most likely. If earnings management activities throughout the year bear little resemblance to those towards the end of the year, forecasters will integrate κ_2 into their forecasts at the latest possible moment, ${}_1r$. Hence, high values of $|Cor({}_1r, {}_1pe)|$, $|Cor({}_3r, {}_1r)|$, and $|Cor({}_2r, {}_1r)|$ would hint that forecasters are particularly aligned with planners, in which case their forecasts are aligned to actuals and therefore associated with beneficial final revision and higher forecast accuracy of the last forecast ${}_1F$, explaining three of the negative associations with *mape* in Table 7.4.

3. Anchoring on κ_1: Similarly, information κ_1 becoming available may explain negative association of patterns in ${}_3r$ with $mape({}_1F)$. In the corporation's setting, information on the previous year's actuals (κ_1) first becomes available at revision ${}_3r$ (Figure 8.4). If earnings management activities are similar over the years, it is reasonable to assume that forecasters aware of such activities are also aware of their repetition. These forecasters will assign high trust to the previous year's actuals, effectively using them as an anchor that implicitly includes the previous year's earnings management. This behavior seems plausible; Boiney et al. (1997), for instance, suggest in their second proposition that "The tendency to adopt a biased decision strategy will be constrained by the decision maker's ability to justify the reasonableness of both the process and the conclusion".
   Hence, systematic adjustments of ${}_3r$ based on the previous year's actuals drive $|Cor({}_3r, {}_3pe)|$, but also hint that forecasters are aware of earnings management and their final forecasts will show lower *mape* (Table 7.4). Furthermore, if actual developments and earnings management are similar over the years, and if there is a set of actuals that can be adjusted more easily (those with long term of credit, for instance), high correlations between ${}_3r$ and ${}_1r$ indicate that the underlying cash flow adjustments are similar—involve a largely overlapping sample of actuals—over the years. If patterns in ${}_1r$ increase accuracy, it follows that patterns in ${}_3r$ (based on similar adjustments) increase accuracy. Hence, emerging patterns for ${}_3r$ could serve as a first indicator for future patterns in ${}_1r$, explaining the positive impact that $|Cor({}_3r, {}_1r)|$ has on the accuracy of ${}_1F$. This would explain why ${}_3r$'s pattern $|Cor({}_3r, {}_3pe)|$ is also associated with increased accuracy (Table 7.4). On the other hand, if forecasters are not aware of earnings management, and

give high weight to their own business expectations rather than the previous year's actuals, no patterns will be observable either in $_3r$ or in $_1r$. This would explain why there is generally an increase in *mape* at $_3r$ observable, while there is no such increase if $_3r$ does exhibit inefficiency patterns.

Interim Result

The explanation framework hypothesizes when to expect structure in forecasting processes to be negative and due to cognitive bias – and where to expect a positive association between accuracy and structure that hints to organizational-level issues masking cognitive biases at the individual forecaster level. In sum, earnings management appears to provide a conclusive explanation for the results regarding individual level biases, *mape* increasing with decreasing lead time, and the four counter-intuitive patterns associated with improvements in the accuracy of the final forecast (Table 7.4). If inefficiencies are found that are associated with increased accuracy, it's recommend to consider organizational-level issues to drive forecasting and rethink organizational structure before wrong conclusions are drawn with respect to the quality of forecasters (individual level).

8.4.2 Testing Aggregate Level Efficiency

As noted before, the forecast efficiency is an important goal of forecasting processes. The baseline of forecast efficiency for $M_{\varnothing}$ on ratio basis is shown in Table 8.3. The result indicates very high inefficiency for revisions and the descending error of the forecast resulting from that revision made by experts. For instance, revision $_{23}R$ and subsequent error $_2E$ exhibit a correlation coefficient of -0.27. Further, the autocorrelation of revisions at shift one exhibits high negative correlation, while there is indeed a high negative correlation between $_{45}R$ and $_{12}R$. This supports the argument of revisions aligned to seasonal pattern, while it is noted that this differs from the argument of end of year values – since these efficiency characteristics does not only start in the last quarter of the year, instead the analyzed forecast processes cover the whole year.

8.5 Organizational Relations

This section covers analyses of organizational influences with dependencies of target ratio and revision ratio. In addition, the section covers ratio analyses on inflicting goals that highlight important implications for the forecasting process within the corporation.

	$_{4}E$	$_{3}E$	$_{2}E$	$_{1}E$	$_{34}R$	$_{23}R$	$_{12}R$
$_{45}R$	-0.24^{***}	-0.11^{***}	-0.08^{***}	0.02	-0.22^{***}	-0.05^{***}	-0.13^{***}
$_{34}R$		-0.19^{***}	-0.02	0.01		-0.23^{***}	-0.03^{*}
$_{23}R$			-0.27^{***}	-0.10^{***}			-0.24^{***}
$_{12}R$				-0.31^{***}			

Note: *p<0.1; **p<0.05; ***p<0.01; Observations: 2,355.

Table 8.3: Spearman correlation and significance levels on ratio level of revisions and errors. Results show correlation values and significance levels of experts, without any correction (baseline model $M_{\varnothing}$). Consecutive revisions and errors (in the diagonals) exhibit very high correlations.

8.5.1 Error Dependencies on Earnings Target

The resulting regression models M_{Basic} (Definition 7) and M_{Orga} (Defintion 8) are shown in Table 8.4. The integration of *TargetDiff* shows clearly strong influence on the response variable (ratio error), while the estimates' magnitude of the other dependent variables are reduced. Analysis of the R^2-values of the models supports Hypothesis 4 (R^2-value of 0.310 for Model M_{Basic} compared to 0.608 for Model M_{Orga}).

Dep. Variables	Estimates Model M_{Basic}	Estimates Model M_{Orga}
Constant	0.178^{***}	-0.027^{***}
$_{1}R$	-0.541^{***}	-0.0003
$_{12}R$	-0.125^{***}	-0.039^{**}
TargetDiff	(Not Utilized)	0.735^{***}
R^2	0.310^{***}	0.608^{***}

Note: *p<0.1; **p<0.05; ***p<0.01; Observations: 2,355.

Table 8.4: Analyses for the influence of target difference by comparison of regression models. The error $_{1}E$ is regressed with two models M_{Basic} and M_{Orga}. Estimate of TargetDiff strongly influences the error in ratio. The explanatory power (R^2-value) nearly doubles by incorporating TargetDiff information.

Detailed results for the regression model of M_{Orga} is shown in Table 8.5. *Difference from target* has by far the strongest association with *ratio error* $_{1}E$, which basically means that at the ratio level, the presumed margin target is the best indicator of how to adjust forecasts in order to increase accuracy. *Last forecast ratio* $_{1}R$ has no significant effect on $_{1}E$. *Last revision* $_{12}R$ has a small but significant negative association with $_{1}E$. Hence, in line with Amir and Ganzach (1998) observed

Variable	Estimate	90 % CI
Constant	-0.027^{***}	$(-0.042, -0.012)$
$_1R$	-0.0003	$(-0.033, 0.033)$
$_{12}R$	-0.039^{**}	$(-0.071, -0.007)$
DiffTarg	0.735^{***}	$(0.706, 0.763)$
Observations	2,355	
R^2	0.608	
Residual Std. Error	0.202 (df = 2351)	
F Statistic	$1{,}216.089^{***}$ (df = 3; 2351)	
Note: *p<0.1; **p<0.05; ***p<0.01; CI = confidence interval.		

Table 8.5: Analytical model for the difference between expert forecast and actual ratio ($_1E$) for the entire year. The model utilizes normalized ratio of the last forecast, relative revision and the ratio difference from the entity specific target ratio. Difference from target has the strongest effect. Actuals and forecast ratios are derived from aggregated cash flow data.

estimates show that the forecasters tend to be pessimistic and underreact with their revisions (*Constant* negative, $_{12}R$ negative).

Table 8.6 shows the results for the same regression performed on the subset of December actuals. Compared to the year model, *difference from target* in December has a greater effect on *ratio error*. This is in line with the previous suggestion that if earnings management is present, effects will be most pronounced towards the end of the year. The explaining conclusion of this finding can be stated as an enhancement of Ball and Watts (1972). Earnings targets of entities drive the sub-martingale process behavior via accounting practices (smoothed cash flow actuals), stating that the expectation of income is a function of time. To find a specific form of time series behavior seems difficult, because incomes seem to depend from an organizational bias that probably varies over time. But yearly earnings targets show one potential and likely explanation.

This interpretation is also supported by the fact that the proportion of explained variance for the December model (*Adj.* $R^2 = 0.729$) is higher than for the year model (*Adj.* $R^2 = 0.608$) and that the regression constant, the corporation-wide baseline for the normalized ratio, indicates lower error in December. The drift towards earnings targets turns out to be a valuable predictor for cash flow forecast accuracy at the aggregate level of annual return.

Table 8.7 shows the results for the same regression performed on the subset of January actuals. The estimate of the *Constant* and $_1R$ has a significant influence, while $_{12}R$ and *DiffTarg* are above the 0.05 significance level. Compared to the

Variable	Estimate	90 % CI
Constant	-0.051^{**}	$(-0.090, -0.013)$
$_1R$	0.052	$(-0.030, 0.133)$
$_{12}R$	-0.060	$(-0.150, 0.030)$
DiffTarg	0.850^{***}	(0.773, 0.927)
Observations	217	
R^2	0.729	
Residual Std. Error	0.158 (df = 213)	
F Statistic	190.621^{***} (df = 3; 213)	
Note: *p<0.1; **p<0.05; ***p<0.01; CI = confidence interval.		

Table 8.6: Analytical model for the difference between expert forecast and actual ratio ($_1E$) for months of December. The model utilizes normalized ratio of the last forecast, relative revision and the ratio difference from the entity specific target ratio. Difference from target has the strongest effect. Actuals and forecast ratios are derived from aggregated cash flow data.

December model, *difference from target* in December has a far smaller effect on *ratio error*, which is in line with the suggestion that earnings management will be most pronounced towards the end of year. While earnings management at the end of year leads to adjustments that entail shifts of cash flows in January, the finding underlines that forecast errors in January seem less systematic. In fact, the linear regression model of January can not account for the shifts that were required to reach the target in the previous year[1].

This interpretation is also supported by the fact that the proportion of explained variance for the January model (*Adj.* $R^2 = 0.324$) is lower than for the December model (*Adj.* $R^2 = 0.729$) and that the regression constant, the corporation-wide baseline for the normalized ratio, indicates higher error in January.

In summary, the results support Proposition (P8), that organizational biases related to targets of earnings margin and earnings management are present and lead (to a large extent) to the ambiguities regarding Proposition (P4). The results show that organizational biases help explain counter-intuitive findings on the individual level, and that individual level analysis will lead to wrong conclusions if organizational-level biases are not accounted for.

[1]One can assume that such information strongly improve the model performance in January.

Variable	Estimate	90 % CI
Constant	0.213***	(0.124, 0.301)
$_1R$	−0.548***	(−0.751, −0.345)
$_{12}R$	−0.058	(−0.195, 0.079)
DiffTarg	0.156*	(0.004, 0.309)
Observations	204	
R^2	0.388	
Residual Std. Error	0.324 (df = 200)	
F Statistic	42.210*** (df = 3; 200)	
Note: *p<0.1; **p<0.05; ***p<0.01; CI = confidence interval.		

Table 8.7: Analytical model for the difference between expert forecast and actual ratio ($_1E$) for months of January. The model utilizes normalized ratio of the last forecast, relative revision and the ratio difference from the entity specific target ratio. Current ratio forecast has the strongest effect. Actuals and forecast ratios are derived from aggregated cash flow data.

8.5.2 Dependencies on Revision

This section considers means of forecast improvement due to regular patterns in forecast revisioning. The focus is analyzing how business forecasts are adjusted to exploit possible improvements for the accuracy of forecasts with lower lead time. The assumption is that direction and magnitude of the final revision in aggregated forecasts can be related to suggested earnings targets, providing the means of improving the accuracy of longer-term cash flow forecasts.

Revision: Direction and Strength Influenced by Targets

Regression outcomes for revision magnitude (Model $M_{\text{Def. 9}}$) are shown in Table 8.8. The outcome shows that an expert's revisioning can indeed be partly explained by *TargetDiff* and *Month*. Changes in forecast ratios through a revisioning of cash flows increases with *TargetDiff* – high distance of a forecast ratio to the presumed target ratio is associated with high the adjustments of the ratio through revisioning, and declines when approaching the end of a fiscal year. The significance of both estimates is surprising, as this means that the magnitude of the final revisions of cash flows, at the aggregated ratio level, is predictable to some extent.

Table 8.9 shows the result of the regression of revision with significance levels ($M_{\text{Def. 10}}$). The results indicate that revision at the ratio level is significantly positively related to the magnitude of difference from target, indicating that forecast

Dep. Variables for $\lvert {}_{12}R \rvert$	Estimates
Constant	0.184 ***
| TargetDiff |	0.085 ***
Month	−0.005 ***
Observations: 2,355	
Significance levels: *p<0.1; **p<0.05; ***p<0.01	

Table 8.8: Analytical model regressing the magnitude in forecast ratio through absolute difference from target and month. The higher the distance of the forecast ratio to the target ratio, the higher the adjustments of the ratio revisioning. Absolute change declines when approaching the end of a fiscal year.

ratios increase through the final revisioning cycle. The higher the absolute distance from $T({}_0R)$, the more the cash flow forecasts (${}_1R$) are adjusted to increase the ratio. In addition, over the months in a year the last revision (${}_{12}R$) decreases the revision and therefore the forecast ratio (${}_1R$). These results hint at experts adjusting their cash flows in a way to reach a position above $T({}_0R)$. Forecast ratios are revised upwards, with adjustments getting smaller when approaching $T({}_0R)$. Considering the negative estimate of *Month*, this leads to approaching $T({}_0R)$ towards the end of a year.

Dep. Variables for ${}_{12}R$	Estimates
Constant	0.025 *
| TargetDiff |	0.054 **
Month	−0.004 ***
Observations: 2,355	
Significance levels: *p<0.1; **p<0.05; ***p<0.01	

Table 8.9: Analytical model regressing the forecast revision through absolute difference from target and month. The adjustments of the ratio revisioning is positively related to the distance of the forecast ratio to the target ratio, indicating that forecast ratios increase through the final revision. Revision declines when approaching the end of a fiscal year.

Regression results for revision based on *TargetDiff* ($M_{\text{Def. 11}}$) are shown in Table 8.10. The significance of the negative estimate indicates that ${}_1R$ decrease when $T({}_0R)$ is already met and increased when ${}_1R$ is below $T({}_0R)$.

Dep. Variables for ${}_{12}R$	Estimate
Sign(TargetDiff)	-0.081^{***}
Observations: 2,355	
Significance levels: *p<0.1; **p<0.05; ***p<0.01	

Table 8.10: Analytical model regressing the last ratio revision with direction of TargetDiff. The binary variable Sign(TargetDiff) indicates whether the forecasted ratio is above or below the suggested target. The negative estimate indicates that ratio forecasts decrease when a target is already met and increase when a forecasted ratio is below target.

Revision: Information Concealment by Targets

Table 8.11 shows the estimates of the trained Model $M_{\text{Def. }12}$. The results show that experts adjust ratios to match these targets. The prediction for ${}_{12}R$ is higher when the target ratio is underachieved ($\mathit{TargetDiff}_{(+)} : {}_{1}R < T({}_{0}R)$) compared to when it is overachieved ($\mathit{TargetDiff}_{(-)} : {}_{1}R > T({}_{0}R)$). A positive *TargetDiff* corresponds to an uptrend, while a negative *TargetDiff* relates to a downtrend. Especially bad performing ratio forecasts have a high absolute estimate to adjust to the target, while already met targets lead to a revision with an absolute estimate half that high, which supports Hypothesis (6). The end of the fiscal year has a significant influence on the revision of the ratio. The revision has a tendency to decrease over the year. But when the target is already met, the monthly reduction of revision is less reduced. This effect is obvious from the estimates when the *Month* and the interaction term are combined: $-0.009 + 0.006 = -0.003$. These results underline that the organizational target bias predefines the revisions, and Hypothesis 5 is supported. Thus, the Model $M_{\text{Def. }12}$ supports the hypotheses for the concealment of bad news (Hypothesis 6) and link to planning figures (Hypothesis 5).

Further, when one assumes that high errors imply high revisions and the distributions of Figure 4.3 is put in dependence with the error size, the result of Table 8.11 provides empirical support for the literature hypothesis (Abarbanell and Lehavy, 2003, p. 114) that extreme forecast errors tend to be optimistic, and small forecast errors are more likely pessimistic.

Interim Result

The empirical outcomes show that the direction and magnitude of the final revision of the aggregated cash flow forecasts can indeed be explained to a large extent by the relation between the ratio that results from current forecasts and

Dep. Variables for ${}_{12}R$	Estimates
$\text{TargetDiff}_{(+)}$	0.145 ***
$\text{TargetDiff}_{(-)}$	−0.063 ***
Month	−0.009 ***
$\text{TargetDiff}_{(+)} \times \text{Month}$	0.006 **
Observations: 2,355	
Significance levels: *p<0.1; **p<0.05; ***p<0.01	

Table 8.11: Analytical model regressing revision with dependencies of TargetDiff and Month. Model $M_{\text{Def. 12}}$ explains dependencies of revision on the difference from the target. The result shows that revision in ratio is higher, if the forecast is below the target ($\text{TargetDiff}_{(+)}$) when compared to forecasts above the target ($\text{TargetDiff}_{(-)}$).

the presumed accountants' earnings targets.

Overall, these results show that forecasting processes do not describe random walks and provide strong indication that cash flow ratios are adjusted to converge to predefined target ratios. The difference of the forecast from this target turns out to be a strong predictor for subsequent revision direction and volume. This allows for anticipating the final revision and therefore the upcoming expert forecasts to some extent. Knowledge of how forecasts will be adjusted later on by experts allows improving longer–term forecast ratios, considering that forecast accuracy overall increases with decreasing lead time. For instance, a model for the last revision ${}_{12}R$ can partially anticipate at time $t = 2$ the final forecast ${}_{1}R$ in advance.

8.5.3 Impact on Organizational Goals

Model $M_{\text{Def. 13}}$ in Table 8.12 shows that *Constant* is not significant, while ${}_{1}E$ has a significant effect on ${}_{12}R$, which supports Hypothesis (7). Revisioning in Model $M_{\text{Def. 14}}$ is organizationally biased by ${}_{1}E$ and experts adjust the ratio in relation to *TargetDiff*. As anticipated, the organizational bias *TargetDiff* distorts the forecasting process according to the result for the Hypotheses (5) and (6). Expecting that accurate forecasting is the primary goal of forecasting processes, the strength of the estimate of ${}_{1}E$ is expected to be the highest. However, estimates clearly show that *TargetDiff* overlays this goal with an estimate more than five times that high. These estimates suggests that the model assign more importance to the target ($T({}_{0}R)$) than to the actual ratio (${}_{0}R$) for the forecaster's revisioning (${}_{12}R$). The goal of managers seems to be different from the corporation's original goal of the forecasting process, which supports Hypothesis (8). However, the comparison of the integrated variables shows that all have negative estimates. This states that revisioning depend on organizational influences – but at least their impact is not diametrically to each other in the practical application.

Dep. Variables for ${}_{12}R$	Estimates Model $M_{\text{Def. 13}}$	Estimates Model $M_{\text{Def. 14}}$
Constant	-0.003	-0.002
${}_{1}E$	-0.246^{***}	-0.049^{*}
TargetDiff	(Not Utilized)	-0.242^{***}
Observations: 2,355		
Significance levels: *p<0.1; **p<0.05; ***p<0.01		

Table 8.12: Comparison of models to explain the revision in ratio. Both models utilize error, but differ on utilization of TargetDiff. Estimates show that revision is strongly influenced by the actual ratio, as long as TargetDiff is not included.

Interim Result

The results with support for Hypotheses 7 and 8 might seem simple, but their implications are wide-ranging, which will be stated with the following conjecture: If theoretically perfect information of the forecaster is assumed by knowing the actual ratio in advance, the estimates of Model $M_{\text{Def. 14}}$ indicate that revisioning behavior primarily depends (linearly) on the difference from the target compared to the information an expert could use to maximize the accuracy. This conjecture gives further support for the Hypothesis 8. Summarizing: From the perspective of the forecaster, the models emphasizes that providing accurate forecasts is not as important as pursuing an annual target. But, other influencing biases on revisions could exist besides the earnings target's influence and managed earnings, and could be integrated into the regression, dampening the effects.

8.6 Summary

Analyzing the cash flow forecast data of a large multinational corporation, this chapter provides the empirical revision analysis of financial forecasting processes with managerial accounting–related organizational biases. The analysis of corporate margins reveals that forecasting processes with organizational biases exist. These organizational-level biases relate to behaviors in operations management, e.g. earnings management, and awareness of planned activities, e.g. difference from target, and lead to systematic biases in forecast revisionsing processes. Results indicate that including organizational biases into accounting is the key to explain results in aggregate level forecasting.

The empirical analysis of cash flow forecasting in the sample corporation confirms that the relation between individual bias and accuracy is indeed ambiguous. The thesis argues that organizational issues—such as the pursuit of annual return targets—introduce organizational-level bias that distorts cognitive bias and explains such counter-intuitive relations. Separating the biases and determining when organizational bias can be expected to distort the diagnosis of individual bias helps to prevent misinterpretation and rethink organization structure.

In this research, two research gaps were addressed: First, providing insights into corporate invoice forecast and revision processes and, second, uncovering systematic effects and biases on the aggregate level, where hedging takes place.

Implications on Hedging, Management, and Innovation

For corporations, it is important to understand how organizational business prerequisites may affect forecasting accuracy in order to decrease hedging costs. In particular, risk management must incorporate planning figures and earnings management to some degree to reach an unbiased perspective. Otherwise, the biased perspective would impair risk management and hedging activities. Even if netting effects take place, with positive invoices (II) canceling the effect of negative invoices (IR), the influence of the findings must not be underrated. In particular skewed distributions of invoices would create additional risks or costs for unnecessary hedging. However, the three biases (ratio difference from planning targets, information concealment, and organizational goals) seem to influence the experts' forecasts.

From a managerial perspective, the results provide new insights into how organizational biases influence the purpose of the forecasting task. The endeavor to align forecasts to target figures determines how revisions are made. The accuracy and the forecast quality become less important for the human forecasters than other external and organizational influences. This does not mean that the human forecasts have a bad accuracy per se. The analyses revealed that reaching the target does not conflict with accurate forecasting for the revision behavior. But aligning the goal of forecasting for individuals to the corporation's goals seems to be beneficial. As a result, organizations that want accurate forecasts for invoice margins from managers should consider motivating purposeful forecasts, i.e. with incentives for forecasters.

In sum, the findings bridge the gap between forecasting research and organizational biases within management research for digital innovation in corporations. The results provided are relevant to corporate leadership, management strategies, information technology, and business analytics. Altering the understanding of "the goal of forecasting", corporate leaders can iteratively measure the impact of a managerial incentive system and build strategies to change organizational dependencies. For instance, to improve awareness of upcoming earnings management activities, the information might be communicated to the forecasters with an information system. Business analytics benefits from the information provided, as forecast correction services could incorporate dependencies stored in the information system in order to improve the forecast accuracy.

Scope of Business Context

The combination of incentivization, earnings management, and organizational planning (organizational biases) leads to forecast revisions most likely depending on the business context. The pursuit of annual return targets and forecast accuracy can be relevant in many companies. In case of another structure or different business model, the dependencies might look different. Also, it seems likely that other business aspects exist, which additionally biases forecasts.

Business aspects beyond corporate financial responsibilities can provide insights to understand interlinks to organizational structures. For example, self-governing departments can have serious implications for corporations, as departments' independence provides no obvious reason to align to corporate goals – besides benevolence. Also, it seems likely that other organizational aspects exist, such as country-specific tax avoidance. Tax avoidance might affect each subsidiary differently by defining upper borders for ratios that subsidiaries must not reach. These aspects can be accounted in correction approaches too, but this thesis can not examine and cover all possible organizational influences.

Correction Opportunities

Improvement processes of corporate risk assessment have an essential need of understanding interlinks of organizational and individual structures, especially beyond the organizational borders of the corporation. An approach for improvement should account for all relevant organizational levels, and besides taking managerial actions, future research work might reveal alternatives. Additional corporation wide research and documentation in the meetings, wherefrom effects might derive, possibly shows a solution how to identify future, unknown organizational biases. The analyzed organizational target bias and further measurement of so far unknown biases might disclose the latent motivations of forecasts in detail. It is concluded that the knowledge of these biases, together with the predictive value for decision support systems, drives subsequent forecast correction approaches to retrieve highly accurate forecasts for accounting information systems. The effort might be high, but the resulting opportunities seem to be even higher.

Chapter 9

Evaluation of Predictive Value

This chapter presents the empirical results for prediction analysis. These consist of the out-of-sample results on individual and aggregate level, analysis of error distribution, t-test evaluation, correlation analysis for weak efficiency, in particular revision and error analysis, and analysis of the extended weak efficiency with an examination of the underlying numbers. The chapter concludes by a summarizing interpretation of the results.

9.1 Predictions on Individual Level

9.1.1 Correction: Anchoring and Adjustment

The two models for lead times $t = 1$ base on $M_{\text{Equ. 5.1}}$, which are exhibited in Table 7.7. They state that the explained variance is below 1 % for each model, questioning whether the models can be applied successfully for statistical debiasing. The results in Table 9.1 show the respective out-of-sample evaluation when applying both models (positive and negative) to correct forecasts.

Overall, the correction model lead to a low mean out-of-sample error reduction compared to the original expert forecasts of 0.29 %. This result states, for example, an error of one million Euro would be reduced by 2,900 Euro only. With netting effect the mean error improvement on net foreign exposure volumes is expected to be further reduced, questioning if the impact of the model in comparison to other forecast correction models is high enough to justify the deployment. However, the extent of improvement varies strongly by month, with error even increasing when applying the correction in months 1 and 2 (January and February). With regard to the low explained variance, this result indicates that different biases might exist that are differently pronounced over the months of a year. For instance, further analyses for earnings management at the end of the year could reason the differences in model performance.

Month	Improvement (in %)	Forecasts (n)
1	−0.64	497
2	−0.07	509
3	0.62	509
4	0.16	506
5	0.37	516
6	0.00	517
7	0.69	512
8	0.20	500
9	0.18	502
10	0.10	515
11	0.99	511
12	0.62	525
All	0.29	6119

Table 9.1: Out-of-sample test results for correction of anchoring and adjustment. Correction results base on the regression models of Table 7.7. Expert forecasts are taken and debiased with the model estimates at $t = 1$, which are nearest to the actuals. For each month the mean improvement in percent of error reduction and number of expert-model comparisons are shown. Percentage improvement values at 0.29 % in 2013 of the mean forecast error.

9.1.2 Correction: Concentration Measures

Evaluation on the predictive value refers to the subselection of content cleaned data[1]. The concentration measure based models ($M_{\text{Equ. 5.3}}$, $M_{\text{Equ. 5.4}}$) compute corrected values for the last forecasts to examine net foreign exchange exposure. The evaluation of the corrected out-of-sample forecast uses R^2-values, improvements of mean error, and netted exposure improvement between the models. The benchmark model $M_{\text{Equ. 5.3}}$, with an Adj. R^2 of 0.055, yields a mean reduction in forecast error by 29,454 (median = 20,396). The full model $M_{\text{Equ. 5.4}}$ performs much better, with an Adj. R^2 of 0.62, showing mean reduction in forecast errors of 625,624 (median = 625,624). The improvement in net foreign exchange exposure is low, due to netting effects, and results in an improvement of 2,145,118 Euros in

[1] The results for the concentration metrics were applied on a particular selection of the content cleaned data (instead of ratio cleaned data). The selection without ratio cleaning serves the purpose to generalize the application onto forecast processes without dependencies of positive and negative forecasts (item type g). But, without ratio cleaning, additional cleaning measures were required. Forecast processes were selected that exhibit an actual volume above 250,000 EUR equivalent, absolute percentage errors below 200 % for all forecasts ${}_tF$. As division-specific differences were in interest for the corporation the analyses omit the subsidiaries of division DV.

comparison to the benchmark model.

The resulting exposure improvement of the full model is in magnitude an acceptable high volume, but relatively speaking, the corrected part counts still for less than 0.1 % of the overall net foreign exposure in the out-of-sample period. Further, the forecast error is reduced by less than 0.1 % of the expert exposure error. Despite the explained variances of the concentration models were very high, these figures clearly motivate the analyses for the aggregate corrections.

9.2 Predictions on Aggregate Level

9.2.1 Forecast Correction

The results of the aggregate correction are presented in Table 9.2. The table shows the date of the month and the amount of ratio forecasts for each month in 2013. Further the table exhibits the aggregated forecast error of the expert forecast ($M_{\varnothing}$) and model predictions (M_{Basic} and M_{Orga}). The last two columns show the percentage improvement of the models in comparison to the baseline $M_{\varnothing}$.

Data Descriptive		Forecast Error			Improvement (in %)	
Date	Amount	$M_{\varnothing}$	M_{Basic}	M_{Orga}	M_{Basic}	M_{Orga}
01/2013	58	18.77	18.01	18.40	4.0 %	2.0 %
02/2013	60	18.11	15.11	14.38	16.6 %	20.6 %
03/2013	60	16.79	14.74	10.86	12.2 %	35.3 %
04/2013	60	16.15	14.82	9.66	8.2 %	40.2 %
05/2013	61	16.59	15.42	9.25	7.1 %	44.3 %
06/2013	61	16.30	15.75	8.34	3.4 %	48.8 %
07/2013	61	16.84	15.38	7.91	8.7 %	53.0 %
08/2013	61	17.30	15.41	7.39	10.9 %	57.3 %
09/2013	61	18.51	16.58	7.35	10.4 %	60.3 %
10/2013	63	17.41	16.67	7.28	4.3 %	58.2 %
11/2013	63	17.79	15.95	7.10	10.3 %	60.1 %
12/2013	63	17.61	15.77	7.05	10.4 %	59.9 %

Table 9.2: Out-of-sample test results for the forecast ratios of experts, the basic statistical model, and the organizational model. Out-of-sample test covers the forecast correction in 2013. Cumulative absolute forecast error for expert forecast $M_{\varnothing}$, M_{Basic}, and M_{Orga} are shown. M_{Orga} predictions have the lowest forecast error (7.05 in December) compared to $M_{\varnothing}$ and M_{Basic} predictions. Percentage improvement compares the specific model error to the baseline of expert error. The improvements at the end of the year show that M_{Orga} reduces error by 59.9 %, which is better than M_{Basic} with 10.4 %.

The organizational information to reach the assumed target ratio clearly relates to the forecast error of Model M_{Orga}, as comparison for column four and five shows. Approaching the end of the fiscal year the Model M_{Orga} reduces the aggregated forecast error to 7.05, while expert $M_{\varnothing}$ and Model M_{Basic} error is stable in a disquieting high way. Considering that 100 % is the full opportunity for improvement as the resulting error would be equals zero, the result shows the advantage of the organizational information. In January the M_{Basic} has an advance of two percent, but for all other months M_{Orga} outperforms the foresaid model. The results show that percentage improvement of the models with solely statistical information reduces the expert error up to 16.6 % in February, while the models that considers business key figures performs with up to 60.3 % improvement in September.

The paired t-test based on the monthly improvements of Model M_{Basic} and Model M_{Orga} (comparison of the last two columns in Table 9.2) provides the following statistics: $t = 6.7299$, $df = 11$, p-value = 3.243e-05. The statistics evidence that the results in the out-of-sample period are significant at the 0.01 % level, supporting Hypothesis 9.

9.2.2 Error Distribution of Forecast Correction

The error analysis starts with a summary of the forecast error ${}_1E$, shown in the Table 9.3. These numbers provide the first support for the superior debiasing performance of M_{Orga}. Quantiles and median of the error are highly improved in comparison to $M_{\varnothing}$ and M_{Basic}.

Approach	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
$M_{\varnothing}$	−1.000	−0.239	−0.038	−0.068	0.125	1.000
M_{Basic}	−0.651	−0.201	−0.021	0.001	0.216	0.824
M_{Orga}	−0.681	−0.129	−0.004	−0.003	0.096	0.926

Table 9.3: Error quantiles of ${}_1E$ for the forecasts of experts, the basic statistical, and the organizational model.

The Figure 9.1 shows important information for the error quantiles of the forecasts utilizing a violin plot. This figure provides further support for the perfomance of M_{Orga} by the ${}_1E$ measure. The organizational model outperforms the statistical model especially for the 1. quartile ($\Delta = 0.072$), median ($\Delta = 0.017$), and 3. quartile ($\Delta = 0.120$). Furthermore, the lower and upper whiskers are improved. Only for minimum, maximum, and for mean error ($\Delta = 0.002$) the statistical model seems beneficial.

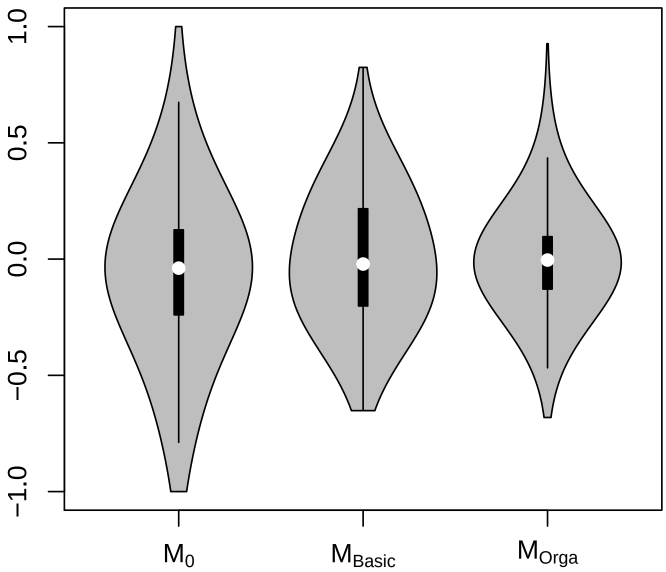

Figure 9.1: Quantiles of error ${}_1E$ for the forecasts of the experts, the statistically, and the organizationally corrected forecasts. Distribution narrows for correction models, especially the organizational model reduces the first and third error quantile.

Overall, the results state an advantage of the organizational model in comparison to the statistical model. The error distribution is narrowed, especially for the 1. and 3. Quartile, and for lower and upper whisker. This finding supports Hypothesis 9.

9.3 Improvement of Aggregate Efficiency

9.3.1 Correction of Weak Forecast Efficiency

The forecast efficiency is an important goal for forecasting processes. The weak efficiency of the resulting prediction of the models M_{Orga} and M_{Basic} are compared to each other and the baseline $M_{\varnothing}$. The baseline $M_{\varnothing}$ for forecast efficiency is shown in Figure 9.2. It should be noted that in the figures all and only the cells relevant for the efficiency analysis as proposed in Nordhaus (1987) are shown, irrelevant cells are hidden (marked using "x" sign). The weak efficiency comparison of the models $M_{\varnothing} - M_{Basic}$ and $M_{Basic} - M_{Orga}$ (differences in correlation) are depicted in Figure 9.3 and Figure 9.4 respectively.

The Figure 9.3 shows that the basic statistical model increases efficiency (marked in blue) compared to the baseline $({}_{12}R, {}_1E) = 92\,\%$ and $({}_{23}R, {}_1E) = 70\,\%$. But, all the other changed dependencies have decreased efficiency (marked in red). Comparison between the basic statistical model and the organizational

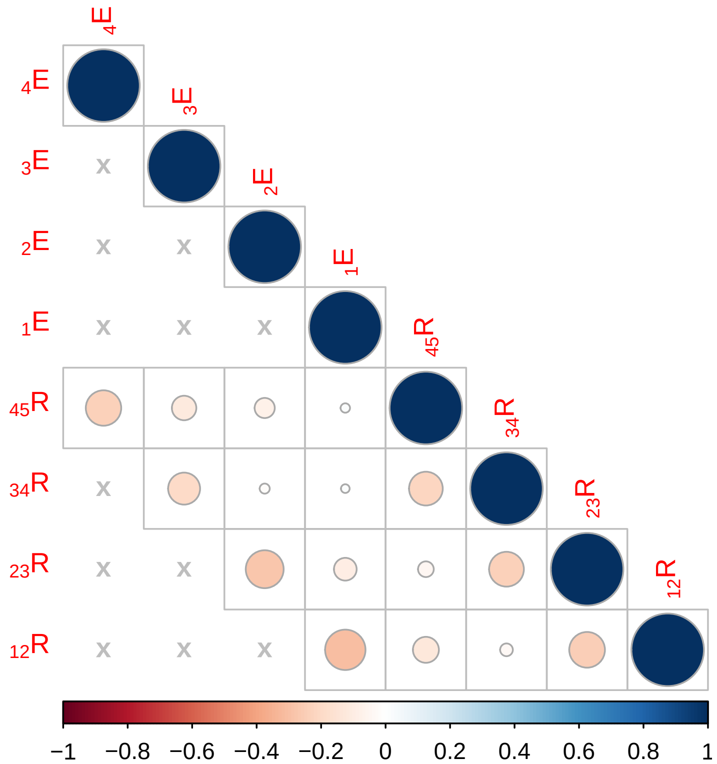

Figure 9.2: Correlation of revisions with errors and revisions of experts, without any correction (baseline model $M_{\varnothing}$).

	$_4E$	$_3E$	$_2E$	$_1E$	$_{45}R$	$_{34}R$	$_{23}R$	$_{12}R$
$_4E$	0							
$_3E$	x	0						
$_2E$	x	x	0					
$_1E$	x	x	x	0				
$_{45}R$	0	0	0	−0.9	0			
$_{34}R$	x	0	0	−0.19	0	0		
$_{23}R$	x	x	0	0.7	0	0	0	
$_{12}R$	x	x	x	0.92	−0.72	−0.85	−0.83	0

Figure 9.3: Percentage improvement in correlation of the basic statistical model M_{Basic} over the baseline model $M_{\varnothing}$ (positive numbers exemplify the improvement).

	$_4E$	$_3E$	$_2E$	$_1E$	$_{45}R$	$_{34}R$	$_{23}R$	$_{12}R$
$_4E$	0							
$_3E$	x	0						
$_2E$	x	x	0					
$_1E$	x	x	x	0				
$_{45}R$	0	0	0	0.73	0			
$_{34}R$	x	0	0	0.16	0	0		
$_{23}R$	x	x	0	0.63	0	0	0	
$_{12}R$	x	x	x	0.56	0.57	0.06	0.19	0

Figure 9.4: Percentage improvement in correlation of the organizational model M_{Orga} over the baseline model M_{Basic} (positive numbers exemplify the improvement).

model in Figure 9.4 shows an increase of efficiency relative to M_{Basic} by 56 % for the final forecast. More remarkable, the whole forecasting revision process is more efficient (see $({}_{12}R, {}_{23}R)$, $({}_{12}R, {}_{34}R)$, and $({}_{12}R, {}_{45}R)$).

Empirical results show that correction techniques can utilize organizational effects to improve forecast efficiency. The reduction of inefficient pattern shows that correction techniques with organizational forecast debiasing is superior to basic statistical approaches.

The results for the correlation of $({}_{12}R, {}_{1}E)$ are not significant after correction due to the high efficiency, but the details are shown in Table 9.4. The Spearman covariance for the approaches states that revisions and errors have a lower joint variability. The organizational model has a positive covariance, while the statistical model has a negative covariance with a higher magnitude. The table shows that M_{Orga} increases standard deviation for the revision, but standard deviation reduces for the error. It is arguable with these numbers that the correction of the organizational model focuses with meaningful revisions on the reduction of the error, while the the correction of the basic statistical model focuses on changing the error with minor corrections. The results imply that M_{Orga} enables future approaches to detect other, currently unknown biases to be identified and removed.

Approach	Covariance($_{12}R$,$_1E$)	Std.Dev.($_{12}R$)	Std.Dev.($_1E$)
$M_{\varnothing}$ (Baseline)	−246092.58	0.24	0.34
M_{Basic} (Statistical)	−20360.87	0.21	0.28
M_{Orga} (Organizational)	8968.19	0.28	0.20

Table 9.4: Spearman correlation details of the last revision and final error for forecast ratios of the experts, the statistically, and the organizationally corrected forecast ratios. M_{Orga} exhibits the highest standard deviation for revision while having the lowest standard deviation for error.

Interim Result

The results state Hypothesis 11 in the terms of Nordhaus's weak form forecast efficiency. The empirical results show that forecasts correction based on organizational information can improve forecast efficiency of $({}_{12}R, {}_{1}E)$ by 56 % in comparison to a statistical approach. The reduction of inefficient pattern show statistics arguing for forecast correction that rely on organizational biases (standard deviation of error 0.20) instead of basic statistical approaches that harm forecast efficiency (standard deviation of error 0.28). Overall, the results state several advantages of the organizational model in comparison to the basic statistical model. First, Hypothesis 10 is supported. The purely statistical model decreased efficiency in five of seven cases (Figure 9.3). Second, in the sense of Nordhaus the organizational model for debiasing improves forecast efficiency for $({}_{12}R, {}_{1}E)$. Moreover, the efficiency of the entire forecast process is improved (Figure 9.4), supporting Hypotesis 11. Third, highly improved efficiency for M_{Orga} over M_{Basic} in $({}_{12}R, {}_{1}E)$ and $({}_{23}R, {}_{1}E)$ and the advantage of meaningful revisions instead of pure error reduction (Table 9.4), which supports Hypothesis 12.

9.3.2 Correction of Extended Weak Forecast Efficiency

The extended weak forecast efficiency of the original forecasts $M_{\varnothing}$ and the resulting ratio prediction of the correction models M_{Basic} and M_{Orga} are compared to each other. The results of the different predictions are presented in Table 9.5. The upper part of the table shows the correlations between the last revisions with revisions and errors of $M_{\varnothing}$, M_{Basic}, and M_{Orga}. The lower part shows the correlations between the last error with revisions and other errors. The performance of the organizational model will be analyzed in the following explanations of extended weak forecast efficiency.

Metric	Approach	${}_{45}R$	${}_{34}R$	${}_{23}R$	${}_{12}R$	${}_{5}E$	${}_{4}E$	${}_{3}E$	${}_{2}E$
		Revision (2)				Timing (3)			
${}_{12}R$	$M_{\varnothing}$	-0.13^{***}	-0.03^{**}	-0.24^{***}	1.00	0.07^{***}	0.15^{***}	0.15^{***}	0.35^{***}
${}_{12}R$	M_{Basic}	-0.22^{***}	-0.06^{***}	-0.44^{***}	1.00	0.06^{***}	0.19^{***}	0.22^{***}	0.55^{***}
${}_{12}R$	M_{Orga}	-0.10^{***}	-0.05^{***}	-0.36^{***}	1.00	0.38^{***}	0.45^{***}	0.50^{***}	0.79^{***}
		Purpose (1)				Impact (4)			
${}_{1}E$	$M_{\varnothing}$	0.02	0.01	-0.10^{***}	-0.31^{***}	0.59^{***}	0.60^{***}	0.63^{***}	0.71^{***}
${}_{1}E$	M_{Basic}	0.03^{*}	0.02	-0.03	-0.03	0.71^{***}	0.71^{***}	0.74^{***}	0.79^{***}
${}_{1}E$	M_{Orga}	-0.01	0.01	-0.01	0.01	0.50^{***}	0.52^{***}	0.55^{***}	0.58^{***}

Note: * *p-value* < 0.1, ** *p-value* < 0.05, *** *p-value* < 0.01.

Table 9.5: Analysis of correction efficiency for the forecasts of the experts, the basic statistical model, and the organizational model. Results show correlation values and p-value levels of the last revision and the last error in ratio.

Extended Weak Forecast Efficiency: Revision

The upper left part with the first six columns of Table 9.5 shows the relevant figures for the weak form forecast efficiency concerning **revision** (Nordhaus's revision dependencies). The model M_{Basic} increases the correlation for all revision variables. The model M_{Orga} increases with it's forecasts the correlation of ${}_{12}R$ to all revision variables, except for ${}_{45}R$. When the correlations between the models and the original forecast are compared, the numbers state that M_{Basic} clearly damages the forecast efficiency the most. M_{Orga} is not beneficial compared to the original forecasts, with one exception the correlation between $({}_{45}R, {}_{12}R)$. Here the model improves the forecast efficiency in comparison to the experts. The decreased correlation between ${}_{45}R$ and ${}_{12}R$ does make sense due to the fact that M_{Orga} in particular incorporates figures of the assumed target (and these figures are at least one year before the current revision). However, M_{Orga} outperforms M_{Basic} in all these correlations. From these numbers it can be concluded that it is difficult but possible to improve forecast efficiency by models (besides error optimization). Overall, the organizational model is superior to the purely statistical.

Extended Weak Forecast Efficiency: Timing

The insight for the **timing** is provided in the upper right part of the Table 9.5 (columns ${}_5E$ to ${}_2E$). Here, high values are a positive result as the subsequent revision ${}_{12}R$ should increase in magnitude to be able to adjust errors. The magnitude of the correlations in the columns ${}_5E$ to ${}_2E$ hint to the fact that the biasing pattern is also existing in earlier forecasts (and their errors). It is argueable that the underlying pattern that a model should correct (for M_{Basic} and M_{Orga}) increases in influence with decreasing lead time from the earliest forecast with error ${}_5E$ until ${}_2E$. Therefore the thesis argues that M_{Basic} corrects (indicated by positive correlation) a pattern that exists less in the beginning (value 0.06) and mainly in the end (value 0.55) of the forecasting process. In contrast, the model M_{Orga} corrects (indicated by positive correlation) an underlying pattern that is existing and more important during the whole forecasting process (correlation values of 0.38 up to 0.79). Altogether, it is expected that M_{Orga} corrects biases that exist for a longer time compared to the biases that M_{Basic} corrects. These results support Proposition 9.

Extended Weak Forecast Efficiency: Purpose

In the lower left part of the table the shown figures are important regarding the **purpose** of the models. The only figures relevant to Nordhaus can be found in the sixth column of the lower part of the table, the correlation between ${}_{12}R$ and ${}_{1}E$. Here, the models strongly improve the correlation from -0.31 to -0.03, respective to 0.01. As both models optimize the error, the results are as expected. Further, the error correlation of both models are compared to those of the expert. The results show that for the revision-columns (${}_{45}R$ to ${}_{12}R$) the correlation is reduced (in magnitude and p-value). The figures state that both models serve their purpose to reduce the relation between the last revision and error, making the forecasts more efficient. One exception is Cor(${}_{45}R$,${}_{1}E$), which states that the error of the prediction of M_{Basic} is less efficient to the previous year adjustments, while M_{Orga} is still efficient.

Extended Weak Forecast Efficiency: Impact

The error-columns (${}_{5}E$ to ${}_{2}E$) in the lower right part exhibits an advantage with regard to the **impact** of the model M_{Orga}. Here, lower correlation-numbers state that the error of the model is less dependent on previous errors, which is a desired result of a bias correction model. The M_{Orga} reduces the inherent organizational bias within the original forecasts and the result shows that the error correlation reduces (e.g. see column ${}_{2}E$, $M_{\varnothing}$: 0.71 vs. M_{Orga}: 0.58). The example of an undesired outcome is visible for M_{Basic} (e.g. see column ${}_{2}E$, $M_{\varnothing}$: 0.71 vs. M_{Basic}: 0.79). Moreover, M_{Basic} increases the correlation between all the errors of the entire forecast process in comparison to $M_{\varnothing}$. This means a high error of the expert in an early phase (such as ${}_{5}E$) probably results in an high error of the statistical model prediction (${}_{1}E$). The model M_{Basic} is therefore highly dependent on the input of $M_{\varnothing}$, and M_{Orga} is less dependent (column-wise perspective). Even more interestingly, the magnitude of error-correlations of model M_{Orga} is below the expert $M_{\varnothing}$, stating that the utilization of organizational information leads to higher independence of forecasts (row-wise perspective). The underlying approach of the statistical model obviously optimize the error of the forecast, leaving the important bias mostly unchanged within the forecasts, while the organizational model focuses especially on an important bias. That explains the different model results. However, the results do not support Proposition 10, even if the models exhibit correlation values for ${}_{2}E$ and ${}_{1}E$, which show that the statistical model requires further improvements to at least reach the results of the organizational model (correlation values of $M_{Basic} > M_{\varnothing} > M_{Orga}$).

Interim Result

Hypothesis 12 is supported in the extended weak forecast efficiency analyses that show the superiority of organizational models for debiasing, namely the revision, the timing, the purpose, and the impact on how the model corrects the expert forecasts.

Overall, the results state several advantages of the organizational model M_{Orga} in comparison to the statistical model M_{Basic}. First, in the sense of Nordhaus the organizational model improves forecast efficiency for $Cor({}_{12}R, {}_{1}E)$ and has no deficits for $Cor({}_{45}R, {}_{1}E)$ (Ext. Efficiency: Purpose). Second, in the sense of Nordhaus the correction improves the forecasts, especially for $Cor({}_{45}R, {}_{12}R)$ (Ext. Efficiency: Revision). Third, the underlying pattern upon the correction is based is important even at the early stages of the forecast process (Ext. Efficiency: Timing). Fourth, improvements of M_{Orga} make the error less dependent from previous errors and from expert inputs (Ext. Efficiency: Impact). The result support Hypothesis 13.

9.4 Summary

Improving information systems and decision support tools can help to reduce hedging costs and the managerial workload (with regard to the manual identification of forecasts items that need revising). The empirical results of forecast correction techniques were comprehensive. This has led to starting a new project with the research partner, the corporation that provided the analyzed data, to utilize the model predictions with organizational debiasing and to automatically check the expert's validity of ratio forecasts within a forecast support system. The organizational model debiases at an aggregate level, where business reasons matter. Overall, the results show that consideration of business key figures makes it easier to identify on an aggregate level the most beneficial work packages of forecasts that need revisions.

Predictive Value: Individual Level

The analyses on individual level cash flow forecasts associated the revisions pattern to forecast accuracy. The metrics used to improve the forecasts in the revision processes show that these have low explanatory power (below 1% for correction models based on A&A) and high explanatory power (above 60% for correction models based on concentration measures). However, the out-of-sample test results suggest that by considering these patterns, the improvement of net foreign exchange exposure is marginally better than the expert forecasts. In both cases less than 0.3% of the expert error could be improved, which suggests to analyze predictive value of aggregate level.

Predictive Value: Aggregate Level

Information systems with services for decision support systems benefit from the insights provided. The empirical analyses show that business information provides meaningful key figures for predictive purposes. Explicitly, forecast correction approaches that incorporate organizational dependencies (EBITDA proxy information) can highly improve forecast accuracy.

The empirical results on ratio show that considering organizational objectives for debiasing techniques can strongly improve forecast accuracy. The total correctable expert error is reduced by up to 60 % for all forecasts of a month, providing better decision support for managers, and reducing the personnel effort to determine forecasts with suspicious pattern that are unaligned with organizational structures.

Besides ratio-level correction, utilizing ratio information for correcting individual forecasts is should be considered. By improving ratio forecasts the error of the net foreign exposure may theoretically improve by up to 60 %, which requires a mapping function from ratio of accumulated invoices issued and invoice received to the accumulated difference between them for each month (net exposure). In sum, the results provide out-of-sample evidence of organizational influences and methodology to analyze fewer issues by identifying those that really matter.

Aggregate Level Efficiency Improvement

For the forecasting community the results might reinforce the link between exploratory data analysis and forecast correction. Exploring data can actually provide essential information. I'd like to underline that the results were not achieved with a neural network, a random forest, or a complex machine learning algorithm. Instead, the results are achieved with a simple linear regression models.

The importance of exploratory data analysis is underlined as data and business understanding additionally allows a differentiation between biases with pattern and errors, stated by aggregate level efficiency. From the perspective of forecast researcher it is important to understand in which way business-related organizational influences may affect forecasts and, indirectly, correction models. In the case of cash flow forecasts in a corporate setting one important bias is the percentage margin target, as these might provide incentivization to alter forecasts and actuals of cash flows. The underlying value of this organizational information on ratios in terms of forecast efficiency. The analysis showed that efficiency increases for the whole process when such information is integrated into a corrective model.

Extended Forecast Efficiency Analysis

An important theoretical result is the conclusion that the different results for corrective models may be inherent to each approach. This thesis contributes with applying the developed approach to test for the extended weak forecast efficiency. This approach states that a basic statistical model mainly tries to optimize the selected component (e.g., the error), while an organizational model tries to reduce the bias itself.

Thus, the organizational model provides the possibility to identify further unknown biases. Even if the debiasing with a single organizational model does not achieve a high error decrease, it is possible to identify and correct further biases with a second subsequent model. Finally, a subsequent set of models for the most important organizational biases will definitely increase the forecast accuracy. Understanding the error components for correction approaches is important. When a forecaster distinguishes the signal from the noise, the error should decrease by the way or making predictions more confident.

Despite the fact that the organizational model has two flaws in efficiency – in $({}_{12}R, {}_{34}R)$ and $({}_{12}R, {}_{23}R)$ – the model M_{Orga} outperforms the expert $M_{\varnothing}$ in all other aspects of extended forecast efficiency. Furthermore, M_{Orga} outperforms M_{Basic} in every aspect. These results state that organizational information is essential for forecast correction, while the extended weak efficiency analysis provides a framework to understand the differences in correction approaches.

Part IV

Finale

Chapter 10

Conclusion and Outlook

10.1 Summary

Forecast efficiency theory is widely used to investigate judgmental forecasts that regularly turn out to be inefficient in terms of weak form forecast efficiency. Influences that lead to individual level biases are usually associated with such inefficiencies. However, influences can also lead to organizational-level biases. This is why particular importance should be given to improve the understanding of the context of forecast processes.

This thesis contributes to the literature with analyses of forecast efficiency, individual biases, organizational biases, forecast correction, and the links in between. Based on corporate data for judgmental cash flow forecasts, this works showed that isolated tests for biases and forecast efficiency must be interpreted with special care. The analyses revealed a need for an integrative view to determine and interpret the respective biases appropriately.

The analyses provided evidence for the pursuit of annual returns targets in relation to earnings management, which not only reveals predictable patterns of how the ratios of accumulated cash inflows and cash outflows are adjusted over time, but also provides reasonable explanations for phenomena that contradict efficiency theory. Explicitly, some of the inefficiencies in the data were found to be associated with improved forecast accuracy, which could be explained by the knowledge of earnings management.

While it is likely that earnings management in pursuit of annual returns targets will be relevant in many business contexts, there might well be additional organizational biases at play. But in practice, however, non-disclosed volumes of presumed earnings targets and missing direct observations of earnings management or other potentially bias-related activities make forecast analyses and model based correction truly challenging. With such information available, it would become much easier to unravel the effects of different biases on forecasting processes. Separating the biases and determining when organizational biases can be expected to distort the diagnosis of individual biases helps to prevent misinterpretations and rethink organization structure.

Despite the potential causes of the predictability of the cash flow forecasts at the cumulative ratio level, the results indicate an enormous potential for improving the longer–term cash flow forecasts and corporate risk assessment that uses the forecast data of the financial system. Specifically, forecast difference from target is the key to explaining results in corporate cash flow forecasting.

In the following part of this chapter, the research results are summarized and discussed in the context of the corporate forecast and its implications for the main research questions. To conclude, further future questions will be outlined on the basis of the thesis.

10.2 Contributions

The objective of this thesis was to investigate forecast efficiency, different biases and forecast correction, and their relation in the context of forecast processes. For empirical forecasts in intra-corporate financial planning, this thesis showed that biases exist already at the level of individual forecasts but that forecasts are influenced in particular by organizational biases. Existing inefficiencies at the organizational level underline these dependencies. Based on research questions 1 – 3, the individual level was investigated. The aspects of the aggregate level were analyzed based on research questions 4 – 6. The research questions discussed in Section 1.2 are summarized as:

RQ 1. Forecast Efficiency — Revision Process
RQ 2. Forecast Efficiency — Efficiency Hypothesis
RQ 3. Revision Process — Anchoring & Adjustment
RQ 4. Revision Process — Organizational Influence
RQ 5. Organizational Influence — Forecast Correction
RQ 6. Forecast Correction — Forecast Efficiency

As a result of my research, I have answered these six complex research questions as follows: For research question 1, it can be summarized that the corporate forecasts analyzed do not exhibit weak efficiency and that, hence, forecast correction potential is available. Save for a few exceptions, forecast horizons are associated positively with the forecast errors. Based on research question 2, an approach to evaluate the efficiency hypothesis was introduced. The results obtained lead to a rejection of the efficiency hypothesis for the corporation's consolidated cash flow data. Further, all violations of the efficiency hypothesis were associated to organizational influences. Regarding research question 3, this thesis has identified and described different patterns of individual biases based on the possibilities of identification. Several Bandwidth Models and concentration measures are pointed out as metrics that can map more complex relationships than the usual metrics. The forecast correction advantages were pointed out for the respective models. Research question 4 can be confirmed on the aggregate level. Here, organizational biases exist in terms of the return ratio relative to annual earnings targets. The dependencies on annual targets, revisions, and forecast errors evaluated in addition gave deep insight into existing forecasting processes. Research question 5 was answered through evaluation of aggregate level forecast correction, where correction of organizational biases provides impressive improvements, in particular in comparison to purely statistical approaches. Finally, research question 6 was answered by means of an efficiency analysis of the corrected forecasts from an organizational and a standard statistical correction method. This thesis's research was able to show that standard statistical corrections focus on the error reduction, are disadvantageous for the efficiency of forecast processes, and that organizational corrections outperform the purely statistical corrections in all aspects of extended weak forecast efficiency. The full list of research questions and their results are exhibited in Appendix A.

10.3 Future Outline

At present, efficiency theory is applied mainly showing that markets and forecasting processes are not efficient, i.e. that there exists improvement potential. The question as to what type of corrections are suitable and necessary to achieve advantages for forecasting processes, among others, was pointed out in this thesis on biases and forecast efficiency in corporate finance. Summarizing: Improved aggregate model forecasting revealed efficiency emendation. This work provides a basis for future research e.g., on forecast efficiency, bias extraction, implications for managers, and forecast correction, that will follow.

10.3.1 Forecast Efficiency

Efficiency at Different Aggregation Levels: Over Time

Efficiency is fundamental in its theory and, hence, can provide meaningful statements. However, there are no basic studies on the statistical properties of weak forecast efficiency. Research, therefore, should focus in particular on assessing the impacts of aggregation for efficiency e.g., of aggregation over time (instead of over different subsamples of the categorical features of a dataset). I expect that a coarser aggregation of units will reveal fundamental changes in forecast efficiency in the context of seasonal aspects.

Efficiency Related to Information

Besides the above, linking of information on efficiency is an aspect to be considered. If already known and important information is newly integrated into processes, this should clearly prove the absence of efficiency. A formal analysis and derivation of this relationship would be desirable. Moreover, the understanding of weak efficiency should be changed in such a way that the concept of efficiency does not focus on the single points of a forecasting process but on the entire process, thus enabling a systematic comparison of different forecasting processes as a whole.

Efficiency for Pre-Evaluation of Predictions

In my opinion, the concept of efficiency could be used also for analyzing forecasts in a pre-evaluation step. The research question would be how far, in a forecasting process, the forecasts of a correction model must be independent from one another. To my mind, independence of forecasts should be guaranteed under the assumption of a random walk, if all corrections concerning content (e.g., organizational debiasing) have been carried out. Such analyses can be applied before the real reference values exist and would, so to speak, be out-of-sample evaluations without the need of real values. However, at least as regards error minimization, corrected forecast revisions should have the same efficiencies as the revisions of the realizations. From the theoretical and practical points of view, it would be particularly interesting to analyze the dependencies of the pre-evaluation results and the resulting real forecast errors.

10.3.2 Formalized Bias Extraction

As is pointed out in the Chapter 4.2.1, important relationships within forecasting processes can be identified by means of efficiency analyses and expert knowledge of extremely complex issues. Automation of this method in order to match the expert knowledge with the advantageous or disadvantageous efficiencies in forecasting processes could improve dealing with the practical questions and advance research, in particular. This would require to formalize the expert knowledge at which point biases are to be expected in the forecast processes. At least from the theoretical point of view, the results of such formalization could be matched automatically to the efficiencies in the respective processes. The dependencies between the efficiencies and individual information from experts could serve to evaluate and confirm drawn up and automated models. In particular, this approach provides a possibility of partially automating the research process, which could lead to machine-based research and human scientific work at a new level of abstraction.

10.3.3 Managerial Implications

From a practical point of view, two implications for management and processes can be derived directly from this thesis. Forecasting processes must be adapted according to the margin targets, either through improved provision and use of existing knowledge (e.g. by central knowledge management of margin definition and relevance within the respective companies), or by lower incentives within the subsidiaries or incentives through the corporation from the outside. In practical terms, this should result in better reconciliation between the participating persons and thus in improvements regarding forecasts and realization values. Moreover, it becomes evident that without expert knowledge, the efficiency results cannot be put in a context. To consolidate the results, the existing knowledge should be well documented and explicit incentives should be given for documentation.

10.3.4 Forecast Correction

Correction Methods

Over a long time, attempts have been made to minimize forecast errors independent of the respective topic. To my mind, this means "improvement of symptoms" and is at the expense of the different correction methods (e.g., regressions versus decision trees versus neural networks). The focus on symptoms has led to diverging views within science and practice and in solitary attempts at finding answers to the question as to "which specific algorithm provides lower error rates". At the present state of research, where low forecast errors are to be expected and where continuous reliability and stability of forecasts are of particular significance, this should not be the only central question anymore, and debiasing should play a role. Usage of organizational biases to correct the inherent relationships is helpful in the case of intra-corporate financial planning. The application to debias forecasts from organizational influences would also be interesting for other correction methods and forecasting in other domains.

Sequential Correction

As a rule, mainly only error metrics are accepted for evaluation of correction approaches. Considering the results of this thesis and the possible future improvements in efficiency theory pointed out above, it suggests itself to compare different sequential correction processes in addition to the individual forecasting processes. Assumed that there are two alternative sequential approaches, A(B(data)) or C(D(data)), one could evaluate which correction process (i.e., AB or CD) is more suitable for mapping and correcting the relationships of the contents. Moreover, the intermediate results of B(data) and D(data) can be compared through efficiency analysis even if the resulting intermediate results are not of the same result type. Inefficient approaches within the sequential (correction) process hence can be identified to show where improvements in such complex (correction) processes can be advantageous.

Bias Correction and Error Reduction

Finally, I would like to recommend to place the focus of scientific research on the reasons for error corrections. Corrections with statistical methods that particularly aim to reduce errors but not to remove (or reduce) biases must be questioned. Without analyzing or correcting the reasons, correction will always stay behind the symptoms. The forecasting community is recommended not to reduce the error component by changing forecasts and revisions marginally but to instead maximize or at least change the forecasts and revisions to an acceptable extent resulting in only marginal errors. The consistency of a high revision will determine in how far the forecast result is aligned to the bias pattern. Based on such results, an understanding of forecasts and best correction techniques is obtained along the way. Overall, consideration of inherent relationships through model-based description and correction can start where errors actually occur. Instead of placing emphasis on the correction of the symptoms, the technique to remove organizational biases and this thesis promote the correction of the underlying original reasons.

Part V

Appendix

Appendix A

Research Overview

This chapter provides an overview for the research questions and their evidence. Each research question follows a reference to the exhibited evidence of the thesis.

RQ 1. **Forecast Efficiency — Revision Process**
Are revisions of cash flow forecasts weak form efficient in a multinational corporation?

RQ 1.A *If forecasts are not weak efficient, which forecast patterns are detectable?*

Evidence: *Table 7.1, Table 8.3 & Figure 9.2*

RQ 1.B *To what extent does the reduction of lead time reduce the forecast error?*

Evidence: *Table 7.2, Table 7.3*

RQ 2. **Forecast Efficiency — Efficiency Hypothesis**
Is the forecast efficiency hypothesis valid in the data of corporate financial controlling?

RQ 2.A *Do forecast processes exist that entail or even violate the efficiency theorem, resulting in inefficient forecasts that are positively associated with forecast accuracy?*

Evidence: *Equations 3.7 and 3.8, Table 7.4*

RQ 2.B *Given that influences can entail or even violate the efficiency hypothesis, can the efficiency hypothesis help to provide a explaining framework to associate the violations to such influences?*

Evidence: *Framework: Section 4.2.1, Explanation: Figure 8.4*

RQ 3. **Revision Process — Anchoring & Adjustment**
Is corporate internal forecasting entailed by Anchoring & Adjustment?

RQ 3.A **Revision Process — Identifying Metric**
Do distinct Anchoring & Adjustment patterns exist and which metric can improve identification?

Evidence: *Table 7.5, Table 7.7, Metrics: Equ.* 3.18 *& Equ.* 3.19*, Table C.2 in combination with Table 7.6, Metrics: Equ.* 3.24 *& Equ.* 3.25 *& Equ.* 3.26

RQ 3.B **Revision Process — Forecast Correction**
To what extent can Anchoring & Adjustment metrics improve judgmental forecast prediction?

Evidence: *Table 9.1, Table C.1, Section 9.1.2, Equ.* 3.28 *& Equ.* 3.29 *in Section 7.4*

RQ 3.C **Revision Process — Concentration Measures**
Is the error of the forecast data related to descriptive metrics for temporal adjustments, revision pattern, and direction?

Evidence: *Figure 7.2, Figure 7.3, Table 7.8*

RQ 4. **Revision Process — Organizational Influence**
Does aggregate level revisioning behavior of experts that produce forecasts for corporate finance depend on organizational influences?

RQ 4.A *Does the revisioning behavior of experts differ over the annual cycle?*

Evidence: *Accountants: Table 8.2 & Figure 8.1, Forecasters: Table 8.5 & Table 8.6 & Table 8.7, (Indication by Tables 7.2 and 7.3)*

RQ 4.B *Can annual return targets explain the revisioning behavior of experts?*

Evidence: *Table 8.8, Table 8.9, Table 8.10*

RQ 4.C *Do organizational influences exist that mask or distort the revisioning behavior of experts?*

Evidence: *Table 8.11, Table 8.12, Figure 8.4, (Indication by Table 7.7)*

RQ 4.D *Is the aggregate level revision process different from the individual level revision process of experts, stated in terms of weak forecast efficiency?*

Evidence: *Table 7.1, Table 8.3*

RQ 5. **Organizational Influence — Forecast Correction**
Do organizational influences provide predictive value and are they beneficially usable in aggregate level forecast correction to remove forecast biases?

Evidence: *Table 8.4, Table 9.2, Table 9.3, Figure 9.1, (Indication by Figure 8.3)*

RQ 6. **Forecast Correction — Forecast Efficiency**
Does the correction of forecasts to remove biases influence the aggregate level forecast efficiency?

RQ 6.A *To what extent does the correction of forecasts influence the temporal pattern of revisions, stated in terms of weak forecast efficiency?*

Evidence: *Figure 9.3, Figure 9.4, Table 9.4, (Partly in Table 9.5)*

RQ 6.B *Exist additional temporal patterns in revisions that explain the type of forecast correction, expressed in an extension of weak forecast efficiency?*

Evidence: *Figure 5.1, Table 9.5*

Appendix B

Sample Data

Delivery Process

Horizon	2010			2011												2012												2013		
	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3
		F														A	A	A												
						F													A	A	A									
5 Quarters									F													A	A	A						
												F													A	A	A			
														F														A	A	A
						F										A	A	A												
									F										A	A	A									
4 Quarters												F										A	A	A						
														F											A	A	A			
																		F										A	A	A
									F							A	A	A												
												F							A	A	A									
3 Quarters														F								A	A	A						
																		F							A	A	A			
																					F							A	A	A
												F				A	A	A												
														F					A	A	A									
2 Quarter																		F				A	A	A						
																					F				A	A	A			
																								F				A	A	A
														F		A	A	A												
																		F	A	A	A									
1 Quarter																					F	A	A	A						
																								F	A	A	A			
																										F		A	A	A

Table B.1: Temporal structure of expert forecast deliveries for cash flows and invoices in 2012, respective first quarter 2013. Table exhibits the months of the actual cash flows (A) and delivery of the corresponding forecasts (F) for different forecast horizons. For instance, the first forecast for cash flows in January 2012 is delivered five quarters ahead in November 2010 (1st row of the table) and is then revised in March 2011 (6th row of the table), in June 2011 (11th row of the table), in September 2011 (16th row of the table), and finally in November 2011 (21th row of the table), when the final forecasts for January 2012 are delivered.

Data Structure

Division	Date	Entity	Partner	Type	Currency	Actual	Forecast 5	Forecast 4	Forecast 3	Forecast 2	Forecast 1
BHC	01-08-2010	0001	0002	Invoice Issued	EUR	95.00	71.79	61.20	71.80	20.10	48.70
BHC	01-08-2010	0001	0002	Invoice Received	EUR	87.10	81.65	65.70	91.59	54.30	52.64

Table B.2: Sample data in the corporate financial portal. This table presents a sample of raw data. In this sample the forecasts and actuals are grouped inline, while the date refers to the realization of the actual.

Appendix C

Analytical Results

Models for A&A in Synthetic Forecast Series

Loss function	Model	Series: Ind	RW-1	RW-T	LogG	ExpG
mse	Bromiley	0.03	0.25	0.40	0.10	0.55
	Lawrence	0.05	−0.20	−0.19	N.A.	N.A.
	Harvey	−0.00	0.25	0.23	N.A.	N.A.
	Amir	−0.10	0.25	0.32	N.A.	0.48
	BWM	−0.08	0.41	0.59	0.08	0.38
	LBWM	−0.08	0.48	0.66	0.08	0.41
rmse	Bromiley	0.06	0.27	0.40	0.23	0.68
	Lawrence	0.04	−0.10	−0.21	N.A.	N.A.
	Harvey	−0.00	0.26	0.26	N.A.	N.A.
	Amir	−0.00	0.25	0.33	N.A.	0.59
	BWM	0.11	0.43	0.60	0.20	0.44
	LBWM	0.12	0.50	0.67	0.21	0.48
mape	Bromiley	0.04	0.22	0.36	0.11	−0.10
	Lawrence	0.04	−0.10	−0.19	N.A.	N.A.
	Harvey	−0.00	0.22	0.23	N.A.	N.A.
	Amir	−0.00	0.23	0.33	N.A.	−0.20
	BWM	−0.10	0.37	0.52	0.10	0.06
	LBWM	−0.09	0.44	0.58	0.10	0.07

Table C.1: Pearson correlation between the anchor probability ν of the A&A models and the three different loss functions.

Series	Model	Bromiley	Lawrence	Harvey	Amir	BWM	LBWM
Ind	Bromiley	1.00	−0.10	0.32	0.26	0.15	0.23
	Lawrence		1.00	−0.10	−0.00	0.09	0.10
	Harvey			1.00	0.83	0.01	0.03
	Amir				1.00	0.01	0.03
	BWM					1.00	0.90
	LBWM						1.00
RW-1	Bromiley	1.00	−0.20	0.36	0.31	0.30	0.35
	Lawrence		1.00	−0.30	−0.20	−0.10	−0.10
	Harvey			1.00	0.87	0.16	0.21
	Amir				1.00	0.15	0.20
	BWM					1.00	0.93
	LBWM						1.00
RW-T	Bromiley	1.00	0.08	−0.17	0.07	0.40	0.45
	Lawrence		1.00	−0.68	−0.55	−0.12	−0.12
	Harvey			1.00	0.80	0.13	0.15
	Amir				1.00	0.15	0.16
	BWM					1.00	0.93
	LBWM						1.00
LogG	Bromiley	1.00	N.A.	N.A.	N.A.	0.92	0.94
	Lawrence		1.00	N.A.	N.A.	N.A.	N.A.
	Harvey			1.00	N.A.	N.A.	N.A.
	Amir				1.00	N.A.	N.A.
	BWM					1.00	0.99
	LBWM						1.00
ExpG	Bromiley	1.00	N.A.	N.A.	0.96	−0.10	−0.10
	Lawrence		1.00	N.A.	N.A.	N.A.	N.A.
	Harvey			1.00	N.A.	N.A.	N.A.
	Amir				1.00	−0.20	−0.20
	BWM					1.00	0.96
	LBWM						1.00

Table C.2: Pearson correlation between the anchor probability ν of the A&A models.

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