Anchor and Adjustment Detection on Empirical Forecast Series

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Abstract. Human involvement in forecasting processes can lead to predictions being influenced by cognitive biases. Anchoring and Adjustment is a cognitive bias that typically reduces the accuracy of forecasts. Considering the influence of forecasts in corporate processes, improving forecast accuracy can be of crucial importance. This study aims to use the newly developed Bandwidth Model to improve forecast accuracy and to detect Anchoring and Adjustment effects in forecasting processes. We demonstrate the potential of the Bandwidth Model by the regression of Anchoring and Adjustment effects on forecast errors, which exhibit higher explanatory power than standard volatility metrics. The results suggest that a forecast support system can use the Bandwidth Model to improve forecast accuracy in enterprises.

Keywords: Anchoring and Adjustment Model, Corporate Cash Flow, Forecasting Process, Forecast Revision, Cognitive Bias

1 Introduction

Cognitive biases can influence human behavior. According to [20] these biases can be divided into three groups: Representativeness, Availability, and Anchoring and Adjustment. Representativeness is a judgmental heuristic in which probabilities of events are valued based on the similarity to other well known events. Second, availability describes the heuristic that a person uses easily available examples to predict probabilities. Third, Anchoring and Adjustment takes place when a person consciously selects a certain numerical value but is influenced by environmental variables, like other predicted values. Especially Anchoring and Adjustment has a strong influence on forecast processes [8, 17, 19]. One needs constantly to account for previous forecasts within forecasts processes, as these forecasts can have influence on the new forecasts. Forecast accuracy can be improved by detecting the influence on the forecast process through Anchoring and Adjustment.

There are several authors who focus on the benefits of revisions in the forecasting process and use statistical methods to evaluate human prognoses and thus enable improvements to be made. For example, the authors of [15] state that revised forecasts are significantly more accurate than unrevised. The authors of [1] and [2] show that

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underreacting to new information is widely spread, while [7] and [9] state that overreaction is common as well.

Other authors focus on how to determine the influence of Anchoring and Adjustment and which forecasts are affected by Anchoring and Adjustment the most [4, 10, 14, 2]. Most of them focus on single forecasts [10] or the mean of the previous forecasts [14]. The authors of [11] analyze timing, magnitude, and trend in revision processes. They state, depending on the volume of the revisions, early and later revisions can reduce forecast errors. Early revisions are beneficial for evenly distributed revisions, while in case of concentrated revisions the effect can be detrimental and later revisions can reduce error levels. The authors of [16] tested the effect of anchoring on Australian earning forecast. They state that analysts tend to overreact for positive revisions and underreact for negative ones. Results in [13] suggest that Anchoring and Adjustment patterns can occur at different levels, for example for organizational influences. Finally, the impact of a decision support system on forecast accuracy was tested by [3] and a clear positive effect was found. The restrictions of this approach are treat by authors like [6]. They analyze macroeconomic forecasts and found that even additional information is not sufficient to improve the GDP forecast.

The usefulness of Anchoring and Adjustment in the forecasting process depends on the correct detection on forecasting series. The authors of [12] developed the *Bandwidth Model (BWM)* and the *Logarithmic Bandwidth Model (LBWM)* to determine the influence of Anchoring and Adjustment on the forecast process. They tested the performance of both models on synthetic forecast processes, which generate several possible patterns that occur in real data. Both Bandwidth Models show a better performance than previously used models.

This paper aims to apply the approach on empirical forecast series. The objective is to investigate whether the model of [12] shows an improved identification of anchoring not only on simulated, but also on real forecast series. Therefore, we formulate the guiding research question:

Research Question 1: Can the Bandwidth Models be used to determine a probability for anchoring on forecast series?

The empirical forecast series originate from an international corporation that is based in Germany. The corporation's activities in various business divisions allow a better transferability of the measured effects to other areas. Further, the use of empirical data allows us to develop an *Empirical Bandwidth Model (EBWM)*. The ability of these three models to improve the precision of revisions will be compared to standard metrics of volatility.

The paper is structured as follows: Forecast process and notation is introduced in Chapter 2. Chapter 3 introduces the Bandwidth Model, the Logistic Bandwidth Model, and the Empirical Bandwidth Model. Afterwards, in Chapter 4 the outcomes of the three models are used to predict the forecast errors. Standard volatility metrics are used as a benchmark to show the impact of Anchoring and Adjustment, as well as the application of the Bandwidth Models for forecast correction.

2 Literature Review

In the literature, the methodology for determining whether a particular forecast or forecast series is influenced by Anchoring and Adjustment (A&A) has been supplemented by five important publications [4, 10, 14, 2, 12]. The author of [4] assumes that the value with the highest amplitude exerts an anchor effect. Therefore, if a proposed forecast lies between the old forecast and the forecast with the highest amplitude, an anchoring is assumed. In addition, the distance between anchor and old forecast must be significantly smaller than that between the anchor and the new forecast. The methodology of paper [2] suggests that the last forecast causes an anchor effect. A new forecast is therefore only influenced by its predecessor. These two approaches concentrate strongly on individual important forecasts with potential anchor effects. Therefore, the authors of [14] assume that not individual values trigger anchoring, but that the mean value of the previous forecasts exerts such an influence. Anchoring therefore occurs when a new forecast lies between the old forecast and the mean value of the previous forecasts. In [10] the authors assume that the direction of the adjustments of the forecasts is important, for example, if successive forecasts are adjusted upwards, anchoring can be responsible. In order to improve these identification methods, [12] has developed a new approach. This new approach, which is examined in this paper on real-world forecast data, does not consider a single forecast or parameter like the mean value, but rather each forecast to determine probabilities for the presence of anchor effects.

3 Notation and Data

The sequence of initial forecast and adjusted forecasts is referred to as *forecasting process*. For each forecast process one *actual item (A)* with the terminal realization value is provided. For each forecasting process a human expert generates the *t*-th forecast F_t in every quarter of the year until the actual value is realized. An example five-step forecasting process of the sample corporation with a maximum lead time of 5 quarters contains five forecasts each. Figure 1 visualizes the structure the forecasting process.

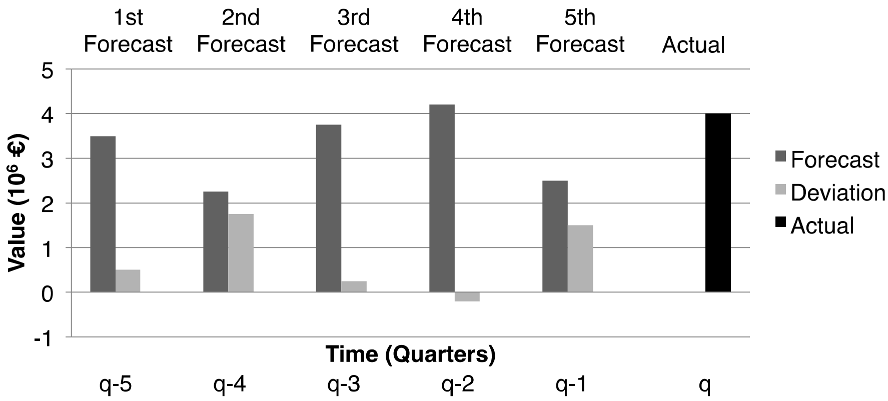

Figure 1. The Empirical Forecast Process.

Several loss functions can be implemented to measure the forecast error. Typically, the difference between the forecasts and the actual is used. However, if the values of the forecast items over different forecast processes vary widely, differences in error may be difficult to interpret and error relative to the actual volume may be preferable. The percentage error loss function takes the actual volume into account, and we calculate the percentage error between the last forecast F_{q-1} and the actual.

$$Err = \frac{F_{q-1} - A}{|A|} \tag{1}$$

The different volumes of the forecasts should also be taken into account when analyzing forecast revisions. The *Revision (Rev)*, as presented in Equation 2, is defined as the difference between two successive forecasts and the first forecast and thus avoid this problem.

$$Rev_t = \frac{F_{t+1} - F_t}{F_t} \tag{2}$$

The used data in this study is a set of forecast processes that contains real-world cash flow forecasts and realizations. It is provided by a large diversified multinational corporation that generates annual revenues in the medium double-digit billion Euro range. The data contains information of judgmental forecasts and actuals of invoice issued and received with additional information such as the currency, region, and business units. The financial cash flow data was selected in accordance with the corporation's recommendations, leading to 34.057 observations. Further, the cleaning process contains the following steps: Forecast processes with missing values or without revision volumes are removed. In addition, the upper and lower 5% percentile is withdrawn to account for outliers. Overall, the data used in the analyses bases on 26.401 observations of forecast processes, with six columns (one actual and five forecasts).

4 The Bandwidth Model

One of the previously mentioned models to detect Anchoring and Adjustment was introduced by [14]. They focus on the mean as anchor value. This model neglects strict positive or negative anchor effects. The model in [12] considers these effects with the BWM. It uses underlying patterns that are based on A&A to predict the final error. These underlying patterns are predicted through the strength of the revisions. The BWM works as follows: Each revision is assigned to one of three groups. These groups are the *Up*-Group, the *Down*-Group, and the *Const*-Group. Positive revisions above a threshold α are assigned to the *Up*-Group (value 1). Negative revisions below -α are allocated to the *Down*-Group (value -1). The remaining revisions are assigned to the *Const*-Group (value 0). The assignment to the groups is shown in Equation 3.

$$\begin{aligned} &Rev_t \in Up \;\Leftrightarrow\; Rev_t > \alpha \\ \textbf{or } &Rev_t \in Down \;\Leftrightarrow\; Rev_t < -\alpha \\ \textbf{or } &Rev_t \in Const \;\Leftrightarrow\; |Rev_t| \leq \alpha \end{aligned} \tag{3}$$

Allocation to the three groups is based on a threshold value that ensures low susceptibility to minor changes in the forecast. As a result the selected groups focus on major changes. The categorization into three groups, as an important part of the model, restricts the model simultaneously. Assigning to three groups without further differentiation, neglects the differences within these groups. Further, the selected α has a high influence on the results. Choosing an optimal α value is crucial to improve the detection of A&A.

Two further models will be introduced to overcome this limitation. One of these models was introduced in [12]. These two models base on the allocation to different groups, which complement the assignment of functions for further differentiation of revisions. Therefore, the requirements for the assignment function are examined in more detail before the models are introduced. The assignment functions needs to fulfill the Equations 4-6.

$$f^{+}(0) = 0 \tag{4}$$

$$f^{+}(\max\ Rev_t) = 1 \tag{5}$$

$$f^{+\,\prime}(Rev_t) \geq 0, \forall\ Rev_t \in\ Rev^{+} \tag{6}$$

The functions value should be 0 for a revision where no adjustment has taken place. The smallest revision should further be assigned to 100% to the *Down*-Group, the largest to 100% to the *Up*-Group. The function should monotonically increase as a higher revision should result in higher assigned values. As assigning functions that can fulfill these conditions, the logarithmic growth function and the empirical distribution function will be examined.

The first model to be considered with an assignment function is the LBWM. This model uses the logarithmic growth function, which induces a sigmoid process. This sigmoid process assigns small anchor probabilities for small revisions (*Rev* close to zero), and assigns large probabilities otherwise. Near the threshold α the transition is steady. The BWM categorizes revisions in three different groups. However, the logarithmic growth function distinguishes between positive and negative revisions.

According to the Conditions 4-6 the revisions of 0 will be assigned to the positive group. The logarithmic growth function will be modified in a way that a weight on every revision can be assigned.

Equation 7 shows the standard logarithmic growth function f_x. The function depends on 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*.

$$f_x = \frac{G}{1+exp^{(-kGx)}(\frac{G}{f(0)} - 1)} \tag{7}$$

First, the saturation limit *G* is set to 1. In addition, the function should assume its turning point at the threshold α equal 0.5. For this purpose, the parameter k is determined as shown in Equation 8.

$$k = \frac{ln(\frac{1}{\mu} - 1)}{\alpha} \tag{8}$$

The parameter μ is introduced to ensure that the function does not convert to zero and the parameter α shifts the Equation 7. The overall effect of both parameters is stated in Equation 9.

$$f(0) = 0.5 \textbf{ and } f(-\alpha) = \mu \tag{9}$$

Equations 10 and 11 present the final function for the LBWM. A distinction is made between positive and negative revisions, which reflect the sign before the revision by means of two different functions. These two equations are obtained through a re-shift of the function with –α.

$$f_{log}^{+}(Rev_t) = \frac{1}{1+exp^{\left(\frac{\ln(\frac{1}{\mu}-1)}{\alpha}(-Rev_t+\alpha)\right)}} \tag{10}$$

$$f_{log}^{-}(Rev_t) = \frac{1}{1+exp^{\left(\frac{\ln(\frac{1}{\mu}-1)}{\alpha}(Rev_t+\alpha)\right)}} \tag{11}$$

Figure 2 shows an example of how the LBWM can assign revisions (x-axis) to different probabilities for anchoring (y-axis). The figure provides the combination of the formulas for positive and negative revisions. For example, the revision $Rev_t = 4$ would be considered as effected by anchoring with a probability of about 43%.

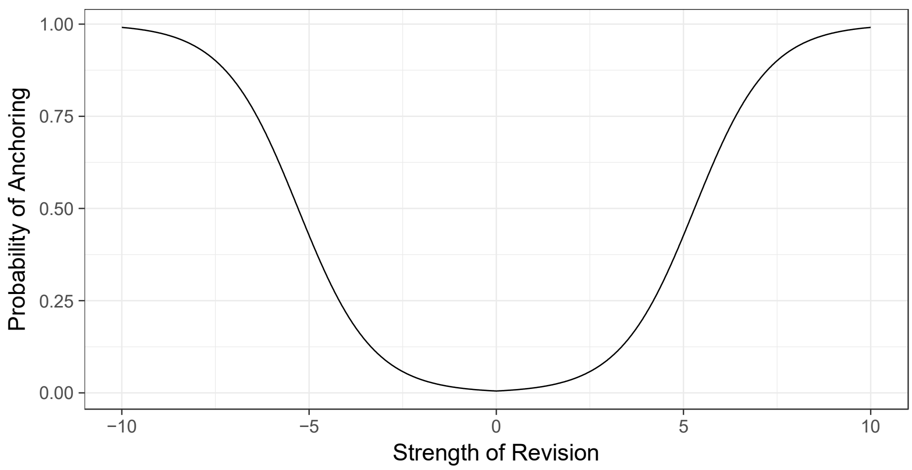

Figure 2. Logistic Function for Positive and Negative Revisions.

The second model with an assigning function is the Empirical Bandwidth Model. The empirical distribution function in this model complies with the Equations 4-6, which is why no further adjustments are necessary. The empirical distribution function assigns revisions in two different groups. The function assigns different revisions to each pair of unequal function values. The function grows in dependence to the sample size. The results of the empirical distribution function depend on the quality and amount of the data basis. The more values the data basis contains, the closer the function is to a continuous one. The dependency on the quality of the data is eminent. The combination of a small data base and poor data can lead to wrong predictions. The data set is thus used entirely and is not split into training and test data.

In total, three different models for the detection of A&A effects were explained. The Bandwidth Model classifies all forecasts in three different groups. The Logistic Bandwidth Model and the Empirical Bandwidth Model consider intergroup differences. The Logistic Bandwidth Model complemented the forecasts by a weight for A&A effects and classifies them in two different groups. The Empirical Bandwidth Model assigns weights based on the range of the forecast and optional training data. These three models will be evaluated in a next step. This evaluation is performed by predicting the forecast error through the models. As a benchmark, regressions with several standard measures for volatility will be used.

5 Empirical Analysis

The evaluation uses the forecast processes of the international corporation to compare regression results of the three models with the results of the benchmark models, intending to show potentials for forecast correction. The benchmark models extract several standard metrics for volatility for revisions, such as the range of the revisions, the sum of the amount of volatility, or the highest absolute revision. The different benchmark models use linear regressions on the forecast series. The values of these series are used to predict the *Err*. Table 1 shows the results of several standard metrics for volatility of the cleaned dataset with 26401 items. For example, the regressions consider revisions with the highest amplitude, or the range between the largest and smallest revision, or the squared revisions.

Table 1. Regression Results of Volatility Metrics.

Model	Intercept	Coefficients	Adj. R^2
$\lvert Err\rvert \sim \beta_0 + \Sigma_{i=1}^{4} \beta_i \lvert Rev_i\rvert$	0.38***	-1.61 x 10^{-5}	-5.93 x 10^{-5}
		-1.80 x 10^{-5}	
		4.66 x 10^{-5}	
		-4.67 x 10^{-6}	
$\lvert Err\rvert \sim \beta_0 + \beta_1 \max \lvert Rev_i\rvert$	0.38***	1.12 x 10^{-5}	-2.96 x 10^{-5}
$Err \sim \beta_0 + \beta_1 \{Rev_i : \max\lvert Rev_i\rvert\}$	0.02	-7.76 x 10^{-6}	-3.55 x 10^{-5}
$\lvert Err\rvert \sim \beta_0 + \beta_1 \sigma\,(\cup\, Rev_i)$	0.38***	9.91 x 10^{-6}	-3.55 x 10^{-5}
$\lvert Err\rvert \sim \beta_0 + \beta_1 (\max\lvert Rev_i\rvert - \min\lvert Rev_i\rvert)$	0.38***	5.27 x 10^{-6}	-3.51 x 10^{-5}
$\lvert Err\rvert \sim \beta_0 + \Sigma_{i=1}^{4} \beta_i\, Rev_i^2$	0.38***	-1.61 x 10^{-5}	-5.92 x 10^{-5}
		-1.80 x 10^{-5}	
		4.66 x 10^{-5}	
		-4.67 x 10^{-6}	

* indicates a significance level of 0.1, ** of 0.05, and *** of 0.01

The regression results on volatility metrics exhibit small revision coefficients, which are all not significant to the 0.1 p-value. The best metric achieved an Adj. R^2 (share of explained variation, devalued by the number of components) of -2.96 x 10^{-5}. This metric uses the strongest revision of a forecast series as predictor for *Err*. Overall, none of the standard metrics provide an Adj. R^2 sufficiently high to improve forecasts. However, the results of the metrics can be used as a benchmark for the Bandwidth Models.

The first model applied to the forecast sequence is the BWM. In the initial paper [12] uses a fixed value of 0.5 for parameter α, which is adopted here. Equation 12 regresses the *Err* to examine the explanation performance (Adj. R^2) of the linear regression.

$$Err \sim \beta_0 + \sum_{t=1}^{4} \beta_t Up_t + \sum_{t=1}^{4} \gamma_t Down_t + \varepsilon \qquad (12)$$

Apart from the intercept, both coefficients are significant. The Adj. R^2 of the BWM on the empirical forecast series is 0.03. The result is shown in the second column of the Table 2.

The Logarithmic Bandwidth Model is the first evaluated model with the logistic assigning function. The LBWM replaces the *Up* and *Down* terms in Equation 12, which is shown in Equation 13. The influence is measured with a linear regression.

$$Err \sim \beta_0 + \sum_{t=1}^{4} \beta_t f_{log}^{+}(Rev^{+}) + \sum_{t=1}^{4} \gamma_t f_{log}^{-}(Rev^{-}) + \varepsilon \quad (13)$$

In a practical implementation, the optimal α value can be estimated with historical training data. The adjustment of the α parameter can improve the results of the Bandwidth Models. Two possible ways to predict the α parameter were considered. Either α is the same for all revisions or a different α is used for earlier forecasts in a series than for later ones. For the case of equal α values for revision we optimize them through the algorithm *BFGS-B* [5]. BFGS-B is an iterative method for solving unconstrained nonlinear optimization problems. Figure 3 shows the effects on the Adj. R^2. The optimal value is reached for α = 0.36.

Table 2. Regression Results of the Bandwidth Models.

Coefficients	BWM	LBWM: Equal α	LBWM: Different α	EBWM
β_0	0.02	0.02***	0.01***	0.00***
β_1	0.12***	0.03***	0.04***	0.03***
β_2		0.07***	0.07***	0.07***
β_3		0.16***	0.15***	0.13***
β_4		0.31***	0.30***	0.25***
γ_1	-0.13***	-0.04***	-0.04***	-0.03***
γ_2		-0.07***	-0.06***	-0.05***
γ_3		-0.15***	-0.14***	-0.11***
γ_4		-0.28***	-0.36***	-0.19***
$Adj. R^2$	0.03	0.07	0.08	0.06
* indicates a significance level of 0.1, ** of 0.05, and *** of 0.01				

The optimal α values for different α for all forecasts are shown in Table 3. Table 2 shows the result of both variants of the LBWM. Column three shows the LBWM with one optimized α value and column four shows the LBWM with different α values for each revision. The LBWM with one specific α reaches an Adj. R^2 of 0.07. The part of the explained variance appears promising when compared to the results of [18]. The authors asked amateurs to estimate the value of houses with a given anchor value. At least 17% of the variance could be explained by the anchor value. However, this is the determination of a single anchor value. In contrast to their work, our forecasts are not single anchor values, but series of anchored forecasts. For this reason, an Adj. R^2 of 0.07 appears promising. As expected, the coefficients for positive revisions are positive and the negative revisions are negative. The influence of the coefficients increases over time, stating that newer forecasts provide more information. Moreover, the intercept is significantly different from zero.

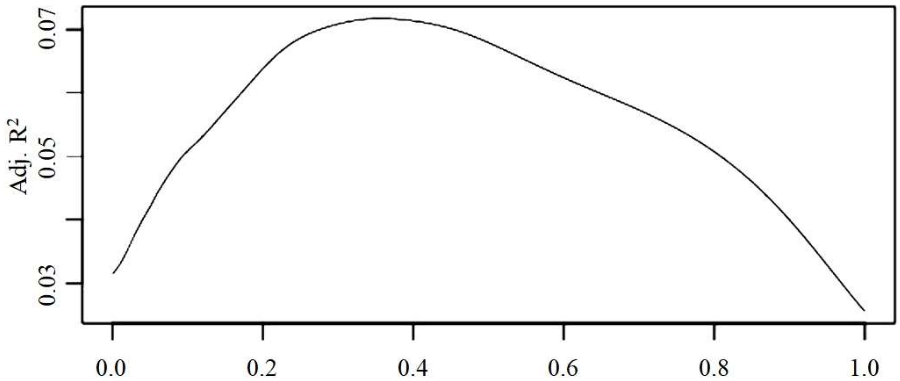

Figure 3. Comparison of α Values.

The LBWM with different α values further improve the results to an Adj. R^2 of 0.08, while the influence of the coefficients increase over time. Further, the α show a positive trend. The comparison with the standard metrics for volatility shows the potential (Adj. R^2) of the LBWM is higher.

Table 3. Optimization of α Values for the Logarithmic Bandwidth Model

Coefficients	β_1	β_2	β_3	β_4	γ_1	γ_2	γ_3	γ_4
α Values	0.36	0.23	0.25	0.31	0.39	0.26	0.33	0.51

The Empirical Bandwidth Model is the second version of a model with assignment function after the LBWM that uses the empirical function to assign the *Up* and *Down* groups. Equation 14 shows the regression model of the BWM extended upon the EBWM. The structure of the results is equal to the results for the Logistic Bandwidth Model.

$$Err \sim \beta_0 + \sum_{t=1}^{4} \beta_t f_{emp,t}^{+}(Rev^{+}) + \sum_{t=1}^{4} \gamma_t f_{emp,t}^{-}(Rev^{-}) + \varepsilon \quad (14)$$

The results in Table 2 show an increase of the coefficients for later revisions. Positive revisions result in positive coefficients and negative revisions in negative coefficients. The Adj. R^2 of the EBWM is 0.06, which is below the values of the LBWM. However, an increase of the sample size is expected to further improve the Adj. R^2 of the EBWM.

Overall the BWM shows better results than the benchmarks. The results of [12] were thus also confirmed on empirical forecast series. However, BWM was surpassed by the LBWM and the EBWM. Especially the LBWM with different α values shows a far higher Adj. R^2 than the standard metrics and a slightly higher value than both other Bandwidth Models. The detected Adj. R^2 of 0.08 shows the importance of A&A effects on forecast series to predict the forecast error. However, the difference of the enhanced models is not very high, as is the influence of α optimization. This suggests that the used assigning function is not as important as the fulfillment of the assigning functions Conditions 4-6. In the work, the regressions use all available information (revisions) to estimate the anchor results, i.e. it is an in-sample test. Thus, the paper shows the improvement of recognizability by optimizing alpha values, while both LBWMs (without and with optimization) achieve comparable Adj. R^2 results. Further evaluations and out-of-sample tests of the forecast series could be carried out in order to ensure the stability of alpha values on the forecast processes. The specific optimization must then take place in the respective context, which is derived from the generalizability of the methodology.

The LBWM and the EBWM tend to show a similar process for the revisions independent from the used assigning function. Positive revisions have positive coefficients and negative revisions always negatives. This suggests that negative revisions of experts tend towards an underestimation whereas positive revisions tend towards an overestimation.

6 Conclusion and Outlook

In this paper we analyzed three models to determine A&A effects on forecast series - the Bandwidth Models: BWM, LBWM and EBWM. These models can relate forecast revisions to the influence of A&A effects. Using this relation, the forecast models provide input for linear regressions to estimate the forecast error. In comparison, the forecast errors were regressed with standard metrics for volatility of the forecast processes. The evaluation based on short empirical forecast series of a large corporation, where forecast accuracy is essential for corporate success.

The results show that all Bandwidth Models exhibit a higher explanatory power on the forecast error than the standard metrics. The increased Adj. R^2 implies that the forecast accuracy is influenced by cognitive biases. Utilizing the information of detected A&A effects for human forecast processes in the case of real-world forecast improved the regression results for error estimation. As a result, the research question can be answered positively. The Bandwidth Model can be used to determine probabilities for anchoring.

This study has some limitations. The introduced LBWM and EBWM were tested on one particular set of empirical corporate data. However, we recommend the analysis of the method on further data samples - and, for example, in other domains.

Overall, we recommend evaluating the Bandwidth Models in a Forecast Support System. The usage of the error regressions that utilize the Bandwidth Models offers a high potential of forecast improvement by the correction of the A&A bias. The correction can be employed within an information system such as a forecasting support system. The forecast support system can identify forecasts that exhibit a high probability for *A&A*. The managerial analysis of these identified forecasts allows experts to optimize forecast revisions and to improve managerial processes.

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