Dynamics of expert adjustment to model-based forecasts

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Abstract

Experts often add domain knowledge to model-based forecasts while aiming to reduce forecast errors. Indeed, there is some empirical evidence that expert-adjusted forecasts improve forecast quality. However, surprisingly little is known about what experts actually do. Based on a large and detailed database concerning monthly pharmaceutical sales forecasts, we examine whether expert adjustment is predictable. We find substantial evidence that the size, the relative size and even the sign of such adjustment show positive-valued dynamics. The main drivers of current expert adjustments are past adjustment and past model-based forecast errors. Our findings are also that experts' adjustment may suffer from double counting and that trust in the statistical model is not large. An implication is that models may need improvement. Also, experts need to focus on other variables than past sales data when adjusting model-based forecasts. Finally, the method to evaluate the quality of experts' adjustment needs to be modified.

Key words: Adjusting forecasts, Automatic forecasting, Decision making, Evaluating forecasts, Judgemental forecasting

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1. Introduction and motivation

There is substantial literature on the consequences of experts adjusting model-based forecasts, see section 5.6 of Lawrence et al. (2006) and the many references cited therein. Interestingly, there not much literature, if at all, that examines how experts actually create their adjustments. Some firms might keep logbooks where experts write down what their motivations were, but to our knowledge in most cases such logbooks do not exist. One way to find out what could possibly have been the drivers of expert adjustment should therefore be data based and this is what we will pursue in this paper.

In this paper we study the case of forecasting monthly sales of pharmaceutical products. Denote a sales series by S_t. The pharmaceutical company has offices in about forty countries, and it is involved in seven product categories in each of these countries. The head office uses a statistical program to create forecasts for the next 25 months, where the program is rerun each month. These forecasts are communicated with the local offices, where local experts have an option to modify these forecasts. The statistical program gets fed by past sales data, and each month it automatically selects a (potentially different than previous month) forecasting model. Each month the model selection and the parameter estimation are redone, while each time using updated sales figures. Given the nature of the products and the sampling scheme (monthly), it is quite likely that the true sales data to some extent depend on past sales, that is, S_t is a function of S_{t-1}, S_{t-2} and so on, but also on other variables (which are not included in the model). The model-based forecast, denoted as MF_t, also is a function of past sales, but quite likely not exactly the same function as the true but unknown dependence of current sales on past sales. The local manager receives this model-based forecast and can decide to modify it into EF_t, the final expert-based forecast. From EF_t and MF_t, one can construct the size of the adjustment and it is this variable that is the focus of our paper.

One possible scenario for expert adjustment (see Section 2 for more details) is that the expert recognizes that the model-based forecast is based on an inappropriate function of past sales, and hence seeks to adapt this function towards the true one (at least, what he or she believes is the true one). Another scenario is that the expert adds knowledge about the un-modelled part, and hence that the added expertise is orthogonal to information already in the model.

When we look at the first scenario, we would observe that each time the expert adds something to the model and that this added part is also a function of past sales. As sales are likely to be correlated over time, the adjustments would then also be correlated over time. When we consider the other scenario about orthogonal knowledge, then we would not find that experts' adjustments are predictable by past sales, or functions of past sales. Indeed, when the local manager foresees local events that would impact future sales, he or she will modify the model-based forecast, and such local events shall not be predictable from the sales data.

In sum, it seems of potential interest to study the dynamic correlation structure of expert adjustment for a variety of reasons. First, it provides an insight if the manager only adds orthogonal knowledge or whether he or she adds value by looking at past sales. Second, it might lead to suggestions for improving the model-based forecasts, at least in the case where such expert adjustment indeed leads to better forecasts. Finally, and this is quite important for subsequent research, if we would find that experts' adjustment is a function of past sales or its own past, we would need to modify tests for forecast accuracy by including extra dynamics.

The outline of our paper is as follows. In Section 2 we provide more details about how experts might adjust model-based forecasts, and we discuss the potential implication of possible empirical findings. In Section 3 we discuss the data that we use. We have access to the full database concerning forecasts for about forty countries and seven categories. However, based on the advice of the managers at the headquarters' office, we draw a representative sample concerning three countries and two product categories. In this section we give some basic statistics of the sign and size of expert adjustment. In Section 4 we start our analysis for a single country and a single category. In Section 5 we discuss the other results. The main conclusion from all our empirical findings is that the size, relative size (relative to the model-based forecast) and sign of expert adjustment are highly predictable. In Section 6 we draw conclusions about these empirical generalizations, and discuss limitations of our study and we provide various suggestions for further research.

2. Modelling dynamics in expert adjustment

We consider the following situation. A company uses an automated statistical package to generate forecasts, each month, for the next 1 to H months. These forecasts will be labelled as the model-based forecast, or MF_t. The expert receives these forecasts some time during a month and adjusts these model-based forecasts such that the end result is EF_t, the expert forecast. When we ignore correlation between MF_t and EF_t, the size of the expert adjustment can simply be computed as $AI_t = EF_t - MF_t$, where AI is an acronym for "adjustment independently". When we do not ignore that correlation we can rely on the regression-based method outlined in Blattberg and Hoch (1990) to arrive at an adjustment dependently, labelled as AD_t. AD_t is determined by regressing the expert's forecast onto the model-based forecast. The residuals of the regression form AD_t, thus $EF_t = \gamma MF_t + AD_t$. Notice that this means that

$$AD_t = AI_t + (1-\gamma)MF_t ,$$

where γ needs to be estimated of course. When γ = 1, $AI_t = AD_t$. When γ > 1 then $AI_t > AD_t$, as the model-based forecast always is a positive number here. The value of γ can also be interpreted as a measure of confidence in the model. When it is 1, there is full confidence, when it is smaller than 1, or even negative, there is much less such confidence.

The database we have concerns information on the model-based forecast, the final forecast delivered by the expert and the realization. The data are presented in monthly format. The company uses an automated statistical forecasting program that gets fed by past sales figures. Hence, the information set for the model-based forecasts only concerns past sales. The expert receives these model-based forecasts and can decide to adjust it. Basically, the expert also has access to past sales figures, so the information set of the model and that of the expert could partly overlap.

In this paper we are interested in the correlation dynamics of AI_t and AD_t, where the adjustment concerns the size of adjustment, the relative size (relative to the model-based forecasts), and the sign of the adjustment. We conjecture that expert adjustment might depend on past adjustment and on past model-based forecast errors, MF_t - S_t. Also, we think that past uncertainty or variance of adjustment and of the forecast errors could be relevant. When we summarize AI_t and AD_t simply by A_t, we therefore conjecture that

$$A_t = f(\text{past } A_t, \text{ past } MF_t - S_t, \text{ past } A_t \text{ squared, past } MF_t - S_t \text{ squared}) \quad (1)$$

where f is a linear function. Denoting D_1 to D_4 as the partial derivatives of A_t to the four components in this function f, there are various insights that can be obtained.

Before we continue with a discussion of the potential interpretation of the signs of these partial derivatives, we discuss a simple example for illustration. Suppose that true sales is generated according to the following data generating process (DGP), that is

$$S_t = \rho_{1,t} S_{t-1} + X_t \beta_{1,t} + \varepsilon_t$$

where X collects variables that sometimes can have an effect on sales (country-specific institutions, rules, policies or events). The subscripts (1,t) of the parameters indicate that the DGP allows for time-varying effects of past sales and current X. Suppose further that the model-based forecast is

$$MF_t = \rho_{2,t} S_{t-1}$$

where the subscript (2,t) indicates that the parameter is re-estimated each month. Finally, suppose that the expert has in mind the following forecasting scheme, that is,

$$EF_t = \rho_{3,t} S_{t-1} + Z_t \beta_{2,t}$$

where Z collects the variables that the expert deems as relevant.

There are now a couple of scenarios that can be examined. Suppose that the expert has full confidence in the model, and in fact believes that the link between current and past sales in the model agrees with his or her opinion, and hence $\rho_{2,t} = \rho_{3,t}$, then

$$EF_t - MF_t = Z_t \beta_{2,t}$$

If Z really contains only once in a while useful information, and when this impact is only once in a while not zero, it is most likely that $EF_t - MF_t$ does not show serious systematic correlation with its own past. On the other hand, if Z is relevant very frequently (like having to always add inflation figures), and Z itself is autocorrelated, then $EF_t - MF_t$ will show such correlation too. Note that in that case it means that the model is perceived as being misspecified most of the time as it lacks the *Z* variable. The expert is aware of this, so he or she can recommend changing the model. Things become even more pronounced in case the expert does not believe that the link between current and past sales in the model agrees with his or her opinion and hence $\rho_{2,t} \neq \rho_{3,t}$,

When D_1 is large and positive, this may be viewed as a sign of potential double counting, see Bunn and Salo (1996). Double counting entails that the expert and the model partly rely on the same information set, and abrupt changes in right-hand side variables are already included in the model, but then also again by the expert. So, a sudden change in the last month's sales is incorporated in the model, but an expert also may feel the need to add something on top of that. All this leads us to conjecture the following.

Past adjustment (D_1)

When $D_1 > 0$ current positive (negative) adjustment follows current positive (negative) adjustment. The model-based output is believed to be off track for a while, which might be due to an inappropriate link with past sales or due to omitted variables that had better be included in the model. When $D_1 < 0$ past adjustment has a negative effect on current adjustment. This shows some signs of error-correction type of behaviour. This could be interpreted as that the expert puts some trust in the model but also in his or her own expertise. When $D_1 = 0$, the expert really adds orthogonal information once in a while.

To see how past model-based forecast errors propagate through the process (so, D_2), consider the one-period lagged forecast errors in the above example again, which are given as

$$\rho_{1,t-1}S_{t-2} + X_{t-1}\beta_{1,t-1} - \rho_{2,t-1}S_{t-2}.$$

When the model would be adequately approximating the DGP, that is, we could believe that $\rho_{1,t} = \rho_{2,t}$, and also assuming for the moment that $\rho_{2,t} = \rho_{3,t}$, then the question is whether there is any correlation between X_{t-1} and Z_t. When the expert is rightfully selecting the proper additional variables, and when indeed these variables are relevant only infrequently and are not well predictable then there would be no correlation between current adjustment and past model-based forecast errors. However, when $\rho_{1,t} \neq \rho_{2,t}$, and $\rho_{2,t} \neq \rho_{3,t}$, then one might expect correlation between current adjustment and past forecast errors. As current sales are most likely positively correlated with past sales, this correlation would then be positive. Such positive correlation would mean that the expert does not trust the link between current and past sales as proposed by the model and, at the same time that this model's link does not match with that in the DGP. In sum, a positive correlation means additional distrust in the model as obviated by the expert. Therefore we state the following.

Past model-based forecast errors (D_2)

When the size of past forecasts errors, which are those of the model-based forecast relative to the realizations, has a positive effect on current adjustment, that is, when $D_2 > 0$, the expert demonstrates that he or she believes that the model-based forecasts are persistently too low or too high and in fact that the model is mis-specified. Additionally, when $D_1 > 0$ and $D_2 > 0$ at the same time, this is again a sign of double counting.

When $D_1 = 0$ and $D_2 = 0$ jointly, the added expertise by the local manager is fully orthogonal to the model-based forecast. This would show that the manager has faith in the model, and only adjusts the forecast when he or she has new and relevant information that is not included in the model.

Past adjustment squared (D_3)

One could expect that past squared adjustment would have an effect on current adjustment. The most plausible case would be where $D_3 < 0$ as this would entail that there is some shrinkage towards smaller adjustment in case past adjustment has been large.

Past model-based forecast error squared (D_4)

In contrast to past adjustment squared, one would want to see that past squared model-based forecasts errors have zero effect, at least on average. This would be established by large positive-valued errors squared having a negative impact on future adjustment and large negative-valued errors having a positive effect.

Finally, if all explanatory variables have no effect, then this would mimic the ideal situation where the expert only adds orthogonal knowledge. The evaluation of the quality of experts' knowledge is then quite simple, as one can compare mean squared errors straightforwardly. Also, one can compare regressions of sales on model-based forecasts and sales on expert-based forecasts. In other cases, and we will see below that these are more commonly found in practice, one needs to modify such analysis by allowing for a dynamic structure of the error term in such regressions and also the comparison of mean squared errors is not straightforward any more, see West (2006) for a survey.

3. The database

In this section we give an outline of the database that we have at our disposal, and which we will only partly use in the present paper. Next, we discuss the empirical methodology that will be used in the sequel of this paper.

The data

The firm uses a statistical package to automatically select a forecasting scheme. Each month the selection occurs anew and also parameters are each time re-estimated. The sample runs from October 2004 through October 2006. Each month sales forecasts are made for 1 step ahead to 25 steps ahead. The company has most interest in the accuracy of the 6-month-ahead forecasts for various managerial, transport and stock-keeping reasons. Each month the local manager can change each of the 25 model-based forecasts. So, we have the same amount of expert-adjusted forecasts as that there are model-based forecasts.

The company has local offices in about forty countries. It is involved in seven product categories in each of these countries. Based on our discussions with company representatives who are responsible for the model-based forecasts and for supply chain management, we selected three countries and two product categories[1] as these are viewed as a representative sample across all country-category combinations. Out of the final combinations, we randomly select one such combination and for this we start our analysis here and in Section 4. Later on, in Section 5 we also look at the other cases.

In Table 1 we provide some key statistics for one country and one category. There are a couple of insights to be gained from this table. The first is that expert adjustment here is more often positive than negative. The second is that when the forecast horizon is further away, the size and fraction of adjustment gets larger. Apparently the expert believes that the model-based forecasts need less adjustment for shorter horizons than for longer horizons, which, given the nature of the forecasting schemes used by the automatic program, makes sense. These schemes are particularly designed for short-run forecasting indeed. Note that this table only contains information for the cases where adjustment is not zero. Looking at the first line of this table, we can conclude that in most cases the expert has felt the need to adjust the model-based forecast.

[1] For one of these three countries we have not enough data for one of the two categories, so in the end we deal with five country-category combinations.

Empirical methodology

In the next section we will analyze the dynamic correlation properties of expert adjustment. For that purpose we need to translate (1) into an estimable regression model. In unreported prior analysis we experimented with various lag structures and we noticed that the inclusion of lag 6 is very important. This comes as no surprise given the interest of the headquarters' office in the quality of 6-months-ahead forecasts.

The first regression model that we consider for h =1, 2, .., 6, is

$$\text{I:} \qquad A_{t+h} = \mu + \rho_1 A_t + \beta_1 (MF_{t-1} - S_{t-1}) + \varepsilon_t \,, \tag{2}$$

which correlates future adjustment with current adjustment and with MF_{t-1}-S_{t-1} measuring the model-based forecast error made in the previous month. This model reflects what the expert actually knows at the end of a month when a new expert-adjusted forecast needs to be made. In a first set of computations the current adjustment and the model-based forecast error concern the one-step-ahead forecast. In a second set of computations the current adjustments and the model-based forecast error concerns the H-step-ahead forecast. So for example, when H=2, first we regress adjustment to the forecast for May on the adjustment made in February to the forecast for March and on the forecast error in February where that forecast was made in January. Next, we consider cases where the adjustment concerns May and regress it on the adjustment made in January to the forecast of March and the forecast error in February when that forecast was made in December the year before. In the tables to come we label these two types of computations as 1-step and H-step.

The second regression model that we consider is

$$\text{II:} \qquad A_{t+h} = \mu + \rho_1 A_t + \beta_1 (MF_{t-1} - S_{t-1}) + \omega_1 A_t^2 + \lambda_1 (MF_{t-1} - S_{t-1})^2 + \varepsilon_t \,, \tag{3}$$

where now also the squared variables are included. Finally, we consider

$$\text{III:} \qquad \begin{aligned} A_{t+h} &= \mu + \rho_1 A_t + \beta_1 (MF_{t-1} - S_{t-1}) + \rho_2 A_{t-1} + \beta_2 (MF_{t-2} - S_{t-2}) \\ &+ \rho_6 A_{t-5} + \beta_6 (MF_{t-6} - S_{t-6}) + \omega_1 A_t^2 + \lambda_1 (MF_{t-1} - S_{t-1})^2 \\ &+ \omega_2 A_{t-1}^2 + \lambda_2 (MF_{t-2} - S_{t-2})^2 + \omega_6 A_{t-5}^2 + \lambda_6 (MF_{t-6} - S_{t-6})^2 + \varepsilon_t \,, \end{aligned} \tag{4}$$

which now also includes information of two months and half a year before.

We will use these three regression models to see which of the three is most informative. For that purpose we use the R-squared values. The models will be run three times. In the first case we consider the actual size of the adjustment, that is, *AI* and *AD*. In the second case we look at the models for the relative values of these adjustments (relative to the model-based forecasts). These two cases both concern simple regression models, and hence we can rely on the standard R-squared values. The third case concerns the sign of the adjustments, where we label a positive sign as 1, and a negative sign as a 0. Here we use the familiar binary logit model, and the relevant R-squared is then the McFadden R-squared. For all three cases we use the overall F-test (first two) and the LR-test (third) to test if the R-squares are significantly different from 0.

Finally, in case we find evidence of significant R-squares (and we certainly will for model III, see below), we report on the parameters in the models by summing across the same variables. The impact of past adjustment is measured by

$$\rho = \rho_1 + \rho_2 + \rho_6 \text{ (persistence)}$$

The total effect of past model-based forecast errors will be measured by

$$\beta = \beta_1 + \beta_2 + \beta_6$$

The effects of the squared variables are summarized by $\omega = \omega_1 + \omega_2 + \omega_6$ (for readability reasons sometimes multiplied by 1000 or more) and by $\lambda = \lambda_1 + \lambda_2 + \lambda_6$ (same). Of course, ρ is associated with D_1, β with D_2, ω with D_3 and λ with D_4 in (1).

4. Results for one country and one category

In this section we present the results of the three regressions in (2), (3) and (4) for data concerning one country and one category. The R-squared values for these models where adjustment concerns its size, its relative size and its sign appear in Tables 2a, 3a and 4a, respectively.

The results in these tables convincingly indicate that expert adjustment is predictable, at least when enough lags and squared terms are included. Model III is strongly preferred in all cases. Also, not only the value, also the relative value and the sign of adjustment are predictable from past adjustment and past model-based forecast errors. This strongly suggests that the experts do not use only orthogonal information when they construct their adjusted forecasts. The values of the R-squared for model III typically are around 0.4, which can be perceived as a pretty large value. Further, we do not observe systematic differences across the outcomes for AI and AD or across the 1-step-ahead and H-step-ahead forecasts.

Now we turn to Table 2b, where we report on the key parameters in model III for the case where we predict the experts' adjustment size. The first result from this table is that again differences across AI and AD are small. The second is that the sign of the parameters, on average, is what we would have expected. The value of adjustment depends positively on past adjustment and past model-based forecasts errors (and squared), and negatively on squared past adjustment. Most weight is given to past adjustment, where the autoregressive parameters sum up to values as high as 0.96. For H-steps-ahead forecasts this autoregressive dependency is much smaller, which would be understandable too as this would concern quite some skills from the expert, that is, to incorporate past H-step-ahead forecasts. When H=6, the impact of past adjustment is very small relative to past 6-step-ahead forecast errors. Basically, we see a strong dependence on past adjustments, in particular when these adjustments concern 1-step ahead forecasts.

Similar qualitative conclusions can be drawn from Table 3b, concerning the relative size of adjustment, although now the autoregressive dependence is even stronger for the 1-step ahead forecasts. Finally, from Table 4b we see that also the sign of the adjustment is predictable based on past adjustment and past model-based forecast errors.

In sum, the results for this country and this category show that expert adjustment is predictable in various dimensions. As we also see that ρ and β are both positive, we also have evidence that this expert is counting double, that is, past sales data are used to improve the description of the functional relationship between sales and past sales, and also these data are used again in a response to past model-based forecast errors.

5. Results for more cases

In this section we provide a summary of all results obtained for three countries and two product categories, thereby including the results discussed in the previous section. Detailed numerical outcomes are presented in Tables 6 through 21b, but for ease of interpretation we summarize the key results in Tables 5a to 5d. The total number of cases that we analyze is 30, so most computations in these last four tables concern 30 data points, although sometimes extremely outlying observations have been excluded from analysis.

In Table 5a we report the average value of the size of adjustment, relative to the model-based forecast error, and of the fraction of positive adjustments. We observe that there are strong and significant differences across the way we define expert adjustment (see last column of Table 5a), where these differences mainly concern the sign of adjustment. For AI_t we see that most adjustments are upwards, while for AD_t these adjustments are downwards. The relative size (on average) of expert adjustment seems to range from about 3 to 7 per cent of the model-based forecast.

Table 5b gives a summary of the fit, where we exclusively look at model III. The detailed results in the various relevant tables strongly suggest that this model fits the data best. The first panel of Table 5b give the average R^2 values of the models for the adjustment, the relative adjustment and the sign of adjustment. For the adjustment value, we can obtain fit values around 50 to 60 per cent, which means that experts' behaviour is strongly predictable[2]. For relative values and signs we get R^2 value around 20 to 30 per cent, which still is quite high. The two next panels in Table 5b report on p-values for tests whether there are any systematic differences across the R^2 values across horizons and definitions of adjustment. We observe that there are some differences in fit for further away horizons, where the predictability of experts' behaviour is higher when H is higher. Also, we see that for AI_t we get smaller values of fit, which is not unexpected given the definitions of AI_t and AD_t. In sum, the main conclusion from this table is that the way how experts adjust forecasts is quite predictable.

Table 5c concerns the value of the persistence parameter (ρ) is the models for the values and relative values of adjustment (in the models for the sign, these parameters have another interpretation). Again, as in Table 5b, we first give the value in the top panel, and below that we give p-values of test statistics for differences across H and measurement. The

[2] An unreported analysis of this model III for all available cases (171 country-category combinations) that we have at our disposal gives a mean R^2 of 0.512. This substantiates the present finding for just five such cases.

values in the top panel indicate that persistence on average is around 0.5 to 0.6, which is rather high. Furthermore, we see that this persistence does not strongly differ across the way adjustment is computed and horizons. In sum, this table shows that past adjustment strongly affects future adjustment.

Finally, Table 5d gives the fractions (across the thirty country-category combinations) of positive values of the parameters ρ, β, ω, and λ. We see that most ρ and β parameters are positive and that this is significantly different from random. For the parameters on the squared variables we seem to find no systematic patterns. In sum, these results suggest that the effects of past adjustment and of past model-based forecast errors both are positive.

6. Conclusions and implications

In this paper we have empirically studied the dynamic correlation properties of experts' adjustment, across definitions of adjustment, across forecast horizons and across countries and product categories. Even though our detailed analysis was confined to just a small sample of the total database we have access to, we feel that we can safely draw three main conclusions from these numerical results.

The first conclusion is that experts' adjustment is strongly predictable and largely depends on past adjustment and past model-based forecasts errors. This has implications for the examination of the contribution of the expert in terms of forecast quality, when we look at regressions like

$$S_t = a + bMF_t + \varepsilon_{1,t}$$

and

$$S_t = a + bEF_t + \varepsilon_{2,t}$$

as the error terms each have autocorrelated dynamics.

The second main conclusion is that experts apparently seem to express not much faith in the model-based forecasts, and the results in fact seem to imply that they believe that the model is mis-specified[3]. An implication for management is then that perhaps they may seek ways to modify the statistical model, as this model is considered to lack important explanatory variables.

The third and final conclusion is that there is a serious possibility that experts count double, that is, they basically rely on past sales data twice, first it is included in new model-based forecasts and second it is again included in additional adjustment. An implication for the experts is that they perhaps better only add information to the model-based forecasts that does not involve recent sales figures.

An overall recommendation that seems to emerge from our work is that it may be useful to both head office managers, statistical model builders and the experts to document

[3] This conclusion is further substantiated by our finding for all available country-category combinations that the mean value of γ when constructing *AD* is 0.388.

exactly what the expert adjustment involves. So, the motivation to adjust is relevant and also the precise value of the adjustment and its origin. With a full documentation of this, modellers can seek to make better models, experts can better understand how improvements can be made, and finally, forecast evaluation becomes easy.

Table 1: Some key statistics of adjustment (independent and dependent), first country, first category

Variable	Forecast horizon H: 1	2	3	4	5	6	12
Observations	250	240	230	220	210	200	139
Mean AI	150.1	183.9	191.6	173.6	189.2	224.1	84.2
Mean AD	63.5	62.0	69.5	98.2	103.0	123.3	220.1
Mean Abs AI	353.1	365.7	384.2	400.5	436.6	462.2	609.4
Mean Abs AD	348.9	360.2	379.6	394.0	430.0	453.2	614.5
Mean AI/MF	0.06	0.09	0.08	0.09	0.09	0.12	0.11
Mean AD/MF	0.03	0.05	0.04	0.07	0.06	0.08	0.15
Sign AI > 0	0.61	0.63	0.64	0.63	0.65	0.66	0.55
Sign AD > 0	0.50	0.49	0.51	0.55	0.54	0.55	0.71
Abs AI-AD	86.6	121.9	122.1	75.4	86.3	100.9	135.9

Table 2a: R-squared values and p-values of the related F-test for the case of the <u>values</u> of adjustment

Horizon	Model	1 step AI	1 step AD	H step AI	H step AD
H=1	I	0.027 (0.000)	0.023 (0.073)	0.027 (0.045)	0.023 (0.073)
	II	0.033 (0.113)	0.024 (0.249)	0.033 (0.113)	0.024 (0.249)
	III	0.257 (0.000)	0.232 (0.000)	0.257 (0.000)	0.232 (0.000)
H=2	I	0.205 (0.000)	0.196 (0.000)	0.153 (0.000)	0.138 (0.000)
	II	0.215 (0.000)	0.204 (0.000)	0.155 (0.000)	0.142 (0.000)
	III	0.350 (0.000)	0.312 (0.000)	0.347 (0.000)	0.320 (0.000)
H=3	I	0.150 (0.000)	0.142 (0.000)	0.016 (0.000)	0.011 (0.341)
	II	0.171 (0.000)	0.162 (0.000)	0.100 (0.001)	0.094 (0.000)
	III	0.360 (0.000)	0.344 (0.000)	0.318 (0.000)	0.260 (0.000)
H=4	I	0.089 (0.000)	0.089 (0.000)	0.011 (0.388)	0.008 (0.504)
	II	0.122 (0.000)	0.114 (0.000)	0.033 (0.231)	0.031 (0.260)
	III	0.345 (0.000)	0.325 (0.000)	0.464 (0.000)	0.343 (0.000)
H=5	I	0.138 (0.000)	0.138 (0.000)	0.067 (0.006)	0.062 (0.009)
	II	0.154 (0.000)	0.150 (0.000)	0.075 (0.023)	0.068 (0.035)
	III	0.332 (0.000)	0.314 (0.000)	0.601 (0.000)	0.432 (0.000)
H=6	I	0.068 (0.002)	0.067 (0.002)	0.039 (0.081)	0.028 (0.165)
	II	0.075 (0.008)	0.074 (0.009)	0.249 (0.000)	0.155 (0.000)
	III	0.394 (0.000)	0.357 (0.000)	0.612 (0.000)	0.369 (0.000)

Table 2b: Key parameter values for model III where adjustment concerns its <u>value,</u> which are ρ, β, ω (times 1000) and λ (times 1000)

Horizon	Forecast	AI ρ	AI β	AI ω	AI λ	AD ρ	AD β	AD ω	AD λ
H = 1	1 step	0.465	0.277	-0.067	0.077	0.426	0.282	-0.073	0.063
	H steps	0.465	0.277	-0.067	0.077	0.426	0.282	-0.073	0.063
H = 2	1 step	0.441	0.182	0.093	0.060	0.498	0.180	0.047	0.044
	H steps	0.301	0.271	-0.058	0.069	0.249	0.262	-0.077	0.056
H = 3	1 step	0.835	0.211	-0.230	0.111	0.766	0.218	-0.222	0.100
	H steps	0.365	0.397	0.014	0.084	0.376	0.399	-0.013	0.064
H = 4	1 step	0.729	0.190	-0.171	0.089	0.681	0.196	-0.157	0.077
	H steps	0.473	0.294	-0.103	0.218	0.432	0.276	-0.132	0.192
H = 5	1 step	0.958	0.136	-0.261	0.120	0.876	0.153	-0.246	0.116
	H steps	0.383	0.365	-0.018	0.171	0.279	0.299	-0.265	0.152
H = 6	1 step	0.803	0.091	-0.045	0.085	0.814	0.108	-0.071	0.067
	H steps	0.005	0.280	0.206	0.195	-0.073	0.292	0.172	0.086

Table 3a: R-squared and p-value of the related F-test for the case of the relative values of adjustment (note that the results for AI and AD are the same, by definition)

Horizon	Model	1 step	H steps
H=1	I	0.055 (0.002)	0.055 (0.002)
	II	0.064 (0.005)	0.064 (0.005)
	III	0.218 (0.000)	0.218 (0.000)
H=2	I	0.086 (0.000)	0.048 (0.006)
	II	0.093 (0.000)	0.092 (0.001)
	III	0.331 (0.000)	0.369 (0.000)
H=3	I	0.173 (0.000)	0.102 (0.000)
	II	0.187 (0.000)	0.189 (0.000)
	III	0.396 (0.000)	0.363 (0.000)
H=4	I	0.124 (0.000)	0.073 (0.002)
	II	0.142 (0.000)	0.149 (0.000)
	III	0.372 (0.000)	0.302 (0.000)
H=5	I	0.180 (0.000)	0.099 (0.000)
	II	0.205 (0.000)	0.116 (0.001)
	III	0.370 (0.000)	0.488 (0.000)
H=6	I	0.125 (0.000)	0.061 (0.019)
	II	0.138 (0.000)	0.092 (0.016)
	III	0.422 (0.000)	0.339 (0.000)

Note: The relative size of independent adjustment is computed as 100 times EF-MF divided by MF, which is equal to 100 times EF/MF minus 100. For dependent adjustment this becomes 100 times EF minus α times MF divided by MF, and this equals 100 times EF/MF minus 100α. So, the models for AI and AD have the same variable to be explained and the same explanatory variables, except for the size of the intercept.

Table 3b: Key parameter values for model III where adjustment concerns its <u>relative value</u>, which are ρ, β, ω (times 1000) and λ (times 1000) (note that the results for AI and AD are the same, by definition)

Horizon	Forecast	AI and AD ρ	β	ω	λ
H = 1	1 step	0.641	0.256	-3.586	-0.433
	H steps	0.641	0.256	-3.586	-0.433
H = 2	1 step	0.661	0.257	-3.809	2.739
	H steps	0.308	0.271	-2.487	3.627
H = 3	1 step	0.900	0.261	-5.669	2.359
	H steps	0.467	0.340	-1.132	2.131
H = 4	1 step	1.062	0.247	-7.408	1.847
	H steps	0.586	0.261	-4.152	3.238
H = 5	1 step	1.136	0.125	-10.80	5.230
	H steps	0.467	0.499	3.222	1.748
H = 6	1 step	1.196	0.191	-8.716	5.661
	H steps	0.024	0.199	-0.265	5.149

Note: The relative size of independent adjustment is computed as 100 times EF-MF divided by MF, which is equal to 100 times EF/MF minus 100. For dependent adjustment this becomes 100 times EF minus α times MF divided by MF, and this equals 100 times EF/MF minus 100α. So, the models for AI and AD have the same variable to be explained and the same explanatory variables, except for the size of the intercept.

Table 4a: R-squared values (McFadden) and p-values of the related LR-test for the case of the signs of adjustment (logit models)

Horizon	Model	1 step AI	1 step AD	H steps AI	H steps AD
H=1	I	0.039 (0.002)	0.034 (0.004)	0.039 (0.002)	0.034 (0.004)
	II	0.044 (0.009)	0.038 (0.016)	0.044 (0.009)	0.038 (0.016)
	III	0.174 (0.000)	0.128 (0.001)	0.174 (0.000)	0.128 (0.001)
H=2	I	0.141 (0.000)	0.106 (0.000)	0.087 (0.000)	0.033 (0.008)
	II	0.149 (0.000)	0.109 (0.000)	0.104 (0.000)	0.040 (0.020)
	III	0.254 (0.000)	0.188 (0.000)	0.307 (0.000)	0.198 (0.000)
H=3	I	0.062 (0.000)	0.075 (0.000)	0.014 (0.174)	0.027 (0.028)
	II	0.070 (0.001)	0.079 (0.000)	0.023 (0.225)	0.036 (0.052)
	III	0.230 (0.000)	0.125 (0.006)	0.204 (0.000)	0.170 (0.001)
H=4	I	0.079 (0.000)	0.069 (0.000)	0.008 (0.418)	0.011 (0.259)
	II	0.112 (0.000)	0.087 (0.000)	0.033 (0.116)	0.026 (0.194)
	III	0.179 (0.001)	0.154 (0.001)	0.463 (0.000)	0.274 (0.000)
H=5	I	0.067 (0.000)	0.081 (0.000)	0.023 (0.110)	0.028 (0.057)
	II	0.096 (0.000)	0.095 (0.000)	0.034 (0.152)	0.042 (0.070)
	III	0.224 (0.000)	0.213 (0.000)	0.356 (0.000)	0.415 (0.000)
H=6	I	0.083 (0.000)	0.075 (0.000)	0.018 (0.225)	0.039 (0.031)
	II	0.111 (0.000)	0.097 (0.000)	0.025 (0.387)	0.092 (0.002)
	III	0.349 (0.000)	0.195 (0.000)	0.332 (0.003)	0.434 (0.000)

Table 4b: Key parameter values for model III where adjustment concerns its sign (logit model) which are ρ, β, ω (times 1000000) and λ (times 1000000)

Horizon	Forecast	AI				AD			
		ρ	β	ω	λ	ρ	β	ω	λ
H = 1	1 step	0.306	0.177	-0.228	0.023	0.228	0.109	0.002	0.129
	H steps	0.306	0.177	-0.228	0.023	0.228	0.109	0.002	0.129
H = 2	1 step	0.500	0.160	0.221	0.018	0.251	0.074	0.125	0.151
	H steps	0.390	0.243	1.373	0.392	0.180	0.154	-0.380	0.404
H = 3	1 step	0.522	0.111	-0.662	0.102	0.198	0.044	-0.256	0.290
	H steps	0.170	0.194	0.676	0.086	0.060	0.146	0.203	0.329
H = 4	1 step	0.312	0.099	-0.698	0.034	0.222	0.043	-0.616	0.073
	H steps	0.289	0.480	-0.899	2.602	0.208	0.166	-0.317	0.333
H = 5	1 step	0.459	0.090	-1.018	0.048	0.403	0.036	-1.164	0.286
	H steps	0.212	0.209	-1.555	2.094	0.182	0.231	-0.553	0.660
H = 6	1 step	0.601	0.079	-1.328	0.149	0.352	0.151	-1.187	0.206
	H steps	0.097	0.260	0.035	2.218	-0.080	0.162	0.988	0.351

Table 5a: Key statistics of adjustment for three countries and two categories. Averages are taken over 6 horizons and 5 cases (while one outlying case-horizon combination is excluded).

Variable	Average (p-value)	p-value for difference AI/AD
AI/MF	0.073 (0.000)	0.000
AD/MF	0.028 (0.062)	
Sign AI > 0	0.541	0.000
Sign AD > 0	0.445	

Table 5b: Summary table on fit (based on all models III)

		Horizon	Values	Relative Values	Sign
Average R^2	AI	1	0.563	0.341	0.194
	AD	1	0.517		0.192
	AI	H	0.611	0.312	0.225
	AD	H	0.534		0.220
Does H matter?*	AI	1	0.108	0.753	0.114
	AD	1	0.033		0.104
	AI	H	0.002	0.827	0.104
	AD	H	0.011		0.001
Are AI and AD different?**		1	0.000	NA	0.682
		H	0.000		0.845
Are 1 and H different?	AI		0.034	0.081	0.035
	AD		0.463		0.017

* P-value of parameter of H in regression of R^2 on a constant and H
** P-value of intercept parameter in regression of difference in R^2 values on a constant

Table 5c: Summary table key parameter value ρ in models for the values and relative values (averaged over 6 horizons and 5 cases)

		Horizon	Values	Relative Values
Average ρ	AI	1	0.645	0.642
	AD	1	0.574	
	AI	H	0.576	0.352
	AD	H	0.471	
Does H matter?*	AI	1	0.790	0.232
	AD	1	0.812	
	AI	H	0.815	0.012 (effect is -)
	AD	H	0.716	
Are AI and AD different?**		1	0.207	NA
		H	0.253	
Are 1 and H different?	AI		0.442	0.001
	AD		0.184	

* P-value of parameter of H in regression of R^2 on a constant and H

** P-value of intercept parameter in regression of difference in R^2 values on a constant

Table 5d: Fractions of positive key parameter values for model III where adjustment concerns its value, relative values and signs

Adjustment	Forecast	ρ	β	ω	λ
Values					
AI	1 step		0.80	0.63	0.40
	H steps		0.83	0.57	0.63
AD	1 step		0.73	0.67	0.30
	H steps		0.80	0.50	0.47
Relative values					
AI = AD	1 step		0.77	0.37	0.37
	H steps		0.70	0.30	0.57
Signs*					
AI	1 step	0.93	0.70	0.67	0.56
	H steps	0.88	0.73	0.69	0.73
AD	1 step	0.97	0.63	0.77	0.63
	H steps	0.86	0.79	0.54	0.68

(Underlined) fractions are 5% significantly different from 0.50 when fractions are smaller than 0.30 or larger than 0.70.

* The NA cases are not included.

Table 6: Some key statistics of adjustment (independent and dependent), first country, second category

Variable	Forecast horizon H 1	2	3	4	5	6	12
Observations	230	221	212	202	194	185	130
Mean AI	-125.0	-58.0	-70.6	-109.8	-49.1	18.5	-415.3
Mean AD	89.3	61.8	80.1	175.0	157.8	123.3	302.4
Mean Abs AI	915.1	873.4	974.8	1087	1109	1100	1603
Mean Abs AD	927.0	871.6	977.6	1095	1110	1103	1378
Mean AI/MF	0.06	0.08	0.15	0.83	0.06	0.08	-0.04
MeanAD/MF	0.09	0.10	0.17	0.86	0.09	0.09	0.03
Sign AI > 0	0.46	0.46	0.46	0.47	0.46	0.43	0.35
Sign AD > 0	0.55	0.51	0.53	0.57	0.55	0.48	0.51
Abs AI-AD	214.3	119.9	150.7	284.8	206.9	104.8	717.7

Table 7a: R-squared values and p-values of the related F-test for the case of the <u>values</u> of adjustment

Horizon	Model	1 step AI	1 step AD	H step AI	H step AD
H=1	I	0.207 (0.000)	0.216 (0.000)	0.207 (0.000)	0.216 (0.000)
	II	0.216 (0.000)	0.226 (0.000)	0.216 (0.000)	0.226 (0.000)
	III	0.563 (0.000)	0.562 (0.000)	0.563 (0.000)	0.562 (0.000)
H=2	I	0.154 (0.000)	0.155 (0.000)	0.243 (0.000)	0.238 (0.000)
	II	0.159 (0.000)	0.156 (0.000)	0.262 (0.000)	0.267 (0.000)
	III	0.586 (0.000)	0.584 (0.000)	0.500 (0.000)	0.497 (0.000)
H=3	I	0.338 (0.000)	0.331 (0.000)	0.374 (0.000)	0.365 (0.000)
	II	0.370 (0.000)	0.359 (0.000)	0.388 (0.000)	0.379 (0.000)
	III	0.616 (0.000)	0.607 (0.000)	0.644 (0.000)	0.633 (0.000)
H=4	I	0.169 (0.000)	0.153 (0.000)	0.186 (0.000)	0.175 (0.000)
	II	0.217 (0.000)	0.161 (0.000)	0.192 (0.000)	0.180 (0.000)
	III	0.553 (0.000)	0.545 (0.000)	0.576 (0.000)	0.536 (0.000)
H=5	I	0.140 (0.000)	0.137 (0.000)	0.277 (0.000)	0.314 (0.000)
	II	0.158 (0.000)	0.139 (0.000)	0.299 (0.000)	0.318 (0.000)
	III	0.550 (0.000)	0.569 (0.000)	0.664 (0.000)	0.593 (0.000)
H=6	I	0.177 (0.000)	0.174 (0.000)	0.332 (0.000)	0.376 (0.000)
	II	0.200 (0.000)	0.185 (0.000)	0.420 (0.000)	0.390 (0.000)
	III	0.608 (0.000)	0.612 (0.000)	0.764 (0.000)	0.672 (0.000)

Table 7b: Key parameter values for model III where adjustment concerns its <u>value,</u> which are ρ, β, ω (times 1000) and λ (times 1000)

Horizon	Forecast	AI				AD			
		ρ	β	ω	λ	ρ	β	ω	λ
H = 1	1 step	0.492	0.232	0.014	-0.013	0.535	0.209	0.003	-0.010
	H steps	0.492	0.232	0.014	-0.013	0.535	0.209	0.003	-0.010
H = 2	1 step	0.758	0.553	0.141	-0.055	0.631	0.475	0.077	-0.060
	H steps	0.659	0.561	-0.035	0.026	0.667	0.557	0.037	0.023
H = 3	1 step	0.654	0.566	0.065	-0.021	0.569	0.525	0.046	-0.024
	H steps	0.340	0.797	0.148	-0.050	0.303	0.788	0.162	-0.056
H = 4	1 step	0.590	0.585	0.081	-0.054	0.629	0.546	0.068	-0.050
	H steps	0.351	0.642	0.128	-0.103	0.211	0.695	0.119	-0.076
H = 5	1 step	1.026	0.584	0.046	-0.031	1.037	0.515	0.021	-0.037
	H steps	0.733	0.635	0.089	0.009	0.558	0.475	0.041	-0.047
H = 6	1 step	1.298	0.573	0.078	-0.035	1.222	0.475	0.041	-0.047
	H steps	0.807	0.281	0.080	0.088	0.783	0.525	-0.045	-0.059

Table 8a: R-squared and p-value of the related F-test for the case of the <u>relative values</u> of adjustment (note that the results for AI and AD are the same, by definition)

Horizon	Model	1 step	H steps
H=1	I	0.332 (0.000)	0.332 (0.000)
	II	0.358 (0.000)	0.358 (0.000)
	III	0.320 (0.000)	0.320 (0.000)
H=2	I	0.377 (0.000)	0.256 (0.000)
	II	0.398 (0.000)	0.303 (0.000)
	III	0.367 (0.000)	0.256 (0.000)
H=3	I	0.302 (0.000)	0.271 (0.000)
	II	0.376 (0.000)	0.355 (0.000)
	III	0.333 (0.000)	0.084 (0.585)
H=4	I	0.317 (0.000)	0.182 (0.000)
	II	0.392 (0.000)	0.195 (0.000)
	III	0.396 (0.000)	0.245 (0.000)
H=5	I	0.028 (0.095)	0.038 (0.077)
	II	0.045 (0.106)	0.141 (0.001)
	III	0.443 (0.000)	0.343 (0.001)
H=6	I	0.037 (0.048)	0.350 (0.000)
	II	0.053 (0.072)	0.752 (0.000)
	III	0.440 (0.000)	0.552 (0.000)

Note: The relative size of independent adjustment is computed as 100 times EF-MF divided by MF, which is equal to 100 times EF/MF minus 100. For dependent adjustment this becomes 100 times EF minus α times MF divided by MF, and this equals 100 times EF/MF minus 100α. So, the models for AI and AD have the same variable to be explained and the same explanatory variables, except for the size of the intercept.

Table 8b: Key parameter values for model III where adjustment concerns its <u>relative value</u>, which are ρ, β, ω (times 1000) and λ (times 1000) (note that the results for AI and AD are the same, by definition)

Horizon	Forecast	AI and AD ρ	β	ω	λ
H = 1	1 step	0.632	0.162	5.156	-0.928
	H steps	0.632	0.162	5.156	-0.928
H = 2	1 step	0.693	0.203	2.174	-0.852
	H steps	0.668	0.386	0.304	-1.747
H = 3	1 step	0.601	0.140	7.357	-1.011
	H steps	0.321	0.115	-0.972	0.496
H = 4	1 step	0.793	0.190	11.719	-1.332
	H steps	0.460	0.154	-.581	0.780
H = 5	1 step	1.757	1.090	5.271	-0.176
	H steps	0.418	-0.115	-1.273	2.837
H = 6	1 step	1.989	1.092	12.46	-1.214
	H steps	0.683	0.118	-1.242	0.606

Note: The relative size of independent adjustment is computed as 100 times EF-MF divided by MF, which is equal to 100 times EF/MF minus 100. For dependent adjustment this becomes 100 times EF minus α times MF divided by MF, and this equals 100 times EF/MF minus 100α. So, the models for AI and AD have the same variable to be explained and the same explanatory variables, except for the size of the intercept.

Table 9a: R-squared values (McFadden) and p-values of the related LR-test for the case of the <u>signs</u> of adjustment (logit models)

Horizon	Model	1 step AI	1 step AD	H steps AI	H steps AD
H=1	I	0.033 (0.009)	0.032 (0.011)	0.033 (0.009)	0.032 (0.011)
	II	0.034 (0.047)	0.036 (0.037)	0.034 (0.047)	0.036 (0.037)
	III	0.134 (0.003)	0.132 (0.003)	0.134 (0.003)	0.132 (0.003)
H=2	I	0.031 (0.015)	0.040 (0.004)	0.012 (0.208)	0.016 (0.128)
	II	0.037 (0.042)	0.046 (0.013)	0.015 (0.430)	0.024 (0.180)
	III	0.102 (0.050)	0.107 (0.033)	0.096 (0.097)	0.094 (0.104)
H=3	I	0.055 (0.001)	0.060 (0.000)	0.053 (0.002)	0.037 (0.013)
	II	0.061 (0.003)	0.067 (0.002)	0.056 (0.010)	0.037 (0.068)
	III	0.125 (0.016)	0.146 (0.004)	0.125 (0.037)	0.105 (0.102)
H=4	I	0.036 (0.011)	0.038 (0.011)	0.052 (0.004)	0.047 (0.008)
	II	0.049 (0.016)	0.063 (0.004)	0.074 (0.004)	0.099 (0.000)
	III	0.151 (0.005)	0.152 (0.005)	0.266 (0.000)	0.265 (0.000)
H=5	I	0.061 (0.001)	0.060 (0.001)	0.064 (0.002)	0.109 (0.000)
	II	0.080 (0.001)	0.091 (0.000)	0.089 (0.002)	0.124 (0.000)
	III	0.224 (0.000)	0.189 (0.001)	0.211 (0.008)	0.187 (0.025)
H=6	I	0.059 (0.002)	0.107 (0.000)	0.094 (0.001)	0.157 (0.000)
	II	0.061 (0.010)	0.111 (0.000)	0.168 (0.000)	0.264 (0.000)
	III	0.281 (0.000)	0.347 (0.000)	0.376 (0.000)	0.410 (0.000)

Table 9b: Key parameter values for model III where adjustment concerns its sign (logit model) which are ρ, β, ω (times E+08) and λ (times E+08)

Horizon	Forecast	AI				AD			
		ρ	β	ω	λ	ρ	β	ω	λ
H = 1	1 step	0.001	0.000	8.516	-5.898	0.001	0.000	1.337	-3.462
	H steps	0.001	0.000	8.516	-5.898	0.001	0.000	1.337	-3.462
H = 2	1 step	0.001	0.000	8.778	-6.111	0.001	0.000	5.845	-6.493
	H steps	0.001	0.001	-7.774	2.069	0.001	0.001	-8.042	2.466
H = 3	1 step	0.001	0.000	16.79	-8.231	0.001	0.001	12.43	-7.049
	H steps	0.001	0.001	14.31	-5.509	0.000	0.001	16.52	-4.584
H = 4	1 step	0.001	0.000	14.83	-7.980	0.001	0.000	9.501	-5.195
	H steps	0.001	0.002	50.27	3.843	0.001	0.002	54.70	-3.179
H = 5	1 step	0.002	0.001	32.76	-21.16	0.002	0.001	1.249	-7.565
	H steps	0.001	0.000	19.73	15.74	0.001	0.000	12.46	9.526
H = 6	1 step	0.003	0.001	46.64	-24.50	0.003	0.001	44.81	-20.10
	H steps	0.003	0.001	38.49	39.65	0.001	0.002	63.17	-33.67

Table 10: Some key statistics of adjustment (independent and dependent), second country, first category

	Forecast horizon H						
Variable	1	2	3	4	5	6	12
Observations	150	144	138	132	126	120	82
Mean AI	1083	1319	1368	1384	1540	1658	518.4
Mean AD	-101.1	-16.3	71.4	244.4	332.6	729.4	355.3
Mean Abs AI	1891	2136	2257	2406	2742	3143	2553
Mean Abs AD	1816	2085	2193	2329	2467	2961	2574
Mean AI/MF	-0.01	-0.01	0.00	0.00	0.01	0.06	-0.06
Mean AD/MF	-0.08	-0.08	-0.08	-0.07	-0.06	0.01	-0.07
Sign AI > 0	0.46	0.46	0.45	0.49	0.46	0.55	0.24
Sign AD > 0	0.33	0.29	0.31	0.31	0.33	0.43	0.23
Abs AI-AD	1184	1336	1297	1139	1208	928.5	163.2

Table 11a: R-squared values and p-values of the related F-test for the case of the values of adjustment

Horizon	Model	1 step AI	1 step AD	H step AI	H step AD
H=1	I	0.361 (0.000)	0.270 (0.000)	0.361 (0.000)	0.270 (0.000)
	II	0.489 (0.000)	0.377 (0.000)	0.489 (0.000)	0.377 (0.000)
	III	0.560 (0.000)	0.482 (0.000)	0.560 (0.000)	0.482 (0.000)
H=2	I	0.307 (0.000)	0.254 (0.000)	0.095 (0.002)	0.057 (0.027)
	II	0.473 (0.000)	0.386 (0.000)	0.152 (0.000)	0.123 (0.003)
	III	0.490 (0.000)	0.477 (0.000)	0.628 (0.000)	0.564 (0.000)
H=3	I	0.274 (0.000)	0.222 (0.000)	0.202 (0.000)	0.123 (0.001)
	II	0.452 (0.000)	0.369 (0.000)	0.218 (0.000)	0.126 (0.005)
	III	0.388 (0.000)	0.423 (0.000)	0.411 (0.000)	0.372 (0.000)
H=4	I	0.237 (0.000)	0.192 (0.000)	0.190 (0.000)	0.135 (0.001)
	II	0.385 (0.000)	0.324 (0.000)	0.230 (0.000)	0.194 (0.000)
	III	0.699 (0.000)	0.789 (0.000)	0.707 (0.000)	0.781 (0.000)
H=5	I	0.200 (0.000)	0.169 (0.000)	0.166 (0.000)	0.129 (0.002)
	II	0.367 (0.000)	0.314 (0.000)	0.167 (0.003)	0.142 (0.011)
	III	0.715 (0.000)	0.720 (0.000)	0.450 (0.002)	0.429 (0.004)
H=6	I	0.167 (0.000)	0.140 (0.000)	0.240 (0.000)	0.234 (0.000)
	II	0.315 (0.000)	0.294 (0.000)	0.490 (0.000)	0.531 (0.000)
	III	0.737 (0.000)	0.739 (0.000)	0.810 (0.000)	0.827 (0.000)

Table 11b: Key parameter values for model III where adjustment concerns its <u>value,</u> which are ρ, β, ω (times 1000) and λ (times 1000)

Horizon	Forecast	AI ρ	AI β	AI ω	AI λ	AD ρ	AD β	AD ω	AD λ
H = 1	1 step	0.805	0.389	-0.035	-0.017	0.465	0.294	-0.001	-0.015
	H steps	0.805	0.389	-0.035	-0.017	0.465	0.294	-0.001	-0.015
H = 2	1 step	0.450	0.303	0.005	-0.011	-0.073	0.091	0.001	-0.009
	H steps	0.714	0.426	-0.003	-0.012	0.551	0.417	-0.003	-0.010
H = 3	1 step	0.336	0.200	-0.094	-0.016	-0.107	-0.038	0.076	-0.012
	H steps	-0.207	0.101	0.019	0.004	-0.145	0.155	0.028	-0.002
H = 4	1 step	-0.337	0.028	0.167	-0.020	-0.602	-0.156	0.103	-0.017
	H steps	-0.177	0.161	0.074	-0.013	-0.301	-0.018	0.081	-0.014
H = 5	1 step	0.155	-0.067	0.159	-0.018	0.091	-0.175	0.114	-0.013
	H steps	0.501	0.129	-0.049	-0.015	-0.072	0.114	0.071	-0.015
H = 6	1 step	-0.674	-0.219	0.373	-0.022	-0.914	-0.326	0.199	-0.027
	H steps	0.359	-0.141	0.086	-0.017	-1.678	-0.943	-0.315	0.026

Table 12a: R-squared and p-value of the related F-test for the case of the <u>relative values</u> of adjustment (note that the results for AI and AD are the same, by definition)

Horizon	Model	1 step	H steps
H=1	I	0.124 (0.000)	0.124 (0.000)
	II	0.132 (0.001)	0.132 (0.001)
	III	0.188 (0.054)	0.188 (0.054)
H=2	I	0.063 (0.015)	0.043 (0.068)
	II	0.073 (0.046)	0.057 (0.131)
	III	0.180 (0.097)	0.136 (0.384)
H=3	I	0.067 (0.014)	0.019 (0.352)
	II	0.119 (0.004)	0.043 (0.309)
	III	0.142 (0.338)	0.109 (0.726)
H=4	I	0.061 (0.025)	0.065 (0.036)
	II	0.076 (0.058)	0.093 (0.048)
	III	0.246 (0.027)	0.155 (0.551)
H=5	I	0.004 (0.780)	0.044 (0.144)
	II	0.008 (0.934)	0.072 (0.167)
	III	0.283 (0.014)	0.230 (0.333)
H=6	I	0.025 (0.264)	0.054 (0.123)
	II	0.048 (0.281)	0.069 (0.256)
	III	0.278 (0.030)	0.321 (0.221)

Note: The relative size of independent adjustment is computed as 100 times EF-MF divided by MF, which is equal to 100 times EF/MF minus 100. For dependent adjustment this becomes 100 times EF minus α times MF divided by MF, and this equals 100 times EF/MF minus 100α. So, the models for AI and AD have the same variable to be explained and the same explanatory variables, except for the size of the intercept.

Table 12b: Key parameter values for model III where adjustment concerns its <u>relative value</u>, which are ρ, β, ω (times 1000) and λ (times 1000) (note that the results for AI and AD are the same, by definition)

Horizon	Forecast	AI and AD			
		ρ	β	ω	λ
H = 1	1 step	0.282	0.028	6.787	-2.600
	H steps	0.282	0.028	6.787	-2.600
H = 2	1 step	0.059	-0.178	-15.24	0.189
	H steps	-0.015	-0.188	-17.41	-0.895
H = 3	1 step	-0.038	-0.145	-19.30	2.145
	H steps	-0.065	-0.170	-0.652	2.788
H = 4	1 step	-0.343	-0.159	-15.00	-2.182
	H steps	0.080	-0.106	-5.493	0.012
H = 5	1 step	-0.287	-0.209	-17.31	-0.442
	H steps	-0.167	-0.250	-10.94	2.887
H = 6	1 step	-0.187	-0.055	-12.28	-2.495
	H steps	-0.223	-0.042	-17.36	1.816

Note: The relative size of independent adjustment is computed as 100 times EF-MF divided by MF, which is equal to 100 times EF/MF minus 100. For dependent adjustment this becomes 100 times EF minus α times MF divided by MF, and this equals 100 times EF/MF minus 100α. So, the models for AI and AD have the same variable to be explained and the same explanatory variables, except for the size of the intercept.

Table 13a: R-squared values (McFadden) and p-values of the related LR-test for the case of the signs of adjustment (logit models)

Horizon	Model	1 step AI	1 step AD	H steps AI	H steps AD
H=1	I	0.176 (0.000)	0.033 (0.049)	0.176 (0.000)	0.033 (0.049)
	II	0.177 (0.000)	0.039 (0.134)	0.177 (0.000)	0.039 (0.134)
	III	0.314 (0.000)	0.275 (0.000)	0.314 (0.000)	0.275 (0.000)
H=2	I	0.037 (0.033)	0.021 (0.158)	0.068 (0.003)	0.031 (0.076)
	II	0.058 (0.031)	0.026 (0.352)	0.109 (0.001)	0.076 (0.014)
	III	0.231 (0.001)	0.200 (0.007)	0.220 (0.003)	0.175 (0.033)
H=3	I	0.015 (0.268)	0.007 (0.553)	0.027 (0.115)	0.031 (0.101)
	II	0.023 (0.398)	0.011 (0.759)	0.097 (0.004)	0.032 (0.315)
	III	0.162 (0.038)	0.234 (0.002)	0.258 (0.002)	0.192 (0.034)
H=4	I	0.008 (0.500)	0.006 (0.618)	0.069 (0.007)	0.034 (0.099)
	II	0.010 (0.796)	0.016 (0.625)	0.109 (0.004)	0.057 (0.096)
	III	0.294 (0.000)	0.224 (0.005)	NA	0.320 (0.001)
H=5	I	0.009 (0.490)	0.002 (0.839)	0.056 (0.032)	0.035 (0.117)
	II	0.011 (0.775)	0.022 (0.487)	0.062 (0.104)	0.068 (0.083)
	III	NA	0.196 (0.033)	0.235 (0.115)	0.229 (0.129)
H=6	I	0.033 (0.049)	0.009 (0.498)	0.042 (0.105)	0.032 (0.176)
	II	0.039 (0.134)	0.015 (0.697)	0.044 (0.310)	0.075 (0.086)
	III	0.275 (0.000)	0.145 (0.186)	0.150 (0.617)	0.199 (0.359)

Table 13b: Key parameter values for model III where adjustment concerns its sign (logit model) which are ρ (times E+03), β (times E+03), ω (times E+08) and λ (times E+08)

Horizon	Forecast	AI ρ	AI β	AI ω	AI λ	AD ρ	AD β	AD ω	AD λ
H = 1	1 step	0.107	0.000	30.03	-2.385	0.140	0.006	22.99	-0.942
	H steps	0.107	0.000	30.03	-2.385	0.140	0.006	22.99	-0.942
H = 2	1 step	0.021	-0.003	23.43	-1.512	0.086	0.004	15.47	-1.590
	H steps	0.046	-0.003	3.905	-0.029	0.046	0.001	2.772	-0.206
H = 3	1 step	0.031	0.011	9.313	-0.534	0.084	-0.015	22.33	-2.616
	H steps	0.006	-0.015	-2.719	3.959	-0.008	-0.009	2.590	1.009
H = 4	1 step	-0.120	-0.061	51.57	-3.648	0.005	-0.033	8.246	-0.308
	H steps	NA	NA	NA	NA	0.028	-0.041	-3.491	3.207
H = 5	1 step	NA	NA	NA	NA	0.004	-0.013	3.368	1.324
	H steps	-0.049	-0.015	23.01	-1.858	0.114	-0.027	31.88	-5.619
H = 6	1 step	-0.079	-0.013	27.85	-0.430	0.009	-0.004	10.32	1.418
	H steps	0.003	-0.012	5.476	0.109	-0.111	-0.060	-28.33	1.856

Table 14: Some key statistics of adjustment (independent and dependent), second country, second category

Variable	Forecast horizon H 1	2	3	4	5	6	12
Observations	299	287	275	263	251	239	168
Mean AI	1736	1906	2025	1473	1499	1712	-333.7
Mean AD	-78.6	-256.9	-167.1	-1.94	-160.0	-193.4	1190.8
Mean Abs AI	3981	4297	4675	4966	5175	5394	7176
Mean Abs AD	3867	4163	4519	4916	5141	5555	7101
Mean AI/MF	0.04	0.05	0.05	0.04	0.04	0.04	0.02
Mean AD/MF	-0.01	-0.02	-0.01	0.00	-0.01	-0.01	0.06
Sign AI > 0	0.62	0.61	0.63	0.57	0.57	0.56	0.42
Sign AD > 0	0.46	0.44	0.48	0.51	0.47	0.44	0.52
Abs AI-AD	1815	2163	2193	1475	1659	1905	1524

Table 15a: R-squared values and p-values of the related F-test for the case of the <u>values</u> of adjustment

Horizon	Model	1 step AI	1 step AD	H step AI	H step AD
H=1	I	0.440 (0.000)	0.353 (0.000)	0.440 (0.000)	0.353 (0.000)
	II	0.488 (0.000)	0.385 (0.000)	0.488 (0.000)	0.385 (0.000)
	III	0.679 (0.000)	0.585 (0.000)	0.679 (0.000)	0.585 (0.000)
H=2	I	0.531 (0.000)	0.439 (0.000)	0.468 (0.000)	0.339 (0.000)
	II	0.566 (0.000)	0.456 (0.000)	0.574 (0.000)	0.457 (0.000)
	III	0.728 (0.000)	0.606 (0.000)	0.759 (0.000)	0.658 (0.000)
H=3	I	0.552 (0.000)	0.476 (0.000)	0.306 (0.000)	0.192 (0.000)
	II	0.607 (0.000)	0.508 (0.000)	0.364 (0.000)	0.203 (0.000)
	III	0.754 (0.000)	0.640 (0.000)	0.802 (0.000)	0.713 (0.000)
H=4	I	0.533 (0.000)	0.463 (0.000)	0.272 (0.000)	0.205 (0.000)
	II	0.596 (0.000)	0.506 (0.000)	0.316 (0.000)	0.232 (0.000)
	III	0.714 (0.000)	0.606 (0.000)	0.578 (0.000)	0.453 (0.000)
H=5	I	0.530 (0.000)	0.458 (0.000)	0.177 (0.000)	0.115 (0.000)
	II	0.605 (0.000)	0.508 (0.000)	0.326 (0.000)	0.139 (0.000)
	III	0.830 (0.000)	0.749 (0.000)	0.750 (0.000)	0.606 (0.000)
H=6	I	0.666 (0.000)	0.597 (0.000)	0.204 (0.000)	0.158 (0.000)
	II	0.696 (0.000)	0.611 (0.000)	0.361 (0.000)	0.201 (0.000)
	III	0.829 (0.000)	0.729 (0.000)	0.947 (0.000)	0.827 (0.000)

Table 15b: Key parameter values for model III where adjustment concerns its <u>value,</u> which are ρ, β, ω (times 1000) and λ (times 1000)

Horizon	Forecast	AI ρ	AI β	AI ω	AI λ	AD ρ	AD β	AD ω	AD λ
H = 1	1 step	0.719	0.345	0.006	-0.004	0.842	0.353	0.007	-0.007
	H steps	0.719	0.345	0.006	-0.004	0.842	0.353	0.007	-0.007
H = 2	1 step	0.663	0.512	0.012	-0.004	0.973	0.475	0.009	-0.008
	H steps	0.718	0.725	0.007	-0.003	0.884	0.793	0.011	-0.009
H = 3	1 step	0.611	0.649	0.012	-0.001	0.910	0.585	0.007	-0.007
	H steps	1.220	1.073	-0.016	0.016	0.860	1.145	-0.018	0.015
H = 4	1 step	0.259	0.422	0.020	-0.005	0.856	0.388	0.015	-0.011
	H steps	0.914	0.709	-0.012	0.017	0.823	0.670	-0.008	0.009
H = 5	1 step	0.774	0.399	0.004	-0.001	1.250	0.416	0.001	-0.003
	H steps	0.782	1.453	0.007	0.001	1.499	1.286	0.002	-0.010
H = 6	1 step	1.034	0.208	0.013	-0.007	1.388	0.209	0.009	-0.010
	H steps	1.290	0.078	0.072	0.020	2.192	0.328	0.072	0.001

Table 16a: R-squared and p-value of the related F-test for the case of the relative values of adjustment (note that the results for AI and AD are the same, by definition)

Horizon	Model	1 step	H steps
H=1	I	0.132 (0.000)	0.132 (0.000)
	II	0.152 (0.000)	0.152 (0.000)
	III	0.218 (0.000)	0.218 (0.000)
H=2	I	0.034 (0.012)	0.047 (0.003)
	II	0.036 (0.050)	0.052 (0.011)
	III	0.108 (0.042)	0.102 (0.082)
H=3	I	0.076 (0.000)	0.048 (0.004)
	II	0.106 (0.000)	0.064 (0.005)
	III	0.135 (0.011)	0.156 (0.010)
H=4	I	0.071 (0.000)	0.073 (0.001)
	II	0.093 (0.000)	0.081 (0.002)
	III	0.155 (0.005)	0.081 (0.519)
H=5	I	0.085 (0.000)	0.031 (0.061)
	II	0.087 (0.000)	0.034 (0.201)
	III	0.227 (0.000)	0.126 (0.259)
H=6	I	0.087 (0.000)	0.031 (0.096)
	II	0.091 (0.001)	0.033 (0.289)
	III	0.188 (0.003)	0.225 (0.039)

Note: The relative size of independent adjustment is computed as 100 times EF-MF divided by MF, which is equal to 100 times EF/MF minus 100. For dependent adjustment this becomes 100 times EF minus α times MF divided by MF, and this equals 100 times EF/MF minus 100α. So, the models for AI and AD have the same variable to be explained and the same explanatory variables, except for the size of the intercept.

Table 16b: Key parameter values for model III where adjustment concerns its <u>relative value</u>, which are ρ, β, ω (times 1000) and λ (times 1000) (note that the results for AI and AD are the same, by definition)

Horizon	Forecast	AI and AD			
		ρ	β	ω	λ
H = 1	1 step	0.421	-0.041	0.139	0.530
	H steps	0.421	-0.041	0.139	0.530
H = 2	1 step	0.343	-0.016	-1.589	0.252
	H steps	0.377	0.056	-0.824	0.138
H = 3	1 step	0.421	0.239	-0.088	-1.265
	H steps	0.427	0.303	-4.528	-1.837
H = 4	1 step	0.476	0.136	0.932	-0.059
	H steps	0.403	0.083	0.230	-0.253
H = 5	1 step	0.556	0.023	3.791	0.154
	H steps	0.359	0.269	1.044	-1.190
H = 6	1 step	0.414	0.019	1.381	0.877
	H steps	0.384	0.528	-2.898	-1.751

Note: The relative size of independent adjustment is computed as 100 times EF-MF divided by MF, which is equal to 100 times EF/MF minus 100. For dependent adjustment this becomes 100 times EF minus α times MF divided by MF, and this equals 100 times EF/MF minus 100α. So, the models for AI and AD have the same variable to be explained and the same explanatory variables, except for the size of the intercept.

Table 17a: R-squared values (McFadden) and p-values of the related LR-test for the case of the signs of adjustment (logit models)

Horizon	Model	1 step AI	1 step AD	H steps AI	H steps AD
H=1	I	0.036 (0.002)	0.050 (0.000)	0.036 (0.002)	0.050 (0.000)
	II	0.049 (0.001)	0.052 (0.001)	0.049 (0.001)	0.052 (0.001)
	III	0.124 (0.001)	0.178 (0.000)	0.124 (0.001)	0.178 (0.000)
H=2	I	0.029 (0.007)	0.042 (0.000)	0.026 (0.014)	0.026 (0.013)
	II	0.036 (0.014)	0.058 (0.000)	0.041 (0.010)	0.034 (0.023)
	III	0.134 (0.001)	0.166 (0.000)	0.092 (0.036)	0.159 (0.000)
H=3	I	0.037 (0.002)	0.084 (0.000)	0.037 (0.005)	0.030 (0.010)
	II	0.052 (0.002)	0.089 (0.000)	0.052 (0.005)	0.031 (0.051)
	III	0.089 (0.045)	0.155 (0.000)	0.165 (0.001)	0.229 (0.000)
H=4	I	0.064 (0.000)	0.050 (0.000)	0.044 (0.003)	0.034 (0.009)
	II	0.081 (0.000)	0.054 (0.000)	0.059 (0.003)	0.043 (0.018)
	III	0.084 (0.084)	0.107 (0.000)	0.142 (0.015)	0.128 (0.026)
H=5	I	0.047 (0.038)	0.068 (0.000)	0.000 (0.998)	0.038 (0.014)
	II	0.058 (0.043)	0.094 (0.000)	0.031 (0.121)	0.040 (0.056)
	III	0.093 (0.092)	0.161 (0.000)	0.105 (0.194)	0.282 (0.000)
H=6	I	0.038 (0.004)	0.079 (0.000)	0.004 (0.654)	0.015 (0.241)
	II	0.043 (0.013)	0.085 (0.000)	0.021 (0.352)	0.057 (0.029)
	III	0.092 (0.093)	0.236 (0.000)	0.117 (0.277)	0.304 (0.001)

Table 17b: Key parameter values for model III where adjustment concerns its sign (logit model) which are ρ (times E+03), β (times E+03), ω (times E+08) and λ (times E+08)

Horizon	Forecast	AI				AD			
		ρ	β	ω	λ	ρ	β	ω	λ
H = 1	1 step	0.024	0.005	-3.980	4.078	0.034	-0.001	5.495	2.170
	H steps	0.024	0.005	-3.980	4.078	0.034	-0.001	5.495	2.170
H = 2	1 step	0.023	0.003	-1.270	8.067	0.032	0.013	5.540	-1.863
	H steps	0.013	0.000	1.469	2.344	0.022	0.014	6.375	-2.413
H = 3	1 step	0.019	0.002	0.926	2.690	0.032	0.014	3.886	-1.477
	H steps	0.030	0.030	4.618	4.664	0.043	0.034	-17.88	10.19
H = 4	1 step	0.005	-0.002	1.211	2.930	0.018	-0.003	3.407	0.061
	H steps	0.019	0.003	-2.231	3.365	0.021	0.004	-1.882	2.209
H = 5	1 step	0.012	-0.005	0.236	2.121	0.030	0.004	0.408	0.746
	H steps	0.010	0.008	6.387	-0.514	0.063	0.013	2.881	0.947
H = 6	1 step	0.008	-0.016	0.905	-0.116	0.041	0.000	-2.924	-5.522
	H steps	-0.010	0.014	10.86	-2.136	0.008	0.022	-63.87	23.92

Table 18: Some key statistics of adjustment (independent and dependent), second country, second category

Variable	1	2	3	4	5	6	12
	Forecast horizon H						
Observations	187	179	170	162	154	146	98
Mean AI	7702	7167	7519	6714	6384	4381	758.8
Mean AD	2020	1578	1095	1405	1453	2429	6414
Mean Abs AI	11468	11439	10552	10921	10952	10919	14623
Mean Abs AD	10328	9296	9570	9685	10191	10691	12916
Mean AI/MF	0.24	0.33	0.11	0.07	0.06	0.05	0.18
Mean AD/MF	0.14	0.23	0.00	-0.01	-0.03	0.02	0.27
Sign AI > 0	0.55	0.56	0.57	0.54	0.51	0.51	0.31
Sign AD > 0	0.38	0.37	0.34	0.38	0.36	0.38	0.44
Abs AI-AD	5683	5589	6424	5310	4932	1952	5655

Table 19a: R-squared values and p-values of the related F-test for the case of the <u>values</u> of adjustment

Horizon	Model	1 step AI	1 step AD	H step AI	H step AD
H=1	I	0.108 (0.000)	0.022 (0.156)	0.108 (0.000)	0.022 (0.156)
	II	0.142 (0.000)	0.034 (0.222)	0.142 (0.000)	0.034 (0.222)
	III	0.447 (0.000)	0.287 (0.000)	0.447 (0.000)	0.287 (0.000)
H=2	I	0.396 (0.000)	0.266 (0.000)	0.392 (0.000)	0.248 (0.000)
	II	0.398 (0.000)	0.279 (0.000)	0.393 (0.000)	0.263 (0.000)
	III	0.479 (0.000)	0.329 (0.000)	0.596 (0.000)	0.395 (0.000)
H=3	I	0.454 (0.000)	0.365 (0.000)	0.380 (0.000)	0.314 (0.000)
	II	0.511 (0.000)	0.391 (0.000)	0.433 (0.000)	0.327 (0.000)
	III	0.602 (0.000)	0.519 (0.000)	0.617 (0.000)	0.523 (0.000)
H=4	I	0.115 (0.000)	0.031 (0.106)	0.150 (0.000)	0.032 (0.147)
	II	0.193 (0.000)	0.062 (0.061)	0.191 (0.000)	0.035 (0.387)
	III	0.537 (0.000)	0.378 (0.000)	0.572 (0.000)	0.272 (0.024)
H=5	I	0.359 (0.000)	0.267 (0.000)	0.326 (0.000)	0.259 (0.000)
	II	0.364 (0.000)	0.275 (0.000)	0.358 (0.000)	0.408 (0.000)
	III	0.567 (0.000)	0.505 (0.000)	0.767 (0.000)	0.835 (0.000)
H=6	I	0.224 (0.000)	0.201 (0.000)	0.253 (0.000)	0.281 (0.000)
	II	0.234 (0.000)	0.217 (0.000)	0.308 (0.000)	0.406 (0.000)
	III	0.628 (0.000)	0.585 (0.000)	0.946 (0.000)	0.966 (0.000)

Table 19b: Key parameter values for model III where adjustment concerns its <u>value,</u> which are ρ, β, ω (times 1000) and λ (times 1000)

Horizon	Forecast	AI ρ	AI β	AI ω	AI λ	AD ρ	AD β	AD ω	AD λ
H = 1	1 step	1.347	0.807	-0.007	0.009	0.957	0.811	-0.004	0.007
	H steps	1.347	0.807	-0.007	0.009	0.957	0.811	-0.004	0.007
H = 2	1 step	0.484	-0.151	0.001	0.002	0.507	-0.014	0.000	0.001
	H steps	0.611	0.161	-0.001	0.006	0.555	0.247	-0.001	0.003
H = 3	1 step	0.574	-0.153	0.002	0.001	0.399	-0.362	0.001	-0.002
	H steps	0.081	-0.343	0.009	0.000	0.374	-0.319	0.003	-0.003
H = 4	1 step	0.887	-0.040	-0.005	0.011	0.692	-0.007	-0.007	0.010
	H steps	-0.593	-0.510	0.014	0.006	-0.201	-0.343	0.005	-0.001
H = 5	1 step	0.739	-0.376	-0.004	0.004	0.217	-0.744	-0.001	-0.001
	H steps	1.249	-1.297	-0.026	0.006	0.407	-1.450	-0.014	-0.009
H = 6	1 step	1.477	0.998	-0.006	0.001	0.674	0.296	-0.002	-0.004
	H steps	1.581	-0.330	0.006	-0.013	1.381	-0.488	-0.017	0.001

Table 20a: R-squared and p-value of the related F-test for the case of the relative values of adjustment (note that the results for AI and AD are the same, by definition)

Horizon	Model	1 step	H steps
H=1	I	0.654 (0.000)	0.654 (0.000)
	II	0.711 (0.000)	0.711 (0.000)
	III	0.759 (0.000)	0.759 (0.000)
H=2	I	0.490 (0.000)	0.517 (0.000)
	II	0.614 (0.000)	0.626 (0.000)
	III	0.671 (0.000)	0.670 (0.000)
H=3	I	0.446 (0.000)	0.448 (0.000)
	II	0.508 (0.000)	0.549 (0.000)
	III	0.583 (0.000)	0.592 (0.000)
H=4	I	0.364 (0.000)	0.373 (0.000)
	II	0.453 (0.000)	0.487 (0.000)
	III	0.515 (0.000)	0.505 (0.000)
H=5	I	0.312 (0.000)	0.327 (0.000)
	II	0.380 (0.000)	0.389 (0.000)
	III	0.487 (0.000)	0.653 (0.000)
H=6	I	0.261 (0.000)	0.291 (0.000)
	II	0.359 (0.000)	0.351 (0.000)
	III	0.458 (0.000)	0.243 (0.000)

Note: The relative size of independent adjustment is computed as 100 times EF-MF divided by MF, which is equal to 100 times EF/MF minus 100. For dependent adjustment this becomes 100 times EF minus α times MF divided by MF, and this equals 100 times EF/MF minus 100α. So, the models for AI and AD have the same variable to be explained and the same explanatory variables, except for the size of the intercept.

Table 20b: Key parameter values for model III where adjustment concerns its <u>relative value</u>, which are ρ, β, ω (times 1000) and λ (times 1000) (note that the results for AI and AD are the same, by definition)

Horizon	Forecast	AI and AD ρ	β	ω	λ
H = 1	1 step	0.737	0.570	-1.277	-0.086
	H steps	0.737	0.570	-1.277	-0.086
H = 2	1 step	0.972	0.618	-1.952	-0.099
	H steps	0.750	0.562	-1.341	-0.122
H = 3	1 step	0.778	0.399	-1.145	-0.075
	H steps	0.631	0.252	-1.157	-0.033
H = 4	1 step	0.878	0.430	-1.402	-0.085
	H steps	0.544	0.390	-1.528	-0.075
H = 5	1 step	0.862	0.375	-1.255	-0.080
	H steps	-0.045	-0.041	0.296	0.045
H = 6	1 step	0.845	0.439	-1.428	-0.091
	H steps	-0.137	-0.220	2.246	1.381

Note: The relative size of independent adjustment is computed as 100 times EF-MF divided by MF, which is equal to 100 times EF/MF minus 100. For dependent adjustment this becomes 100 times EF minus α times MF divided by MF, and this equals 100 times EF/MF minus 100α. So, the models for AI and AD have the same variable to be explained and the same explanatory variables, except for the size of the intercept.

Table 21a: R-squared values (McFadden) and p-values of the related LR-test for the case of the <u>signs</u> of adjustment (logit models)

Horizon	Model	1 step AI	1 step AD	H steps AI	H steps AD
H=1	I	0.019 (0.110)	0.012 (0.252)	0.019 (0.110)	0.012 (0.252)
	II	0.030 (0.133)	0.022 (0.306)	0.030 (0.133)	0.022 (0.306)
	III	0.143 (0.014)	0.255 (0.000)	0.143 (0.014)	0.255 (0.000)
H=2	I	0.120 (0.000)	0.052 (0.004)	0.119 (0.000)	0.045 (0.010)
	II	0.122 (0.000)	0.060 (0.012)	0.124 (0.000)	0.052 (0.030)
	III	0.227 (0.000)	0.204 (0.001)	0.312 (0.000)	0.097 (0.237)
H=3	I	0.068 (0.001)	0.106 (0.000)	0.086 (0.000)	0.112 (0.000)
	II	0.095 (0.000)	0.112 (0.000)	0.166 (0.000)	0.125 (0.000)
	III	NA	0.186 (0.005)	NA	0.211 (0.006)
H=4	I	0.009 (0.391)	0.012 (0.309)	0.028 (0.095)	0.032 (0.074)
	II	0.026 (0.261)	0.049 (0.048)	0.034 (0.225)	0.039 (0.166)
	III	0.189 (0.005)	0.167 (0.017)	NA	0.126 (0.282)
H=5	I	0.149 (0.000)	0.050 (0.011)	0.143 (0.000)	0.044 (0.046)
	II	0.156 (0.000)	0.051 (0.054)	0.186 (0.000)	0.107 (0.005)
	III	NA	0.293 (0.000)	NA	NA
H=6	I	0.069 (0.002)	0.052 (0.011)	0.051 (0.043)	0.017 (0.349)
	II	0.088 (0.003)	0.054 (0.054)	0.082 (0.039)	0.034 (0.387)
	III	0.355 (0.000)	0.299 (0.000)	0.426 (0.002)	NA

Table 21b: Key parameter values for model III where adjustment concerns its <u>sign</u> (logit model) which are ρ, β, ω (times 1000000000) and λ (times 1000000000)

Horizon	Forecast	AI ρ	AI β	AI ω	AI λ	AD ρ	AD β	AD ω	AD λ
H = 1	1 step	0.000	-0.002	0.639	0.107	0.026	0.023	-1.018	2.548
	H steps	0.000	-0.002	0.639	0.107	0.026	0.023	-1.018	2.548
H = 2	1 step	0.000	-0.011	0.210	1.328	0.020	-0.014	0.848	-1.307
	H steps	0.030	-0.007	41.32	0.058	0.001	-0.002	0.252	-0.252
H = 3	1 step	NA	NA	NA	NA	-0.001	-0.017	1.625	-2.931
	H steps	NA	NA	NA	NA	-0.008	0.012	-0.035	-1.941
H = 4	1 step	0.009	0.003	-0.255	0.694	0.006	0.007	-0.363	1.495
	H steps	NA	NA	NA	NA	0.004	-0.005	-0.137	-0.728
H = 5	1 step	NA	NA	NA	NA	0.040	-0.024	0.380	-2.604
	H steps	NA	NA	NA	NA	NA	NA	NA	NA
H = 6	1 step	0.055	0.015	-3.898	3.927	0.031	0.034	9.679	-12.27
	H steps	-0.080	-0.088	-29.59	102.1	NA	NA	NA	NA

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