Expert Opinion versus Expertise in Forecasting[1]

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Abstract

Expert opinion is an opinion given by an expert, and it can have significant value in forecasting key policy variables in economics and finance. Expert forecasts can either be expert opinions, or forecasts based on an econometric model. An expert forecast that is based on an econometric model is replicable, and can be defined as a replicable expert forecast (REF), whereas an expert opinion that is not based on an econometric model can be defined as a non-replicable expert forecast (Non-REF). Both replicable and non-replicable expert forecasts may be made available by an expert regarding a policy variable of interest. In this paper we develop a model to generate replicable expert forecasts, and compare REF with Non-REF. A method is presented to compare REF and Non-REF using efficient estimation methods, and a direct test of expertise on expert opinion is given. The latter serves the purpose of investigating whether expert adjustment improves the model-based forecasts. Illustrations for forecasting pharmaceutical SKUs, where the econometric model is of (variations of) the ARIMA type, show the relevance of the new methodology proposed in the paper. In particular, experts possess significant expertise, and expert forecasts are significant in explaining actual sales.

Key words: Direct test, efficient estimation, expert opinion, replicable expert forecasts, generated regressors, non-replicable expert forecasts.

“There are as many opinions as there are experts.”

Franklin D. Roosevelt, 32^{nd} U.S. President (1933-1945)

1. Introduction

Econometric models are useful for forecasting key policy variables in economics and business. Sometimes the outcomes of these models are adjusted by experts, and there are many reasons why an expert could do so (see, for example, Goodwin (2000) for a useful summary). Expert adjustments to model-based forecasts occur in economics (see, for example, Franses, Kranendonk and Lanser (2007) and Romer and Romer (2008)), and in business (see Bunn and Salo (1996), and Franses and Legerstee (2009) for an extensive empirical survey). Interestingly, the inclination of experts to adjust model-based forecasts is independent of the size of the econometric model (see Franses (2008)). Indeed, forecasts from both large scale macro-econometric models and from small scale ARIMA models might be adjusted by an expert.

In this paper we examine to what extent we can capture expert adjustment in an econometric modelling framework, with the ultimate purpose of investigating whether expert adjustment improves the model-based forecasts. For this purpose, we need some definitions in order to be perfectly clear where we are heading. As is well known, a forecast is an inference about an event that was not observed at the time of the inference. Forecasts generated from econometric models are replicable, and this feature will become transparent below.

Expert opinions are opinions given by experts, and much has been made of the value of expert opinions, especially in regard to their potential value in forecasting key policy variables in economics and finance. However, expert forecasts that are replicable need to be distinguished from expert opinions that are not. Expert forecasts that are replicable are forecasts made by an expert, or by others using the same information that is available to the expert, using an appropriate econometric model. In contrast, expert opinions are non-replicable forecasts provided by experts relating to a policy variable of interest. Although expert opinions may be expressed as quantitative measures, they inherently contain a qualitative (or latent) component, namely expertise, and hence also contain measurement error.

The preceding discussion leads to the following three definitions:

Definition 1: Expertise is latent.

Definition 2: Expert forecasts from an econometric model are replicable expert forecasts (REF).

Definition 3: Expert opinions are non-replicable expert forecasts (Non-REF)

Although expertise is unobserved, it can be estimated using an appropriate econometric model.

The primary purpose of the paper is to develop an econometric model to generate replicable expert forecasts, and to compare REF with Non-REF. A method is presented to compare REF and Non-REF using efficient estimation methods, and a direct test of expert opinion is given.

The plan of the remainder of the paper is as follows. Section 2 presents the econometric model specification, compares replicable and non-replicable expert forecasts, considers optimal forecasts and efficient estimation methods, and presents a direct test of expertise on expert opinion. Some relevant empirical examples are presented in Section 3. Concluding comments are given in Section 4.

2. Model Specification

In this section, we develop an econometric model to generate replicable expert forecasts, and to enable a comparison to be made with non-replicable expert forecasts.

2.1 Econometric Model

Let the econometric model be given as

$$y = X_1\beta_1 + u_1, \quad u_1 \sim (0, \sigma_1^2 I), \tag{1}$$

where y is a (T x 1) vector of the dependent variable, X_1 is a (T x k_1) matrix of explanatory variables, where the first column corresponds to the intercept term, and u_1 is a (T x 1) vector of errors. The y vector and X_1 matrix are observed, and $X_1 \subset I_{-1}^M$, where I_{-1}^M is the information set of the econometric modeller at time t-1 (t = 2,..,T).

It is assumed that the econometric model is appropriately specified, that is, the model passes relevant diagnostic checks, I_{-1}^M contains publicly known information and E($X_1'u_1$) = 0. Under these conditions, OLS in (1) is consistent and efficient, and hence is optimal in estimation. Moreover,

$$\hat{y}_1 = X_1\hat{\beta}_1 = X_1(X_1'X_1)^{-1}X_1'y = P_1 y, \tag{2}$$

where $P_1 = X_1(X_1'X_1)^{-1}X_1'$ is the standard ‘hat’ matrix.

If the model is correctly specified, under the assumption of mean squared error (MSE) loss, the optimal forecast of y, given the information set I_{-1}^M, is its conditional expectation (see Patton and Timmermann (2007a, 2007b)).

2.2 Replicable and Non-replicable Expert Forecasts

The fitted values (or in-sample model-based “forecasts”) of y from (2) are made available to an expert, who is expected to improve on the forecast of y through adding information to $\hat{y}_1$. The expertise possessed by the expert is latent as it is not publicly available, and may not even be quantifiable to the expert. Expertise is, in effect, a trade secret[3], which may be known only to the expert. If expertise can be estimated through an appropriate econometric model, the public would be able to replicate expertise if they were to have access to the expert's information set.

Therefore, an important issue to be addressed is whether an expert forecast can be replicated. Let a (T x 1) vector X_2 represent observable expert opinion, as announced by an expert. The connection between the observed expert opinion and latent expertise is given as

$$X_2 = X_2^* + \eta, \qquad \eta \sim (0, \sigma_\eta^2 I), \tag{3}$$

where X_2, X_2^* and η are (T x 1) vectors, X_2 denotes expert opinion, X_2^* represents latent expertise, η is the measurement error, and X_2^* and η are assumed to be uncorrelated.

Let the observed expert opinion be given as

$$X_2 = W\delta + \eta, \qquad \eta \sim (0, \sigma_\eta^2 I), \tag{4}$$

where the (T x k_2) matrix W is in the information set available to the expert at time t-1, and the first column of W is the unit vector. It is assumed that E($W'\eta$) = 0, δ is a (k_2 x 1) vector of constant parameters, and that

$$W = \{\hat{y}_1, W_1\} \subset I_{-1}^E,$$

which is the information set of the expert at time t-1, W_1 is (T x (k_2-1)), and $\hat{y}_1$ is available to the expert in providing an expert opinion, X_2.

[3] A trade secret is defined under the Uniform Trade Secrets Act of 1985 as "information that derives independent economic value, actual or potential, from not being generally known, and not being readily ascertainable by proper means, by any other person, and is the subject of efforts that are reasonable under the circumstances to maintain its secrecy" (see Hoti, McAleer and Slottje (2006) for further details).

Even though the econometric model in (1) may be well specified, the expert may believe that an expert model is superior as it incorporates expertise. Hence, if the model in (4) is correctly specified, under the assumption of MSE loss, the optimal replicable expert forecast of y, given the information set I_{-1}^{E}, is its conditional expectation, so that the expert forecast is still optimal. OLS is consistent and efficient, and hence is optimal in estimation.

However, if the expert does not have an appropriate econometric model in forming expert opinion, the resulting non-replicable expert forecast will not be optimal assuming a MSE loss function.

It follows from (4) and I_{-1}^{E} that

$$\mathrm{E}(X_2 \mid I_{-1}^{E}) \equiv X_2^* = W\delta , \tag{5}$$

so that W also denotes expertise as X_2^* is a linear combination of the columns of W. The rational expectations estimate of $\mathrm{E}(X_2 \mid I_{-1}^{E})$, which is a replicable expert forecast, is given as

$$\hat{X}_2^* = \hat{X}_2 = W\hat{\delta} = W(W'W)^{-1}W'X_2 = P_W X_2 , \tag{6}$$

so that the estimate of the latent expertise, X_2^*, is equivalent to the estimate of the observable expert opinion, X_2.

Remark 1: The information set of the expert, W, includes $\hat{y}_1$ but does not necessarily include X_1.

Remark 2: A replicable expert forecast can be consistently estimated as

$$\hat{X}_2^* = P_W X_2 = \hat{X}_2 .$$

Remark 3: Expertise differs from expert opinion as $X_2 - X_2^* = \eta$, and the difference can be estimated as $X_2 - \hat{X}_2^* = X_2 - \hat{X}_2$, namely the difference between Non-REF and REF, or the sample measurement error.

The expert's econometric model for forecasting y is given by

$$y = \delta_0 \hat{y}_1 + \beta_2 X_2^* + u_2, \qquad u_2 \sim (0, \sigma_2^2 I), \tag{7}$$

where β_2 is a scalar parameter. As X_2^* is latent and hence unobservable, an observable, and thereby estimable, version of (7) is given as

$$y = \delta_0 \hat{y}_1 + \beta_2 \hat{X}_2 + \varepsilon, \tag{8}$$

where

$$\begin{aligned} \varepsilon &= u_2 + \beta_2 (X_2^* - \widehat{X}_2) \\ &= u_2 + \beta_2 (W\delta - P_W X_2) \\ &= u_2 + \beta_2 (W\delta - P_W (W\delta + \eta)) \\ &= u_2 - \beta_2 P_W \eta. \end{aligned} \tag{9}$$

Remark 4: Under the null hypothesis that $\beta_2 = 0$ in (7), it follows that $\varepsilon = u_2$ in (9).

Remark 5: Although $\hat{y}_1$ is not correlated with ε in (9), the correlation between $\hat{X}_2$ and ε is given by $-\beta_2 \sigma_\eta^2 (T - k_2)$. However, OLS estimation of the parameters in (8) is consistent as $\hat{X}_2$ is asymptotically uncorrelated with ε.

Remark 6: The null hypothesis $\delta_0 = 0$ in (8) is a test of whether the expert should use the model forecasts, $\hat{y}_1$, as a complement to replicable expert forecasts, as given in $\hat{X}_2$.

Definition 4: The expert's forecast of y from (8) is given by

$$\hat{y}_E = \hat{\delta}_0 \hat{y}_1 + \hat{\beta}_2 \hat{X}_2 . \tag{10}$$

Under a MSE loss function, the forecast given in (10) is optimal relative to the expert's information set I_{-1}^E.

If u_1 in (1), u_2 in (7), and η in (3) are mutually and serially uncorrelated, then

$$\mathrm{E}(\varepsilon\varepsilon') = \mathrm{E}(u_2 u_2') + \mathrm{E}(P_W \eta\eta' P_W)\beta_2^2 ,$$

and hence

$$\Sigma_\varepsilon = \sigma_2^2 I + \beta_2^2 \sigma_\eta^2 P_W . \tag{11}$$

Remark 7: Serial correlation and heteroskedasticity are generated in (11) through the measurement error, η, in X_2 in (3).

Remark 8: If the null hypothesis in (8) is $\beta_2 = 0$, then $\Sigma_\varepsilon = \sigma_2^2 I$ in (11).

Remark 9: Equations (7) and (8) can be interpreted as comprehensive approaches to testing non-nested hypotheses, namely the model-based forecast, $\hat{y}_1$, versus expertise, as captured in the latent variable, X_2^*, and observable variable, $\hat{X}_2$, respectively (for further details see, for example, McAleer (1995)).

2.3 Efficient Estimation

In order to derive the conditions under which OLS estimation of the parameters in (8) is efficient, we appeal to Kruskal's Theorem, which is necessary and sufficient for OLS to be efficient (see Fiebig et al. (1992) and McAleer (1992) for further details). Kruskal's Theorem states that OLS is efficient for (δ_0, β_2) if and only if:

(i) $\Sigma_\varepsilon \hat{y}_1 = \hat{y}_1 A_1$, for some A_1,

(ii) $\Sigma_\varepsilon \hat{X}_2 = \hat{X}_2 A_2$, for some A_2.

where A_1 and A_2 can be matrices or scalars. The Gauss-Markov Theorem is a special case of Kruskal's Theorem, and hence is sufficient for OLS to be efficient.

In the context of OLS estimation of (8), the necessary and sufficient conditions for OLS to be efficient are given as follows:

Proposition 1: OLS in (8) is efficient if and only if conditions *(i)* and *(ii)* hold simultaneously.

Proof:

$$(i) \quad \Sigma_\varepsilon \hat{y}_1 = (\sigma_2^2 I + \beta_2^2 \sigma_\eta^2 P_W) P_1 y$$

$$= P_1 y(\sigma_2^2 + \beta_2^2 \sigma_\eta^2) = P_1 y A_1, \qquad if \;\; X_1 \subset W;$$

$$= P_1 y(\sigma_2^2) = P_1 y A_1, \qquad if \;\; X_1 \perp W.$$

$$(ii) \quad \Sigma_\varepsilon \hat{X}_2 = (\sigma_2^2 I + \beta_2^2 \sigma_\eta^2 P_W) P_W X_2$$
$$= P_W X_2 (\sigma_2^2 + \beta_2^2 \sigma_\eta^2)$$
$$= \hat{X}_2 A_2.$$

The necessary and sufficient conditions *(i)* and *(ii)* are satisfied either if $X_1 \subset W$ or if $X_1 \perp W$ (see Pagan (1984) for the case of generated regressors, and McAleer and McKenzie (1991) for a simple proof of efficiency of related two-step estimators).

Remark 10: It is likely that $X_1 \subset W$ will hold as $\hat{y}_1 = X_1\hat{\beta}_1 \subset W$, whereas orthogonality between X_1 and W (that is, $X_1 \perp W$) is not possible by virtue of $\hat{y}_1 \subset W$.

Let X_3 = [$\hat{y}_1 : \hat{X}_2$] in (8) be a (T x 2) matrix, and let β_3 = (δ_0, β_2) be a (2 x 1) vector, so that (8) can be written as

$$y = X_3\beta_3 + \varepsilon . \qquad (12)$$

Regarding inference, the OLS covariance matrix for (12) is given by

$$\mathrm{var}(\hat{\beta}_{3,OLS}) = (X_3{}'X_3)^{-1} X_3{}'\Sigma_\varepsilon X_3 (X_3{}'X_3)^{-1}. \qquad (13)$$

Substituting for Σ_ε from (11) in (13) gives

$$\mathrm{var}(\hat{\beta}_{3,OLS}) = \sigma_2^2 (X_3{}'X_3)^{-1} + \beta_2^2\sigma_\eta^2 (X_3{}'X_3)^{-1} X_3{}'P_W X_3 (X_3{}'X_3)^{-1}. \qquad (14)$$

Remark 11: If the incorrect downward biased OLS standard errors are used, namely from $\sigma_2^2 (X_3{}'X_3)^{-1}$, then the t-ratios for $\hat{\beta}_{3,OLS}$ will be biased upward (a similar result was given in Pagan (1984) for generated regressors; see also Oxley and McAleer (1993)).

Remark 12: The covariance matrix in (14) may be estimated consistently using the Newey-West HAC standard errors. In practice, the HAC standard errors may not be accurate in the context of generated regressors, so that (14) should be calculated for purposes of testing hypotheses and constructing confidence intervals (see Smith and McAleer (1994) for further details).

2.4 A Direct Test of Expertise on Expert Opinion

The analysis presented above relates to generating a replicable expert forecast, and a test of the significance of the REF, in explaining y. Expert opinion, as manifested in X_2, can be tested separately by substituting from (3) into (1) to give

$$y = \delta_0 \hat{y}_1 + \beta_2 X_2 + (u_2 - \beta_2 \eta) . \qquad (15)$$

OLS will be inconsistent in (15) as X_2 is correlated with η through (3). Therefore, IV should be used whenever expert opinion is used to forecast the variable of interest. In empirical practice, OLS rather than IV is typically used, incorrectly, to estimate the parameters in (15). Moreover, under a MSE loss function, the forecast of y in (15) is not optimal relative to the information set ($\hat{y}_1, X_2$).

The effect of expertise on expert opinion can be tested directly by testing appropriate hypotheses in (4), which may be rewritten as

$$X_2 = W\delta + \eta = \delta_0 \hat{y}_1 + W_1 \delta_1 + \eta, \qquad \eta \sim (0, \sigma_\eta^2 I) . \qquad (16)$$

OLS is efficient for δ_0 and δ_1 in (16), and various null hypotheses, such as

$$H_0 : \quad \delta_0 = \delta_0^* ,$$

can be tested directly. Interesting values of δ_0^* would be 0, 1 or ½. In conjunction with a scalar value of δ_1 = ½ when W_1 is a (T x 1) vector, δ_0 = ½ in (16) yields the 50:50 “model versus expert” decision rule (see Blattberg and Hoch (1990)).

Under a MSE loss function, the forecast of X_2 in (16) is optimal relative to the expert’s information set I_{-1}^E.

A direct test of expertise, namely whether the expert adds any additional information to $\hat{y}_1$ in formulating expert opinion, X_2, is given by

$$H_0: \quad \delta_1 = 0. \tag{17}$$

If the null hypothesis in (17) is not rejected, expertise does not add significantly to $\hat{y}_1$ in determining expert opinion, regardless of the value of δ_0.

Remark 13: The auxiliary regression equation used in Blattberg and Hoch (1990), namely to correlate expert opinion and model-based econometric forecasts, can be written as[4]

$$X_2 = \delta + \delta_0 \hat{y}_1 + v. \quad . \tag{18}$$

In comparison with (16), it is clear that OLS applied to (18) omits W_1, which denotes expertise in the information set of the expert. As it is highly likely that W_1 and $\hat{y}_1$ are correlated, OLS will be inconsistent and inferences will be invalid.

For (16) and (18) to be equivalent, it follows that:

$$v = W_1 \delta_1 + \eta, \tag{19}$$

in which case expertise cannot be tested in (18) as it is not included in the specification. It is also quite likely that v in (18) will be serially correlated, especially if the missing W_1 contains lagged values of variables (see Franses and Legerstee (2009) for empirical evidence of such serial correlation). Therefore, inferences based on (18) will be biased

[4] The appropriate regression in Blattberg and Hoch (1990) is given as $X_2 + \hat{y}_1 = \delta + \delta_0^* \hat{y}_1 + v$, which can be rewritten as (18), where $\delta_0 = \delta_0^* - 1$.

and invalid. Moreover, under a MSE loss function, the forecasts from (18) will not be optimal.

3. Empirical Example

The estimation, testing and forecasting methods described above are illustrated in this section using data for three experts who provide their expert forecasts, X_2, after they have been given the model forecasts, $\hat{y}_1$. The three experts are employed by a Netherlands-based pharmaceutical company, and are based in The Netherlands, Germany and Sweden. They are responsible for the supply chain management in local offices, and hence need to have accurate forecasts for monthly sales of various products. The company offers products within seven distinct categories, and each expert is responsible for the products within a single category. Each month the Headquarters of the company deliver the one-step-ahead model forecasts, and the experts are permitted to provide different quotes. The company uses an automated program that creates model-based forecasts, where the forecasting scheme can be based on ARIMA models, exponential smoothing, Holt-Winters techniques, and several other standard forecasting methods. The input variables of the models are lagged sales only. Each month, the program estimates a range of models, and selects the model with the best in-sample forecasting performance. Hence, parameter estimates are updated each month. The experts are aware of how the company creates their forecasts, so that the model forecasts are contained in their respective information sets.

The sample is from October 2004 to October 2006. The three experts in our sample are responsible for a different number of products, specifically, 9, 32 and 8 for The Netherlands, Germany and Sweden, respectively. The numbers of observations range from 210 for The Netherlands and Sweden, and 800 for Germany. We have data on actual sales, y, on the model forecast $\hat{y}_1$, and the expert forecast X_2. In expertise, W_1, we include y_{t-2} (as this is known to the expert at the time when a forecast is made for time *t*), $X_{2,t-2} - y_{t-2}$, $\hat{y}_{1,t-2} - y_{t-2}$, and $X_{2,t-1} - \hat{y}_{1,t-1}$.

Table 1 provides a comparison of the model forecasts and expert forecasts in terms of median squared prediction error. It is clear that the three experts provide far superior forecasts than the model used by Headquarters. In this sense, the experts seem to know what they are doing.

The results for regression equations (4) and (18), namely the separate effects of the model forecast and expertise on expert opinion, are reported in Table 2. The estimates for equation (18) are biased and inconsistent, and inferences are invalid, because of the omitted variables bias. For all three experts, it would appear that the effect of the model forecast is extremely close to unity in the absence of expertise (equation (18)), but decreases considerably when expertise is included (equation (4)). Moreover, the F test of excluding expertise rejects the null hypothesis for all three experts. In short, expertise matters.

Estimates of the model forecast, $\hat{y}_1$, and replicable expert forecast, $\hat{X}_2$, in predicting the actual values of y are given in Table 3. OLS is efficient, according to the information sets, but the standard errors need to be corrected using the Newey-West HAC formula. The inferences are not qualitatively affected, whether the incorrect OLS or HAC standard errors are used. For Expert 1, the expert forecast dominates the model forecast, which is not significant, whereas for Experts 2 and 3, both the model and replicable expert forecasts are significant. However, in each of the latter two cases, the replicable expert forecast dominates the model forecast.

Table 4 reports the estimates of the model forecast, $\hat{y}_1$, and expert opinion (or non-replicable expert forecast), X_2, in predicting the actual values of y. As the expert opinion is correlated with the equation error, OLS is inconsistent and GMM is used to provide consistent estimates. The instrument list uses two-period lagged sales, the model forecast error two periods lagged, expert forecast error two periods lagged, and expert adjustment of the model forecast one period lagged. The results are broadly consistent with the estimates presented in Table 3. For Experts 1 and 3, GMM has the effect of increasing the influence of the expert opinion in predicting actual sales, whereas for expert 2 it is the reverse. In summary, both model forecasts and expert opinions are important in predicting sales.

4. Conclusion

Expert opinion is an opinion given by an expert, and hence can have significant value in forecasting key policy variables in economics and finance. Expert forecasts can either be expert opinions, or forecasts based on an econometric model. An expert forecast that is based on an econometric model is replicable, and can be defined as a replicable expert forecast (REF), whereas an expert opinion that is not based on an econometric model can be defined as a non-replicable expert forecast (Non-REF). Both replicable and non-replicable expert forecasts may be made available by an expert regarding a policy variable of interest.

In this paper we developed a model to generate replicable expert forecasts, and compared REF with Non-REF. A method was presented to compare REF and Non-REF using efficient estimation methods, and a direct test of expertise on expert opinion was given. Illustrations for forecasting pharmaceutical SKUs, where the econometric model is of the ARIMA type, highlighted the ease of implementation of the estimation and testing procedures developed in the paper, and showed the relevance of the new methodology. In particular, experts were found to possess significant expertise, and expert forecasts were significant in explaining actual sales.

We foresee two areas for further research. The first is to allow the contribution of the expert to change over time, making some of the parameters time-varying. A second issue concerns an investigation into which aspects of an expert make them a good forecaster. Is it experience, or is it moderate behaviour (meaning little adjustment, only when it matters)?

Table 1

A Comparison of Model Forecasts and Expert Forecasts

	Median Squared Prediction Errors	
Country-Category	Model	Expert
Expert 1	203,855	28,731
Expert 2	197,136	166,464
Expert 3	17,031	15,751

Table 2

Testing the Effect of Expertise on Expert Opinion
(Standard errors are in parentheses)

	Expert 1		Expert 2		Expert 3	
Included variables	(4)	(18)	(4)	(18)	(4)	(18)
Intercept	-22.34	95.56	-26.43	207.7	42.08	119.3*
	(77.59)	(128.5)	(59.46)	(90.04)	(39.88)	(49.47)
Model Forecast (*t*)	0.09	0.97**	0.24**	1.01**	0.30**	0.96**
	(0.05)	(0.01)	(0.03)	(0.00)	(0.10)	(0.01)
Sales (*t*-2)	0.91**		0.78**		0.67**	
	(0.05)		(0.03)		(0.10)	
Model Forecast -Sales (*t*-2)	0.19**		0.16**		0.47**	
	(0.03)		(0.03)		0.06	
Expert forecast -Sales (*t*-2)	0.59**		0.46**		0.26**	
	(0.05)		(0.03)		(0.07)	
Expert Forecast -Model Forecast (*t*-1)	-0.07		0.17**		0.25**	
	(0.04)		(0.03)		(0.06)	
R^2	1.00	0.98	0.99	0.98	0.98	0.95
F test	145.0**		292.5**		76.45**	

Notes: The regression model (18) correlates the expert opinion, X_2 , and model forecast, $\hat{y}_1$, in

$$X_2 = a_0 + b_0\hat{y}_1 + v,$$

but omits the effect of expertise on expert opinion. Expertise in (4) is approximated by two-period lagged sales, the model forecast error two periods lagged, expert forecast error two periods lagged, and expert adjustment of the model forecast one period lagged. * and ** denote significance at the 5% and 1% levels, respectively. The F test is a test of the omitted expertise variables.

Table 3

Model and Replicable Expert Forecasts in Predicting Actual Values (Standard errors are in parentheses)

Estimation method	Intercept	Model Forecast $\hat{y}_1$	Expert Forecast X_2	R^2
		Expert 1		
OLS	159.92 (176.54)	-0.05 (0.09)	1.03^{**} (0.09)	0.98
HAC	[138.05]	[0.19]	[0.21]	
		Expert 2		
OLS	21.10 (111.7)	0.42^{**} (0.06)	0.51^{**} (0.05)	0.96
HAC	[122.3]	[0.16]	[0.14]	
		Expert 3		
OLS	-82.94^{**} (30.78)	0.30^{**} (0.05)	0.66^{**} (0.05)	0.99
HAC	[24.18]	[0.07]	[0.07]	

Notes: The regression model is

$$y = a + b\hat{y}_1 + c\hat{X}_2 + e.$$

* and ** denote significance at the 5% and 1% levels, respectively. The Newey-West HAC standard errors are given in brackets.

Table 4

Model and Expert Forecasts in Predicting Actual Values
(Standard errors are in parentheses)

Estimation method	Intercept	Model Forecast $\hat{y}_1$	Expert Forecast X_2	R^2
		Expert 1		
OLS	104.9	0.07	0.92**	0.97
	(177.0)	(0.08)	(0.08)	
GMM	150.2	-0.18	1.15**	0.97
	(102.0)	(0.28)	(0.30)	
		Expert 2		
OLS	22.92	0.37**	0.56**	0.96
	(101.1)	(0.04)	(0.04)	
GMM	21.41	0.68**	0.26	0.96
	(95.08)	(0.18)	(0.17)	
		Expert 3		
OLS	-9.28	0.52**	0.43**	0.97
	(43.63)	(0.06)	(0.06)	
GMM	-95.20**	0.31**	0.65**	0.98
	(31.28)	(0.08)	(0.08)	

Notes: The regression model is

$$y = \varphi + \delta_0 \hat{y}_1 + \beta_2 X_2 + e .$$

The instrument list uses two-period lagged sales, the model forecast error two periods lagged, expert forecast error two periods lagged, and expert adjustment of the model forecast one period lagged.
* and ** denote significance at the 5% and 1% levels, respectively.

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