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RESEARCH ARTICLE

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Combining expert-adjusted forecasts

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Abstract

It is well known that a combination of model-based forecasts can improve upon each of the individual constituent forecasts. Most forecasts available in practice are, however, not purely based on econometric models but entail adjustments, where experts with domain-specific knowledge modify the original model forecasts. There is much evidence that expert-adjusted forecasts do not necessarily improve the pure model-based forecasts. In this paper we show, however, that combined expert-adjusted model forecasts can improve on combined model forecasts, in the case when the individual expert-adjusted forecasts are not better than their associated model-based forecasts. We discuss various implications of this finding.

KEYWORDS
combined expert forecasts, expert adjustment, forecast combination

1 | INTRODUCTION

The combination of forecasts is a common and sensible practice in many empirical situations. There is ample evidence that combined or averaged forecasts outperform their individual constituent forecasts. As discussed in Wallis (2014), the notion that the "wisdom of the crowd" may outperform forecasts of specific individuals goes back at least to Galton (1907). The earliest, more formal, account of this phenomenon is provided by Bates and Granger (1969), where it is shown that the combination of two model-based forecasts can improve upon each of the individual model forecasts. The extensive surveys of applications of forecast combinations provided in Clemen (1989) and Timmermann (2006) demonstrate its popularity and success in various areas in economics and finance.

Bates and Granger (1969), and many others following, have mainly relied on the combination of econometric model forecasts. In practice, however, for many publicly available forecasts (like those of the International Monetary Fund or the World Bank) we do not know if these forecasts are fully based on econometric models or whether they originate immediately from personal expertise, or a combination of the two. In fact, there is substantial empirical evidence that quite rarely it is the pure model-based forecast that is used and published, but rather many forecasts seem to be first adjusted based on expert opinion. Such expert-adjusted forecasts could be contained in, for example, the Survey of Professional Forecasters and the Consensus Economics survey-based forecasts, where some forecasters could rely on econometric modes and manually adjust the forecasts that come out of those models. Expert adjustment can entail adding a number to the model forecast, or changing the value of a parameter in the underlying econometric model, or changing the value of an explanatory variable at the forecast origin, amongst others.

Obviously, experts adjust model-based forecasts with the best of intentions (or at least one may hope so); that is, in particular they aim to improve the accuracy of their forecasts. Interestingly, there is much recent literature documenting that at the *individual* level experts fail to reach this objective, in the sense that expert-adjusted forecasts are often not better than the original model-based forecasts; see Franses (2014) and references cited therein. By contrast, Ang, Bekaert, and Wei (2007), Dovern and Weisser (2011), and Loungani (2001), among others, show that "consensus" (i.e., combined) survey- or expert-based forecasts do outperform model-based forecasts. This also transpires in Armstrong's (2001) review of the literature on forecast combination, which includes forecasts ranging from model-based forecasts to expert forecasts and expert-adjusted model-based forecasts. Whichever application or setting, combined forecasts turn out to be more accurate. Additionally, Song, Gao, and Lin (2013) and Lin, Goodwin, and Song (2014) document that combined expert-adjusted forecasts can improve on the individual model forecasts. So, apparently, even if experts adjust the model-based forecasts in the wrong direction, combined expert-adjusted forecasts may be more accurate. It is this feature that we address in this paper, where we provide a theoretical argument why inappropriately adjusted model-based forecasts, when combined, can outperform the underlying (and possibly combined) model-based forecasts.

In this paper we address how a combination of expert-adjusted forecasts also benefits from the very fact that they are combined. Obviously, as we will show, when one of the two model-based forecasts is adjusted in the right direction, then the combination of another model forecast and this properly adjusted forecast performs well indeed. Matters become different, however, when we consider combining two expert-adjusted forecasts. In fact, we shall see that even in the case that two experts modify the model forecasts such that their individual forecast accuracy worsens (relative to the underlying model-based forecast), the combined forecast can still improve upon the combination of the constituent model-based forecasts. This intriguing result possibly sheds some light on the success of various familiar consensus forecasts or other averages of experts' predictions.

To keep the exposition simple, we assume that the forecasts to be combined are unbiased individually. Of course, it may happen that the expert-adjusted forecasts are biased; see, for example, Song et al. (2013). But it can also happen otherwise. For example, Franses, Kranendonk, and Lanser (2011) document that original model forecasts are mainly biased, whereas expert-adjusted forecasts are predominantly unbiased. We confine our analysis to the case of unbiased expert-adjusted forecasts for simplicity, and also because this already makes our main point. Similar to the derivations in Timmermann (2006, p. 148) and Min and Zellner (1993), we can relax this assumption and consider situations where one or more forecasts are biased. This would result in rather lengthy and cumbersome expressions, but for sure there will then be cases where combined biased expert-adjusted forecasts (modified in the wrong direction) *still* give more accurate forecasts.

The outline of our paper is as follows. In Section 2 we reiterate some issues on combining pure econometric model-based forecasts. In Section 3 we examine the idea of combining two expert-adjusted forecasts in general. In Section 4 we discuss some specific cases, amongst which are rather trivial ones, but we also give some numerical illustrations of nontrivial cases. We show that the key parameter determining the accuracy of the combined expert-adjusted forecast is the covariance between the adjustments of the two experts. When this covariance is sufficiently negative, the combined, but individually poorly performing, adjusted forecasts can still outperform the combined model forecasts. In Section 5 we provide an empirical illustration involving expert-adjusted forecasts of US gross domestic product (GDP) growth. In the final Section 6 we dwell on the implications of this finding.

2 | COMBINING MODEL-BASED FORECASTS

Consider a univariate time series variable y (where we suppress the time subscript t for notational convenience). Assume the availability of two one-step-ahead point forecasts F_1 and F_2, which are obtained from econometric (time series) models for y. Assume that both forecasts are unbiased; that is:

$$\mathsf{E}[e_i] = \mathsf{E}[y - F_i] = 0, \quad \text{for} \quad i = 1, 2,$$

where $e_i \equiv y - F_i$ denotes the forecast error associated with F_i. The variance of the forecast error e_i is denoted by σ_i^2, $i = 1, 2$, while the covariance between e_1 and e_2 is denoted by σ_{12}. Note that the variance σ_i^2 equals the mean squared prediction error (MSPE) of the forecast F_i due to the assumption of unbiasedness.

Consider the combined forecast given by

$$F_c = \omega F_1 + (1 - \omega) F_2,$$

with ω denoting the weight given to the forecast F_1. The combined forecast error $e_c \equiv y - F_c$ can be expressed as

$$e_c = \omega e_1 + (1 - \omega) e_2,$$

such that its variance is equal to

$$\sigma_c^2(\omega) = \omega^2 \sigma_1^2 + (1 - \omega)^2 \sigma_2^2 + 2\omega(1 - \omega)\sigma_{12}. \qquad (1)$$

Note that for any value of ω the combined forecast F_c is unbiased due to the unbiasedness of the individual forecasts F_1 and F_2, such that the MSPE of F_c is equal to $\sigma_c^2(\omega)$. We use the notation $\sigma_c^2(\omega)$ in Equation (1) to make explicit that this forecast error variance is a function of the combination weight ω. Obviously, this allows us to determine the "optimal" weight that minimizes the MSPE of the combined forecast. Setting the derivative of $\sigma_c^2(\omega)$ with respect to ω equal to zero, the optimal weight is found to be

$$\omega^* = \frac{\sigma_2^2 - \sigma_{12}}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}}. \quad (2)$$

Substituting this optimal value in the expression for the combined forecast error variance results in

$$\sigma_c^2(\omega^*) = \frac{\sigma_1^2\sigma_2^2 - \sigma_{12}^2}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12}}. \quad (3)$$

The expression for ω^* in Equation (2) shows that the optimal weight is 0.5 if σ_1^2 is equal to σ_2^2, irrespective of the covariance σ_{12}. Furthermore, it is straightforward to show that $\sigma_c^2(\omega^*)$ is always smaller than σ_1^2 and σ_2^2, except in the case where σ_1^2 or σ_2^2 is equal to σ_{12} (because then ω^* becomes equal to 1 or 0).

3 | COMBINING EXPERT-ADJUSTED FORECASTS

Suppose now that both model-based forecasts F_1 and F_2 are modified by experts. The expert-adjusted forecasts are denoted by E_1 and E_2 and are assumed to be of the form

$$E_i = F_i + A_i, \qquad \text{for} \quad i = 1, 2.$$

We assume that the adjustments A_i are zero, on average—that is, $\mathsf{E}[A_i] = 0$—and have a variance $\mathsf{E}[A_i^2]$ denoted by v_i^2, $i = 1, 2$. This assumption implies that the forecasts remain unbiased after the experts' adjustment. Similar to the derivations in Timmermann (2006, p. 148) and Min and Zellner (1993), we can relax this assumption and derive our results for biased forecasts. This would result in lengthy expressions with more parameters, but even then we shall be able to provide cases where combined biased expert-adjusted forecasts still give more accurate forecasts, using the methodology as in Timmermann (p. 148).

Furthermore, the adjustments may be correlated, and in fact this will turn out to be a crucial feature, as we shall see below. We denote the covariance $\mathsf{E}[A_1A_2]$ by v_{12}. Importantly, we assume that the adjustments may be correlated with the corresponding model forecast (error) but not with the other forecast (error); that is:

$$\mathsf{E}[(y - F_i)A_i] = z_i, \quad \text{for} \quad i = 1, 2,$$
$$\mathsf{E}[(y - F_i)A_j] = 0, \quad \text{when} \quad i \neq j, \text{ for } i, j = 1, 2.$$

This last expression, in words, says that the adjustment made by one expert is independent from the forecast errors made by the model employed by the other expert, which seems a quite reasonable assumption. Moreover, note that for the individual adjustments to be meaningful we would expect the covariances z_i to be positive, as in that case the adjustment could improve the individual model-based forecasts. Again, for the combinations, the key covariance is v_{12}.

From the above set-up, it is straightforward to derive the following properties of the expert-adjusted forecasts E_i and the associated forecast errors $y - E_i$, $i = 1, 2$. First, as noted above, the expert-adjusted forecasts are unbiased, as

$$\mathsf{E}[y - E_i] = \mathsf{E}[y - (F_i + A_i)] = \mathsf{E}[y - F_i] - \mathsf{E}[A_i] = 0 - 0 = 0.$$

Second, the variance of the forecast error $y - E_i$ is given by

$$\begin{aligned}\sigma_{i,E}^2 &\equiv \mathsf{E}[(y - E_i)^2]\\ &= \mathsf{E}[(y - (F_i + A_i))^2]\\ &= \mathsf{E}[(y - F_i)^2] + \mathsf{E}[A_i^2] - 2\mathsf{E}[(y - F_i)A_i]\\ &= \sigma_i^2 + v_i^2 - 2z_i.\end{aligned}$$

Note that this implies that the expert adjustment A_i is worthwhile (in terms of reducing the MSPE) if and only if $v_i^2 - 2z_i < 0$. This is equivalent to the condition that $\rho_i > v_i/2\sigma_i$, where $\rho_i = z_i/(v_i\sigma_i)$ denotes the correlation between $y - F_i$ and A_i. This implies that expert adjustments are most likely to be valuable when they are not too volatile (v_i^2 should preferably be small) and when they are positively correlated with the model-based forecast error (ρ_i should preferably be large).

Third, the covariance between the forecast errors $y - E_1$ and $y - E_2$ is equal to

$$\begin{aligned}\sigma_{12,E} &\equiv \mathsf{E}[(y - E_1)(y - E_2)]\\ &= \mathsf{E}[(y - (F_1 + A_1))(y - (F_2 + A_2))]\\ &= \mathsf{E}[(y - F_1)(y - F_2)] + \mathsf{E}[A_1A_2]\\ &= \sigma_{12} + v_{12},\end{aligned}$$

where we have used the assumption that $\mathsf{E}[(y - F_i)A_j] = 0$ when $i \neq j$, for $i, j = 1, 2$.

Now we turn to combining E_1 with E_2. Combinations of the expert-adjusted forecasts are of the form

$$E_c = \omega E_1 + (1 - \omega)E_2.$$

From Section 2 it follows that the optimal weight ω^* (in terms of minimizing the MSPE of E_c) is given by

$$\omega_E^* = \frac{\sigma_{2,E}^2 - \sigma_{12,E}}{\sigma_{1,E}^2 + \sigma_{2,E}^2 - 2\sigma_{12,E}}.$$

Using the expressions for $\sigma^2_{i,E}$ and $\sigma_{12,E}$ derived above, this can be written as

$$\omega^*_E = \frac{\sigma_2^2 + v_2^2 - 2z_2 - \sigma_{12} - v_{12}}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12} + v_1^2 - 2z_1 + v_2^2 - 2z_2 - 2v_{12}}.$$

Similarly, the corresponding MSPE value is obtained from Equation (3) as

$$\sigma_c^2(\omega^*_E) = \frac{\sigma^2_{1,E}\sigma^2_{2,E} - \sigma^2_{12,E}}{\sigma^2_{1,E} + \sigma^2_{2,E} - 2\sigma_{12,E}},$$

or

$$\sigma_c^2(\omega^*_E) = \frac{\sigma_1^2\sigma_2^2 - \sigma_{12}^2 + \sigma_1^2(v_2^2 - 2z_2) + \sigma_2^2(v_1^2 - 2z_1) + (v_1^2 - 2z_1)(v_2^2 - 2z_2) - 2\sigma_{12}v_{12} + v_{12}^2}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12} + v_1^2 - 2z_1 + v_2^2 - 2z_2 - 2v_{12}}. \quad (4)$$

In the next section we focus on various special cases of this expression and provide some numerical examples.

4 | VARIOUS SPECIFIC CASES

The general result in Equation (4) is difficult to appreciate, and therefore we discuss a few specific cases in this section. Each time the focus is on whether $\sigma_c^2(\omega^*_E)$ is smaller than $\sigma_c^2(\omega^*)$ as given in Equation (3)—that is, whether the variance of the forecast errors of the combined expert-adjusted forecast is smaller than the variance of the forecast errors of the combined model forecast.

4.1 | Uncorrelated adjustments

When the expert adjustments to the two (model-based) forecasts are uncorrelated, that is, in the case that $v_{12} = 0$, the expression for the MSPE of the optimal combined expert-adjusted forecast in Equation (4) simplifies to

$$\sigma_c^2(\omega^*_E) = \frac{\sigma_1^2\sigma_2^2 - \sigma_{12}^2 + \sigma_1^2(v_2^2 - 2z_2) + \sigma_2^2(v_1^2 - 2z_1) + (v_1^2 - 2z_1)(v_2^2 - 2z_2)}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12} + v_1^2 - 2z_1 + v_2^2 - 2z_2}. \quad (5)$$

A sufficient condition for this to be smaller than the MSPE of the combined model-based forecast in Equation (3) is $v_1^2 - 2z_1 < 0$ and $v_2^2 - 2z_2 < 0$. This makes perfect sense intuitively. Under these conditions, the forecast error variances of both expert-adjusted forecasts are smaller than the forecast error variances of the corresponding model-based forecasts; that is, $\sigma^2_{i,E} < \sigma^2_i$ for $i = 1, 2$. Furthermore, the expert adjustments do not affect the covariance between the two forecast errors, such that $\sigma_{12,E} = \sigma_{12}$. Obviously, combining two more accurate forecasts with the same covariance will result in a more accurate combined forecast.

Note, however, that this is only a sufficient condition. Indeed, it may be that adjustment makes one of the forecasts worse, but if this is "compensated" by a sufficient improvement in accuracy of the other expert-adjusted forecast, the optimal combined forecast may still be better than the combination of the original model-based forecasts.

4.2 | Combining one expert-adjusted forecast with one model forecast

Suppose that only the forecast F_1 is adjusted (to become E_1) and this is combined with the original (model-based) forecast F_2. This situation can also be analyzed in terms of the general set-up above, by setting $v_2^2 = 0$, $v_{12} = 0$ and $z_2 = 0$. In that case, the expression for the MSPE of the optimal combined expert-adjusted forecast in Equation (4) further simplifies to

$$\sigma_c^2(\omega^*_E) = \frac{\sigma_1^2\sigma_2^2 - \sigma_{12}^2 + \sigma_2^2(v_1^2 - 2z_1)}{\sigma_1^2 + \sigma_2^2 - 2\sigma_{12} + v_1^2 - 2z_1}. \quad (6)$$

Now, $v_1^2 - 2z_1 < 0$ is a necessary and sufficient condition for this combined forecast to be more accurate than the combination of the two original forecasts F_1 and F_2. This follows from the fact that again the expert adjustment does not affect the covariance between the two forecasts, such that an improved combined forecast can only be achieved when the expert adjustment makes E_1 more accurate compared to F_1, which exactly occurs under the stated condition.

4.3 | Numerical examples for the general case

Of course, a formal expression can be derived for which parameter configurations $\sigma_c^2(\omega^*_E)$ is smaller than $\sigma_c^2(\omega^*)$, but for illustrative purposes we will rely only on some numerical examples. Imagine setting σ_1^2 and σ_2^2 equal to 1, and σ_{12} equal to 0. This renders $\sigma_c^2(\omega^*) = \frac{1}{2}$. At the same time, assume that v_1^2 and v_2^2 are also equal to 1, and that $z_1 = z_2 = z$.

In Figure 1 we show the variance of the combined expert-adjusted forecast versus the value of v_{12} in the case of $z = 0.5$. This is the case where the expert-adjusted forecasts are equally good as the underlying model-based forecasts. Clearly, for almost all values of v_{12}, which here are all negative, we see that the combined expert-adjusted forecast improves on the combined model-based forecast. Figure 2 draws a similar picture for the case where $z = 0.45$: the case where the expert-adjusted forecasts are worse than the model forecasts. There we see that for a majority of values of z the combined expert-adjusted forecast is still better.

In other words, these results indicate that even when experts each modify the model-based forecasts in the wrong direction, and when the covariance between the adjustments is negative, the combined expert-adjusted forecast can be better than the combined model-based forecast.

4.4 | Equal weights

This result can be further amplified by looking at the very simple case of equal weights. Equally weighted combined forecasts have been extremely popular in practice, mostly because this "naive" way of pooling different forecasts has been found to be very difficult to beat by more advanced weighting schemes; see the surveys of empirical evidence provided in Clemen (1989) and Timmermann (2006). If we set $\omega = \frac{1}{2}$, even when it is not the optimal value, the variance of the combined forecast based on F_1 and F_2 becomes

$$\frac{1}{4}\sigma_1^2 + \frac{1}{4}\sigma_2^2 + \frac{1}{2}\sigma_{12}. \quad (7)$$

For the equally weighted combination of the expert-adjusted forecasts E_1 and E_2 we find

$$\frac{1}{4}\sigma_1^2 + \frac{1}{4}\sigma_2^2 + \frac{1}{2}\sigma_{12} + \frac{1}{4}(v_1^2 - 2z_1) + \frac{1}{4}(v_2^2 - 2z_2) + \frac{1}{2}v_{12}. \quad (8)$$

This is smaller than the variance in Equation (7) in the case when

$$\frac{1}{4}(v_1^2 + v_2^2 + 2v_{12}) < \frac{1}{2}(z_1 + z_2).$$

Note that the left-hand side of this inequality corresponds to the variance of the average adjustment $(A_1 + A_2)/2$, whereas the right-hand side corresponds to the average covariance of the adjustments with the model-based forecast errors.

Again, it is fairly easy to find numerical cases where the combined expert forecasts have smaller MSPE than the combined model forecasts when the individual expert forecasts are not doing better than the individual model forecasts.

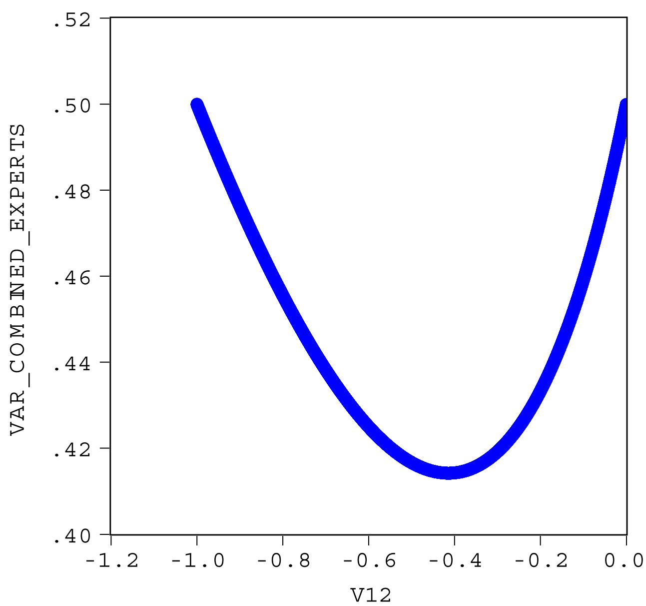

FIGURE 1 Variance of the forecast error of the combined expert-adjusted forecasts in the case of $z = 0.5$ [Colour figure can be viewed at wileyonlinelibrary.com]

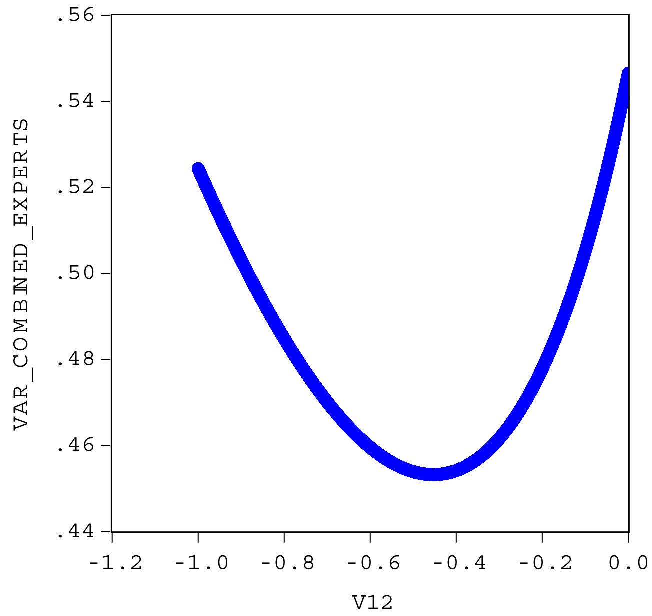

FIGURE 2 Variance of the forecast error of the combined expert-adjusted forecasts in the case of $z = 0.45$ [Colour figure can be viewed at wileyonlinelibrary.com]

5 | AN EMPIRICAL ILLUSTRATION

To illustrate some of the above material, consider the FOMC forecasts made in 2012 for US real GDP growth

TABLE 1 FOMC and Consensus Economics (CE) quotes for real GDP growth in 2013. The actual value (currently available) is 2.5

Date	Forecaster	Quotes range	Mean
January 25, 2012	FOMC	2.8–3.2	3.0
February 13, 2012	CE	1.4–3.5	2.5
April 2, 2012	FOMC	2.7–3.1	2.9
May 14, 2012	CE	1.4–3.8	2.52
June 20, 2012	FOMC	2.2–2.8	2.5
July 9, 2012	CE	1.6–3.3	2.33
September 13, 2012	FOMC	2.5–3.0	2.75
October 8, 2012	CE	1.4–2.7	2.0

for 2013. There are four such FOMC quotes available, dated January 25, April 2, June 20, and September 13, 2012.[1] Here we assume that these are viewed as the model quotes. A few weeks after the FOMC quotes are released, survey-based forecasts provided by Consensus Economics become available.[2] We treat these as the expert-adjusted forecasts, because they may have incorporated the FOMC quotes as the model-based input prior to their own judgment. Each of the Consensus Economics (CE) surveys includes 25–30 individual forecasts.

Table 1 shows the minimum and maximum of the individual forecasts for both the FOMC and the CE surveys (under "Quotes range" as well the equally weighted averages, which we consider as the combined forecasts. The two sets of forecasts provided later during the year, in June/July and September/October, show that the mean values of the FOMC quotes outperform those of the CE forecasters.

The first two sets of forecasts are particularly interesting. The forecast error of the mean FOMC quote released on of January 25, 2012, is 0.5%, whereas the CE mean is spot on at 2.5%. Looking at the range of the individual forecasts included in the CE survey, we observe that several experts have given quotes that increase the forecast error relative to the FOMC. More precisely, three experts provide forecasts below 2.0%, and four experts are overly optimistic, with forecasts exceeding 3.0%. Thus, in total, seven experts deviate from the model forecast, whereas the overall mean is very accurate.

Something similar occurs for the forecasts released in April/May 2012. The mean of the FOMC quotes is 2.9%, and hence the forecast error is still 0.4. By contrast, the mean of the CE forecasters is only 0.02 away from the actual GDP growth rate of 2.5%. For the CE experts who provide quotes in the survey of May 14, 2012, we observe three experts predicting growth below 2.1% and three experts with quotes above 2.9%. So, here we have six experts who adjust the FOMC model-based forecast in the wrong direction, while the overall mean is very accurate.

6 | CONCLUSION AND IMPLICATIONS

The results in this paper have various implications. We have shown that combined model-based forecasts can be beaten by combined expert-adjusted forecasts, even when the individual expert-adjusted forecasts themselves are less accurate than the underlying model forecasts. We also saw that the expert adjustments most likely should then have a negative covariance, meaning that the experts would perhaps interpret news in a different way.

Our findings may explain why various consensus-type forecasts are so successful. Apparently, it is not the way in which the experts agree, but in some sense it is the way that they do not agree that makes the average forecast work well. It also sheds light on the combined forecasts themselves. Usually, much effort is put into designing high-quality econometric models, but then it is often seen that experts with perhaps alternative or more recent domain knowledge modify these forecasts. These modified forecasts individually are often not that good, but, apparently, together they may have better forecast performance. Perhaps we should therefore address a change of efforts; that is, perhaps we should spend less time and effort designing high-quality econometric models, and spend more time on educating experts who adjust model-based forecasts.

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