Competence and confidence effects
in experts' forecast adjustments

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Abstract

It frequently occurs that experts adjust forecasts from statistical models. There is some evidence that such adjusted forecasts can lead to substantially better performance. Little is known about competence and confidence effects in what these experts do. Theoretical and experimental results in the decision-making literature suggest that those effects should well exist for experts' adjustment. We examine this possibility for a unique data set concerning managers in thirty-seven countries who adjust statistical model-based forecasts delivered by the headquarters of a large pharmaceutical firm. Our literature-consistent findings are that older and younger managers adjust more than middle-aged managers and that a female manager adjusts less, except in the case where she has more experience.

Key words: Forecast adjustment, Competence effect, Confidence effect, Gender effect

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1. Introduction

It frequently occurs that experts adjust model-based forecasts. Managers who receive forecasts from statistical packages modify such forecasts using up-to-date information on the industry and its stakeholders and economists who advise local governments adapt their macroeconomic model-based forecasts to the latest information on the economy. While such a combination of model and expert used to be something to be discouraged some time ago (Hogarth and Makridakis, 1981), more recent insights seem to advocate such an interaction, which is exemplified by an extensive growth of literature showing the usefulness of imposing experts' judgment in forecasting (Mathews and Diamantopolous 1989, 1990, and Nikolopolous, Fildes, Goodwin and Lawrence, 2005, among many others). This literature largely focuses on the evaluation of forecasts which are a combination of a model-based forecast and experts' intuition and on the pitfalls of adjusting statistical forecasts, see Blattberg and Hoch (1990) and Bunn and Salo (1996), among others. Interestingly, there is not much academic literature, if at all, that investigates how experts adjust model-based forecasts and which factors influence these adjustments. It is this area in which the present paper aims to contribute.

There is some related literature on the behavior of experts or decision-makers that might be relevant though. For example, there are some studies on the behavior of professional forecasters, see Lamont (2002) and others. There the focus is on the pattern of forecast herding (that is that forecasts of different experts lie close to each other) and forecast scattering (forecasts are dispersed) and its relation with the professional lifetime of forecasters. Lamont (2002) studies published macroeconomic forecasts of numerous forecasters and he concludes that as forecasters become older and more established, they produce more radical and less accurate forecasts. It is suggested that this is due to the fact that macroeconomic and financial forecasters have to build reputation and have to get media attention in order to stand out in a crowd of forecasters. So far, this literature only focuses on final forecasts whereas we want to address adjustments to model-based forecasts.

Another literature of relevance to our study deals with ambiguity and gender differences in decision-making, see for example Powell and Ansic (1997). The competence effect as put forward in Heath and Tversky (1991) is concerned with the phenomenon that people who perceive themselves as more competent are more ambiguity seeking, which in our context would mean that they adjust more than others would. Furthermore, Barber and Odean (2001) document male experts to be more overconfident than women.

In the next section of this paper we draw upon these two literatures to formulate hypotheses on competence and confidence effects in experts' adjustments to model-based forecasts. We do so as we want to shape our next empirical analysis of a large and unique data base. We have access to a large amount of forecasts for sales of pharmaceutical products, for which we have model-based forecasts, generated with a statistical package, and expert adjusted forecasts. Additionally, we have three characteristics of the experts who made the adjustments, that is, their age and the number of years they are adjusting the model-based forecasts, which we take as measures of competence (experience), and their gender. In Section 3, we give a description of the data and the regression models used. In Section 4 the main findings are discussed. Section 5 gives conclusions and suggestions for further research.

2. Hypotheses

Experts who adjust model-based forecasts are decision-makers who have loss functions and also who have to rely on available information in the best possible way. The statistical model that is used in our empirical study weights past sales data to predict future sales data, and hence it does not include additional potentially relevant variables. Experts may feel that these functions of past data do not fully capture the predictive content of the full information set, and hence they may decide to add or subtract some value, depending on their own insights. There is no documentation of what it is that the experts actually do, although there is some evidence that they take past adjustments and past model-based forecast errors into account. Each expert has his or her own experience, as they use the model-based forecasts as a starting point, and each expert also has his or her own way of including domain knowledge. But, as they can be viewed as decision makers, we may expect that perceived competence and also confidence in own capabilities matter when making adjustments.

Competence and confidence

There is substantial literature on the effects of own perceived competence and own confidence on decision making, see for example Heath and Tversky (1991), and part of that can be translated to our situation at hand. When an expert feels very competent, and feels that he or she knows that local market better than the statistical model could possible do, he or she would adjust model-based forecasts more and more often. In the words of Heath and Tversky (1991), he or she would be more willing to accept ambiguity. So, the size of expert adjustment will depend on the own perceived competence. Our data set, to be described in more detail below contains the variables age and years in position, that is how long one is in a position of the local expert who can adjust the forecasts, and we take these as proxies for competence. So, our first hypothesis would be

H_1: More experienced experts are more confident in their own capabilities and less so in the adequacy of the statistical model, and hence the size of adjustment for these experts is larger than for less experienced experts.

Additional to the size of the adjustment, we also have information on the sign of adjustment. The model-based forecasts draw from the recent past of sales data, where such a statistical model typically has a tendency to converge to the mean value of the sales data, in particular when it comes to more steps ahead. The local manager is responsible for the sales performance of the local unit. His or her risk function is perhaps asymmetric, as having too much stock is less harmful than having too small an amount as shipping takes some time. So, one would expect that on average most managers would adjust upwards. Such a tendency is of course more risky or ambiguous as having predicted too high means that one shows too much confidence in the local firm's abilities to attain high sales levels. As more experience leads to a higher willingness to accept risk, we hypothesize that this competence effect implies

H_2: More experienced experts more often adjust upwards than downwards.

Gender

Recently, the decision-making and judgment literature also looked at potential gender effects in decision making and in accepting risk. A rather consistent finding in this literature is that women indicate preferences for less riskier prospects and that women are less overconfident than men are, see Beyer and Bowden (1997) and some of the other references cited in Gysler et al. (2002). This leads us to the hypothesis that

H_3: Male experts are more overconfident, and hence the size of adjustment for female experts is smaller than for male experts

Finally, the recent study of Gysler et al. (2002) obtains an interesting result (based on a range of experiments) and that is that among experts ("high knowledge individuals") women are more prone to accept risk and ambiguity. This suggests that

H_4: The size of adjustment is larger for more experienced female experts than for similarly experience male experts.

In terms of our models below, this last hypothesis entails that experience and gender somehow interact.

In contrast to the hypotheses for the size of adjustment, our literature search did not reveal any findings on potential correlations between gender and the sign of adjustment. This means that, in that respect, our results below should be treated as mainly exploratory.

3. Methods

We have access to a very large dataset containing information on forecasts made for monthly sales for a large pharmaceutical company. We have model-based forecasts, expert-adjusted forecasts and realizations of sales concerning products in various product categories for thirty-seven countries covering a period of twenty-five months. The first forecasts made and registered concern October 2004 and the last concern October 2006. Forecast horizons vary from one month to twenty-five months, but in this paper, as per suggestion of the company itself as these horizons are most important for the managers, we only investigate one-month-ahead and six-month-ahead forecasts. The model-based forecasts are generated using a statistical package that automatically selects a forecasting scheme. Each month the selection occurs anew and also each time parameters are estimated. The model-based forecasts are sent to the local managers (one or two per country), and these experts are allowed to add to these model-based forecasts their own expertise. Observations for which the model-based forecast is zero are excluded, as we believe that these forecasts are not reliable. We have access to hundreds of forecasts for each of these countries. The company makes bonus payments partly dependent on forecast performance of the experts, and this prevents us from disclosing actual figures and countries.

Variables

Additional to the forecasts, we also have some information about the characteristics of the experts who adjust the model-based forecasts. More precise, we know their age, their gender, and the number of years that they are in the very position to adjust the forecasts. We code the variable gender as 0 for males and 1 for females. For some countries we know that two experts are responsible for the forecasts in a certain country and then we average the characteristics of the experts. In relation to the hypotheses above, we operationalize competence and experience by age and years in position. In Table 1 we give some key statistics of these variables, see also Figures 1 and 2. We observe that the distribution of these explanatory variables reflects population features and that they are not strongly skewed towards certain outcomes. The correlation between age and years in position is 0.726, and this is considered as not too strong.

To investigate how the experts adjust the model-based forecasts we need to compute that adjustments themselves. We choose to use $A_{c,h,i} = EF_{c,h,i} - MF_{c,h,i}$ where $EF_{c,h,i}$ is the expert adjusted forecast and $MF_{c,h,i}$ is the model-based forecast for country c, forecast horizon h (in months) and observation i. There are other ways to define the adjustment, see for example Blattberg and George (1990), but we found that the results are robust to slight definitional changes.

To translate these adjustments to cross-sectional variables to be explained, we do the following. First we consider the mean of the absolute adjustments relative to the model-based forecast, calculated per country and per forecast horizon. This variable "size of adjustment" is thus defined as

$$A_{c,h} = \frac{1}{n} \Sigma_i\, (abs(A_{c,h,i}) / MF_{c,h,i}\,),$$

where n is the number of observations for a country c and a horizon h. As said, we confine the analysis to the cases of $h = 1$ and $h = 6$.

The second variable to be explained is the amount of upward adjustments as a percentage of all adjustments. We calculate this per country and per forecast horizon, that is, we have the variable

$$pA_{c,h} = \frac{1}{n} \Sigma_i I(A_{c,h,i} > 0),$$

where $I(.)$ is an indicator function which takes the value 1 when its argument is correct and zero otherwise. Again, we construct this variable for all countries and for just $h = 1$ and $h = 6$.

Models

To investigate if the characteristics of the experts are correlated with the experts' adjustment we consider two regression models (each for one of the two horizons). The first is

$$A_h = \mu + \beta_1 age + \beta_2 age^2 + \beta_3 gender + \beta_4 position + \beta_5 gender \times age + \beta_6 gender \times position + \varepsilon. \quad (1)$$

The parameters can be estimated using OLS and the sample size is thirty-seven. Based on hypothesis H_1 we would expect β_1 and β_4 to be positive. Hypothesis H_3 suggests that β_3 is negative. And, hypothesis H_4 would imply that β_5 and β_6 are positive. Finally, we also include the squared age as the results in Lamont (2002) suggest that there is non-linear effect with older and younger experts being less risk-averse than medium-aged experts. So we expect β_2 to be non-zero and if it is, we expect to see a parabolic effect of age with the largest effect at both ends. This would mean that β_1 is negative while at the same time β_2 is positive.

For the sign of the adjustment we consider a logistic regression model, which reads as

$$\log(pA_h/(1- pA_h)) = \mu + \beta_1 age + \beta_2 age^2 + \beta_3 gender + \beta_4 position + \beta_5 gender \times age + \beta_6 gender \times position + \varepsilon. \quad (2)$$

The parameters can be estimated using OLS. For reasons of comparability we include the same variables in (2) as in (1), even though we do not have specific prior thoughts about all signs of the parameters. However, hypothesis H_2 would imply that β_1 and β_4 are positive (at least in the absence of an effect of age^2).

4. Results

In this section we present and discuss the estimation results of regressions (1) and (2) with $h = 1$ and $h = 6$. Coefficient results and summary statistics are given Tables 2 to 5. The left-hand panel of each table shows results when all variables as in (1) and (2) are included, whereas the right-hand panel shows results when the explanatory variables which are insignificant at the 10% significance level are omitted from models (1) and (2). We use the 10% significance level as the number of observations used to estimate the model parameters is not large.

In Table 2, the estimation results are shown for model (1) with $h = 1$. We see that the final reduced model contain three relevant variables, and that, based on the overall F-statistic, the model itself is significant too. First of all, we obtain support for H_1 in conjunction with the empirical results in Lamont (2002) and that is that age has a non-linear effect with younger and older experts having large adjustment size, while medium-aged experts adjust less. This impact of age is depicted graphically in Figure 3 and we see that around the age of 40, experts are least inclined to adjust strongly. The estimation results in Table 2 also provide support for H_4, that is, more experienced female experts adjust more.

Quite similar results are found for h = 6, which is not unexpected. The estimation results in Table 3 show a similar effect of age and the graph in Figure 4 displays a similar effect curve as in Figure 3. For this six-month-ahead horizon we see that women adjust less, and this confirms H_3. At the same time, we see that gender x age has a strong positive effect, and this confirms H_4. Comparing the models in Tables 2 and 3 we see that the explanatory power of the model for six-steps-ahead adjustments to forecasts is much higher than for closer horizons.

As far as the sign of the adjustments are concerned, the estimation results in Table 4 and 5 are quite easy to summarize. The only relevant variable is age, and it has an impact as predicted by H_1, that is, more experienced and confident experts more often adjust upwards. Concerning the other hypotheses, we do not find any statistically relevant results.

5. Conclusion

We have investigated whether certain characteristics as age, gender and years in position of experts who adjust model-based forecasts have an impact on the properties of adjustment. As this is the first study of its kind, most results are of an exploratory nature, although we could relate some of our findings to existent literature on decision making. That literature predicts that men are more overconfident than women and that experience make people feel more confident and less risk averse. When their expertise is strong, women are however less risk averse. Based on a very large and informative new dataset, we could confirm several of these hypotheses.

Table 1: Key statistics of explanatory variables (37 observations)

Variable	Mean	Median	Maximum	Minimum
Age	39.53	37.50	60	20
Gender	0.486	0.500	1	0
Years in position	8.41	5	20	1

Table 2: Estimation results for size of adjustment and one-step-ahead horizon

	All variables			only 10% significant variables		
Variable	β	se	p value	β	se	p value
Intercept	8.520	4.479	0.067	7.259	3.667	0.056
Age	-0.399	0.210	0.068	-0.346	0.183	0.067
Age^2	0.005	0.002	0.058	0.004	0.002	0.060
Position	0.008	0.091	0.930			
Gender	-1.328	2.398	0.584			
Gender*Age	0.046	0.076	0.545			
Gender*Position	0.056	0.132	0.673	0.115	0.049	0.026
Adjusted R^2	0.151			0.216		
Prob(F-statistic)	0.087			0.011		

Table 3: Estimation results for size of adjustment and six-steps-ahead horizon

	All variables			only 10% significant variables		
Variable	β	se	p value	β	se	p value
Intercept	28.92	9.746	0.006	26.47	9.256	0.007
Age	-1.390	0.468	0.005	-1.270	0.432	0.006
Age^2	0.016	0.005	0.004	0.015	0.005	0.005
Position	0.017	0.199	0.934			
Gender	-12.67	5.218	0.021	-10.64	4.576	0.027
Gender*Age	0.396	0.164	0.022	0.302	0.111	0.010
Gender*Position	-0.230	0.287	0.428			
Adjusted R^2	0.325			0.345		
Prob(F-statistic)	0.005			0.001		

Table 4: Estimation results for sign of adjustment and one-step-ahead horizon

Variable	All variables β	se	p value	only 10% significant variables β	se	p value
Intercept	-2.222	1.220	0.079	-0.492	0.271	0.078
Age	0.100	0.057	0.091	0.019	0.007	0.007
Age^2	-0.001	0.001	0.262			
Position	-0.025	0.025	0.329			
Gender	0.653	0.653	0.325			
Gender*Age	-0.020	0.021	0.339			
Gender*Position	0.008	0.034	0.818			
Adjusted R^2	0.149			0.167		
Prob(F-statistic)	0.089			0.007		

Table 5: Estimation results for <u>sign of adjustment</u> and <u>six-steps-ahead</u> horizon

	All variables			only 10% significant variables		
Variable	β	se	p value	β	se	p value
Intercept	-2.425	1.547	0.127	-0.595	0.335	0.085
Age	0.107	0.073	0.150	0.020	0.008	0.021
Age^2	-0.001	0.001	0.286			
Position	-0.011	0.032	0.741			
Gender	0.554	0.828	0.508			
Gender*Age	-0.017	0.026	0.519			
Gender*Position	0.002	0.045	0.959			
Adjusted R^2	0.053			0.119		
Prob(F-statistic)	0.273			0.021		

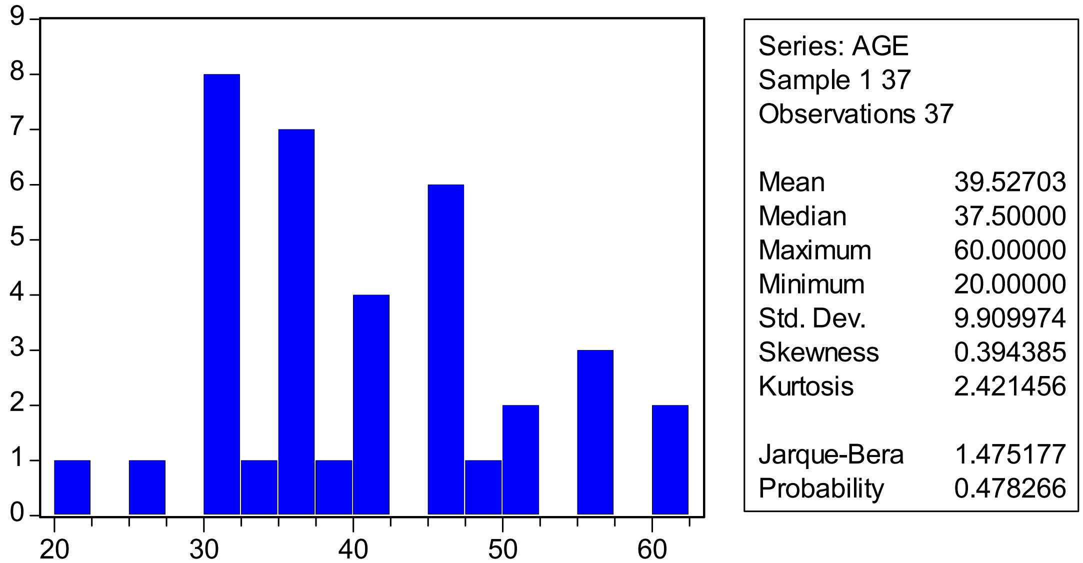
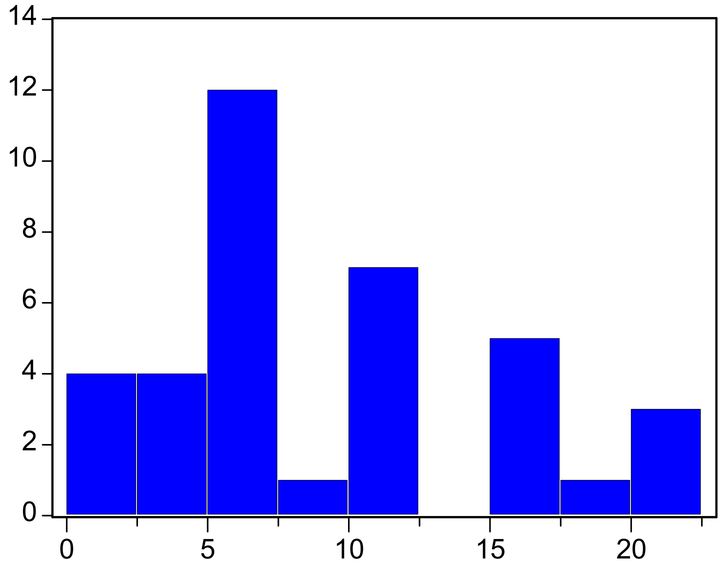


Figure 1: Age of experts



Series: POSITION	
Sample 1 37	
Observations 37	
Mean	8.405405
Median	5.000000
Maximum	20.00000
Minimum	1.000000
Std. Dev.	5.652971
Skewness	0.710174
Kurtosis	2.358564
Jarque-Bera	3.744446
Probability	0.153781

Figure 2: Years of experience

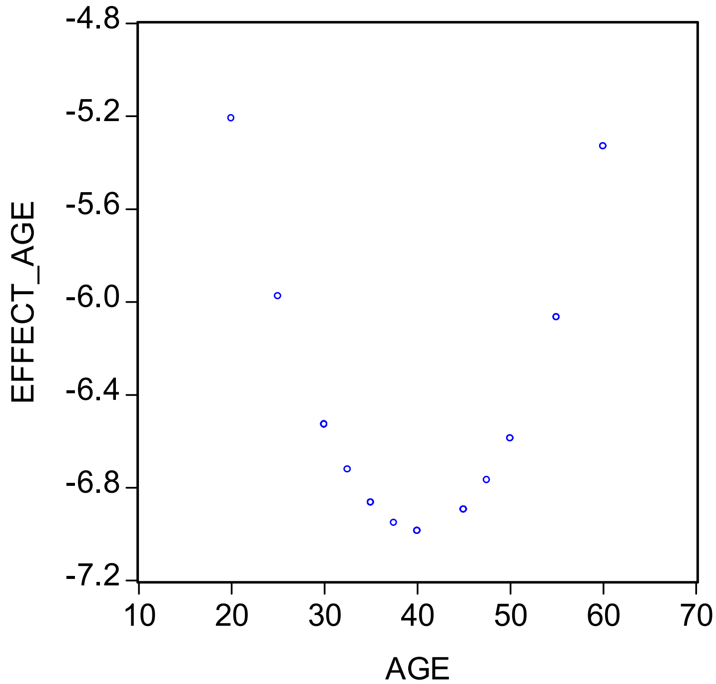


Figure 3: Effect of age on size of adjustment, one-step-ahead forecasts

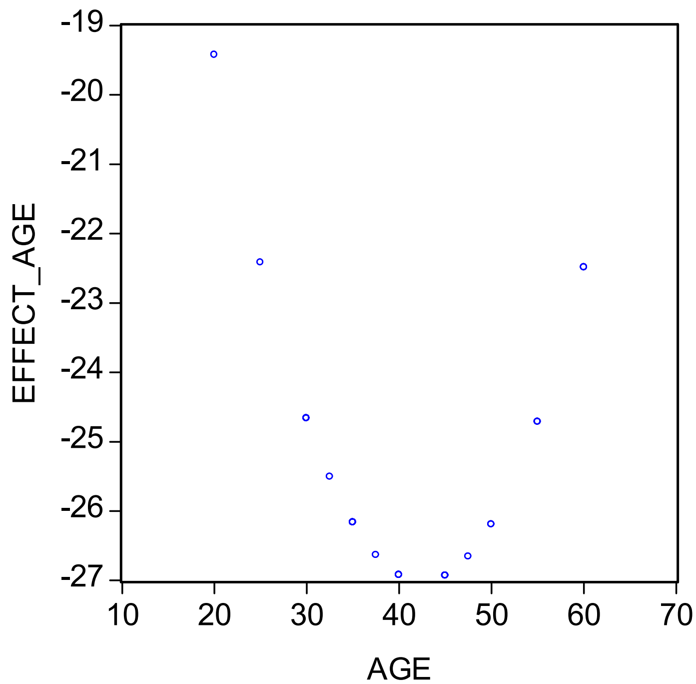


Figure 4: Effect of age on size of adjustment, six-step-ahead forecasts

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