

TESTS FOR FORECAST ENCOMPASSING WHEN FORECASTS DEPEND  
ON ESTIMATED REGRESSION PARAMETERS

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ABSTRACT

This paper presents analytical and simulation results on the properties of two tests for forecast encompassing, allowing throughout for dependence of the forecasts on estimated regression parameters. One test, which was intended for forecasts that do not depend on regression parameters, was developed by Harvey, Leybourne and Newbold (1998). This test works relatively well when the size of the sample of forecast errors is small. A second test, which explicitly accounts for uncertainty about the regression parameters, otherwise is comparable or preferable.

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In a recent paper, Harvey, Leybourne and Newbold (1998, henceforth HLN) developed and evaluated tests for forecast encompassing. The theory and simulations of HLN assume that forecast errors are observed without error. But many if not most economic forecasts rely on regression estimates. Forecast errors thus often are regression residuals that are contaminated by error in estimation of the regression parameters.

This note considers forecast encompassing when forecasts rely on regression estimates. It concludes that even when forecasts are based on regression estimates, the test statistic proposed by HLN (1998) is relatively attractive under the following condition: the size of the sample of forecast errors is small, as measured either by number of observations (say,  $n \leq 8$ ) or as a fraction of the size of the sample used to compute the regression estimates (say,  $n$  less than a tenth of the regression sample size). But otherwise, attempting to apply this statistic when forecasts rely on regression estimates—an application not considered or recommended by HLN (1998), I hasten to point out—probably is unadvisable. A test statistic that explicitly accounts for the dependence of the forecast errors on regression estimates seems comparable or preferable.

For expositional clarity, I use an example with univariate least squares forecasting models, one step ahead forecast errors, and forecasts made using a single estimate of the regression parameters. The Appendix presents the generalization to nonlinear and multivariate models, multistep forecasts and forecasting schemes in which parameter estimates are updated as new data become available so that different forecasts use different regression estimates.

Specifically, one is comparing two models for a scalar variable  $y_t$ . The two models are

$$\begin{aligned} y_t &= X_{1t}\beta_1 + e_{1t} \\ y_t &= X_{2t}\beta_2 + e_{2t}. \end{aligned} \tag{1}$$

In (1), all variables are scalars, and  $\beta_1$  and  $\beta_2$  are unknown parameters. The variables are assumed to be stationary and well-behaved in the sense made precise in Diebold and Mariano (1995), HLN (1998) and

West and McCracken (1998). In this simple example I also impose the conditions that the regression disturbances  $e_{1t}$  and  $e_{2t}$  are martingale differences satisfying  $Ee_{it}X_{it} = 0$ .

To compare the two models, one performs an encompassing test. Let

$$d_t = e_{1t}^2 - e_{1t}e_{2t}.$$

As explained in HLN (1998), if model 1 encompasses model 2,  $Ed_t=0$ , and that is the null.

If  $\beta_1$  and  $\beta_2$  were observed, one could test  $H_0: Ed_t=0$  by examining

$$\tilde{d} \equiv n^{-1} \sum_{t=R+1}^{R+n} d_t \equiv n^{-1} \sum_{t=R+1}^{R+n} (e_{1t}^2 - e_{1t}e_{2t}). \quad (3)$$

(See below for why the sample starts at  $R+1$ .) Let  $S$  denote the variance of  $d_t$ . HLN (1998) note that it follows from Diebold and Mariano (1995) that under standard assumptions about forecast errors,

$$\sqrt{n}(\tilde{d} - Ed_t) \sim_A N(0, S), \quad S \equiv E(d_t - Ed_t)^2. \quad (4)$$

This suggests obtaining a standard error as the square root of the sample variance of  $d_t$ . The simulations in HLN (1998) show, however, that using degrees of freedom adjustment, and using critical values from a  $t$ - rather than normal distribution, result in distinctive improvement in test statistics.

What are the implications of  $\beta_1$  and  $\beta_2$  being unknown? Evidently, they will be estimated before forecasts are made. So suppose that data from  $t=1, \dots, R$  are used to obtain least squares estimates  $\hat{\beta}_1$  and  $\hat{\beta}_2$ . These estimates are then used to make forecasts from  $t=R+1, \dots, R+n$ . (I take as given the split of the sample into  $R$  and  $n$ .) One examines not  $\tilde{d}$  but

$$\bar{d} \equiv n^{-1} \sum_{t=R+1}^{R+n} (\hat{e}_{1t}^2 - \hat{e}_{1t}\hat{e}_{2t}), \quad \hat{e}_{1t} = y_t - X_{1t}\hat{\beta}_1, \quad \hat{e}_{2t} = y_t - X_{2t}\hat{\beta}_2 \quad (5)$$

Define

$$V_\beta = (2 \times 2) \text{ asymptotic variance-covariance matrix of the estimator of } \beta \equiv (\beta_1, \beta_2)' \quad (6)$$

$$D = E \frac{\partial d_t}{\partial \beta'} = (1 \times 2) \text{ expectation of the vector of derivatives of } d_t \text{ with respect to } \beta',$$

$$D = (-2Ee_{1t}X_{1t} + Ee_{2t}X_{1t} \quad Ee_{1t}X_{2t}) = (Ee_{2t}X_{1t} \quad Ee_{1t}X_{2t})$$

$$\pi = \text{limit as sample size goes to infinity of } \frac{n}{R}, \pi < \infty$$

Under the conditions of West and McCracken (1998),

$$\sqrt{n}(\bar{d} - Ed_t) \sim_A N(0, \Omega), \quad \Omega = S + \pi DV_\beta D' \equiv E(d_t - Ed_t)^2 + \pi DV_\beta D'. \quad (7)$$

Upon comparing (7) and (4), we see that parameter estimation introduces extra uncertainty, since  $\pi DV_\beta D'$  is nonnegative and except in very special cases will be strictly positive (see below). Evidently, using  $S$  (or a consistent estimate of  $S$ ) to perform inference, which is appropriate when there is no parameter estimation error, will result in too many asymptotic rejections at any specified significance level. In considering use of HLN's (1998) test, the question is whether the distortion is trivial and so can be ignored in practice. I first consider the asymptotic formulas (4) and (7) analytically, and then turn to simulations to quantify the effects of parameter uncertainty in finite samples.

One simple condition that insures that the distortion is small is that  $\pi$  is small, because for arbitrarily small  $\pi$ ,  $\pi DV_\beta D'$  is arbitrarily small compared to  $S$ . When  $\pi$  is small, one keeps  $n \ll R$  as the sample size grows, so that many more observations are used to obtain the estimates of  $\beta$  than are used to obtain the estimate of  $Ed_t$ . As one might expect, in such a case uncertainty about  $\beta$  will be small compared to uncertainty that would be present even if  $\beta$  were known. If one uses  $\frac{n}{R}$  as the obvious finite sample analogue to  $\pi$ , then a range of values of  $\pi$  are suggested, some small (e.g.,  $\frac{n}{R} \approx .15$  in Ericsson and Marquez (1993)), some moderate (e.g.,  $\frac{n}{R} \approx .4$  in Cooper (1972)), some, especially in financial applications, large (e.g., the range of values of  $\frac{n}{R}$  is from about 5 to 18 in Engle et al. (1990)).

Of course, the term  $\pi DV_\beta D'$  is small for any  $\pi$  if  $V_\beta$  is small: ceteris paribus, the smaller the variance of the estimator of  $\beta$ , the less important is such variance for inference about  $Ed_t$ . (Note, however, that (in contrast to  $\pi$ ) one is typically not free to vary  $V_\beta$  without also varying  $D$  and  $E(d_t - Ed_t)^2$ .) To gauge the magnitude of  $DV_\beta D'$ , let us impose the null hypothesis that model 1

encompasses model 2. Then  $e_{1t}$  cannot be predicted by model 2, so

$$D = (Ee_{2t}X_{1t} \ 0) \Rightarrow DV_{\beta}D' = (Ee_{2t}X_{1t})^2V_{\beta}(1,1) = (Ee_{2t}X_{1t})^2(EX_{1t}^2)^{-2}(EX_{1t}^2e_{1t}^2). \quad (8)$$

(In (8), the usual heteroskedasticity-robust formula has been used for the asymptotic variance of the least squares estimator of  $\beta_1$ .) To get a precise, and simple, statement about the relative size of the two terms in (7), let us further assume that  $\beta_2=0$  ( $\Rightarrow e_{2t}=X_{1t}\beta_1+e_{1t}$ ) and that  $X_{1t}$  and  $e_{1t}$  are i.i.d. normal.

With some algebra, one can then establish that

$$DV_{\beta}D' = S \Rightarrow \sqrt{n}(\bar{d}-Ed_t) \sim_A N(0,\Omega), \Omega = (1+\pi)S \equiv (1+\pi)E(d_t-Ed_t)^2. \quad (9)$$

It is easy to calibrate the asymptotic magnitude of the distortion from using  $S$  (or a consistent estimate of  $S$ ) to perform inference. If (say)  $\pi=.1$ , asymptotic t-statistics using  $\sqrt{S}$  rather than  $\sqrt{(1+\pi)S}$  will be too small by a factor of  $\sqrt{1.1} \approx 1.03$ , implying that nominal 5 percent tests will have actual size of about 6 percent. This is arguably a small distortion; it affirms Chong and Hendry's (1986) view that if  $\frac{n}{R}$  is small, one can sometimes safely abstract from error in estimation of parameters when performing encompassing tests. But for larger values of  $\pi$ , the distortion is larger. If  $\pi=(\text{say}) .5$ , nominal 5 percent t-tests using  $\sqrt{S}$  rather than  $\sqrt{(1+\pi)S}$  will asymptotically have actual size of about 11. If  $\pi=2$ , the implied size is about 26. As noted above, many applications do involve ratios of prediction to regression samples that are moderate or large, indicating that accounting for parameter estimation error will be important in samples large enough for the asymptotic approximation to be accurate.

To get a sense whether “samples large enough” includes ones of relevant size, I performed a small Monte Carlo experiment. As in HLN (1998), I tried prediction sample sizes  $n = 8, 16, 32, 64, 128, 256$ . For each choice of  $n$ , I tried a range of values of  $R$ , subject to the constraint that  $n+R \leq 768$ :  $\frac{n}{R} = 2, 1, .5, .25, .125, .0625$ . (The upper bound of 768 was imposed to limit the amount of computation. For  $n=256$ , for example, this choice allows  $\frac{n}{R} = 2, 1$  and  $.5$ , but not  $\frac{n}{R} = .25, .125$  or  $.0625$ .) The

range of values of  $\frac{n}{R}$  tends toward the smaller side of values found in the empirical work that I am familiar with (see the references above). I lean toward smaller values because the asymptotic theory suggests that there will be a smaller distortion from ignoring dependence on estimated regression parameters for smaller values of  $\frac{n}{R}$ . The number of replications was 10,000. I generated the data according to (1), with  $\beta_2=0$ ,  $\beta_1=1$ , and  $(e_{1t}, X_{1t}, X_{2t})'$  i.i.d. normal with diagonal variance-covariance matrix with diagonal elements (1,1,2).

Using data from 1 to R, least squares was used to obtain estimates  $\hat{\beta}_1$  and  $\hat{\beta}_2$  and  $\hat{V}_\beta(1,1)$ , the usual heteroskedasticity-consistent estimate of  $V_\beta(1,1)$ . (No heteroskedasticity is present in the data, but to be conservative I assume that the investigator does not know this.) I used sample averages of  $\hat{e}_{2t}X_{1t}$  and of  $(\hat{d}_t - \bar{d})^2$  to construct  $\hat{D}(1)$  and  $\hat{S}$ , where the sample was over the n forecast errors. Two t-tests were performed. The first mimicked HLN (1998), making a degrees of freedom adjustment to  $\hat{S}$  and using critical values from a  $t(n-1)$  distribution. The second used conventional asymptotics:

$$\text{Test 1: compute } \frac{\sqrt{nd}}{\sqrt{\frac{n}{n-1}\hat{S}}}, \text{ compare to } t(n-1) \text{ distribution.} \quad (10a)$$

$$\text{Test 2: compute } \frac{\sqrt{nd}}{\sqrt{\hat{\Omega}}}, \text{ compare to } N(0,1) \text{ distribution,} \quad (10b)$$

$$\hat{\Omega} = \hat{S} + \left(\frac{n}{R}\right)\hat{D}(1)^2\hat{V}_\beta(1,1).$$

Results for two-sided nominal 5 percent tests are presented in Table 1. (As documented in an Additional Appendix that is available on request, results were similar for 10 percent tests; for 5 and 10 percent tests that use  $t(6)$  rather than normally distributed data; for tests that construct  $\hat{\Omega}$  imposing homoskedasticity in estimation of  $V_\beta(1,1)$ ; and for tests that do not impose  $Ee_{1t}X_{2t}=0$  in estimation of  $DV_\beta D'$ .) The "8.3" near the upper left hand of the table, for example, indicates that in about 830 of the 10,000 simulations, equation (10a) was greater than 2.365 in absolute value (2.365 is the critical value for a two sided .05 test for a  $t(7)$  distribution).

As may be seen from the upper left hand corner of the table, the statistic (10a), which does not explicitly account for sampling error in estimation of  $\beta_1$  and  $\beta_2$ , is more accurate when  $n=8$  and  $\frac{n}{R}=1.2$ . Neither statistic is especially accurate when  $n=8$  and  $\frac{n}{R}=2$ , a perhaps unsurprising finding since the size of the sample used to estimate the  $\beta$ 's is so small ( $R=4$ ). The statistic (10b), which explicitly accounts for such sampling error, typically is more accurate when  $n \geq 16$  and  $\frac{n}{R} \geq .125$ , though there are exceptions ( $n=16$ ,  $\frac{n}{R}=.125$ ) and a number of cases where the ranking depends on the loss function for over- versus under-rejection. In connection with the loss function, my own sense is that most economists would prefer to underreject slightly rather than overreject sharply, and that sense underlies my interpretation of (10b) as preferable (e.g., for  $n=256$  nominal sizes of 4.7 and 4.8 are preferable to 16.7 and 10.8). By the same token, the last column of the table suggests that for  $\frac{n}{R}=.0625$  the test (10a) is, overall, preferable. This is consistent with the interpretation above, that abstracting from error in estimation of regression parameters is safe when the ratio of forecast size to regression size is small. For larger  $\frac{n}{R}$ , the asymptotic tendency of equation (10a) to reject too much is reflected in the simulation. Indeed, for  $n \geq 32$  the sizes of the statistic (10a) predicted by the asymptotic approximation are roughly reflected (for example, the asymptotic size is about 26 for  $\lim_{R,n \rightarrow \infty} \frac{n}{R} = \pi = 2$ , versus the 22.3-25.6 range reported in the table).

I conclude that even when forecasts are based on regression estimates, the test statistic proposed by HLN (1998) is relatively attractive for small  $n$  (say,  $n \leq 8$ ) or when  $n$  is small compared to the size of the sample used to compute the regression estimates (say,  $\frac{n}{R} < .1$ ). But otherwise, it looks advisable to apply instead a test statistic that explicitly accounts for the dependence of the forecast errors on regression estimates. Unfortunately, perceptible size distortions remain, and alternative procedures that lead to more accurately sized tests are highly desirable.

## Appendix

This appendix sketches the general version of the asymptotic distribution of the estimate of  $Ed_t$ , taking account of dependence of the prediction errors on estimated parameters. Technical conditions and further discussion may be found in West (1996) and West and McCracken (1998).

Let  $y_t$  denote the scalar variable being forecast by two models. As above, write the parameter vector from model  $i$  as  $\beta_i$ , and stack the two vectors in a  $(k \times 1)$  vector  $\beta \equiv (\beta_1', \beta_2')$ . Let the total amount of data available be  $R+n+h-1$ , where “ $h$ ” is the forecast horizon ( $h=1$  in the analysis above). Three schemes for obtaining parameter estimates figure prominently in the literature. The schemes must be distinguished because asymptotic results vary across the three. The fixed scheme was the one illustrated above: data from 1 to  $R$  are used to estimate  $\beta_1$  and  $\beta_2$  and this single set of estimates is used in all predictions. In the rolling scheme the investigator rolls through the sample, first using data from 1 to  $R$  to estimate the  $\beta_i$ 's and predict  $y_{R+h}$ , then data from 2 to  $R+1$  are used to estimate the  $\beta_i$ 's and this new set of estimates is used to predict  $y_{R+1+h}$ , ..., and finally data from  $n$  to  $R+n-1$ . In the recursive scheme the sample size used to estimate the  $\beta_i$ 's grows: investigator first uses from 1 to  $R$  to estimate the  $\beta_i$ 's and predict  $y_{R+h}$ , then re-estimates using data from 1 to  $R+1$  and uses the new estimates to predict  $y_{R+1+h}$ , ..., finally re-estimates using data from 1 to  $R+n-1$  to predict  $y_{R+n+h-1}$ .

As above, define  $\pi < \infty$  as  $\pi = \lim_{R, n \rightarrow \infty} \frac{n}{R}$ . Define the scalars  $\lambda_{dh}$  and  $\lambda_{hh}$  as follows:

Sampling scheme	$\lambda_{dh}$	$\lambda_{hh}$	(A.1)
recursive	$1 - \pi^{-1} \ln(1 + \pi)$	$2[1 - \pi^{-1} \ln(1 + \pi)]$	
rolling, $\pi \leq 1$	$\frac{\pi}{2}$	$\pi \frac{\pi^2}{3}$	
rolling, $\pi > 1$	$1 - \frac{1}{2\pi}$	$1 - \frac{1}{3\pi}$	
fixed	0	$\pi$	

I assume predictions at time  $t$  rely on an estimate of  $\beta \equiv (\beta_1', \beta_2')$  that can be written  $\hat{\beta}(t) = B(t)G(t)$ . Here,  $B(t)$  is a  $(k \times q)$  matrix that converges to a rank  $k$  matrix  $B$ ,  $G(t)$  is a  $(q \times 1)$  mean

zero orthogonality condition used to estimate  $\beta$ .  $G(t)$  is an average of a random variable  $g(t)$  that has expectation zero; the average is taken over 1 to  $R$  (fixed scheme),  $t-R+1$  to  $t$  (rolling scheme) or 1 to  $t$  (recursive scheme). When maximum likelihood is used,  $q=k$ ,  $B(t)$  is the Hessian evaluated on the line between  $\hat{\beta}(t)$  and  $\beta$ , and  $G(t)$  is the score. When instrumental variables (more generally, GMM) is used,  $q \geq k$  ( $q > k$  in overidentified models) and  $B(t)$  is a matrix selecting which combination of orthogonality conditions to set to zero. When the models are non-nested, as is usually the case in practice,  $B(t)$  and its large sample counterpart  $B$  are block diagonal, and  $G(t)$  simply stacks the orthogonality conditions from the two models. (The results here allow the two models to share some orthogonality conditions, as will also often be the case in practice.)

Write the forecast error (which may be multi- rather than one-step ahead) as  $e_{it} = e_{it}(\beta_i)$ , with sample counterpart  $\hat{e}_{it}$ . Define

$$\begin{aligned} S &\equiv \sum_{j=-\infty}^{\infty} E(d_t - Ed_t)(d_{t-j} - Ed_{t-j}), & S_{gg} &\equiv \sum_{j=-\infty}^{\infty} E g_t g_{t-j}', & S_{dg} &= \sum_{j=-\infty}^{\infty} E(d_t - Ed_t) g_{t-j}', & V_{\beta} &\equiv B S_{gg} B', \\ (1 \times 1) & & (q \times q) & & (1 \times q) & & (k \times k) & \\ d_t &= d_t(\beta) = [e_{1t}(\beta_1)]^2 - e_{1t}(\beta_1) e_{2t}(\beta_2), & D &\equiv E[\partial d_t / \partial \beta]', & \bar{d} &\equiv n^{-1} \sum \hat{d}_t = n^{-1} \sum (\hat{e}_{1t}^2 - \hat{e}_{1t} \hat{e}_{2t}). \\ (1 \times 1) & & (1 \times k) & & (1 \times 1) & \end{aligned}$$

$V_{\beta}$  is the asymptotic variance-covariance matrix of the estimator of  $\beta$ . For an  $h$  horizon forecast, the autocorrelations of  $d_t$  will typically be zero after the  $h$ 'th, so  $S = \sum_{j=-h+1}^{h-1} E(d_t - Ed_t)(d_{t-j} - Ed_{t-j})$ . In most models, the orthogonality condition is presumed serially uncorrelated, so  $S_{gg} = E g_t g_t'$ . Similarly, it will often be the case that  $S_{dg} = \sum_{j=-h+1}^{h-1} E(d_t - Ed_t) g_{t-j}'$ .

Then

$$\sqrt{n}(\bar{d} - Ed_t) \sim_A N(0, \Omega), \quad \Omega \equiv S + \lambda_{dh}(D B S_{dg}' + S_{dg} B' D) + \lambda_{hh} D V_{\beta} D'. \quad (A.2)$$

The obvious sample analogues may be used in estimation of the quantities in (A.2).

Autocovariances of  $\hat{d}_t$  and  $\hat{g}_t \equiv g_t(\hat{\beta}_t)$  may be used to estimate  $S$ ,  $S_{gg}$  and  $S_{dg}$ , using nonparametric kernel estimators if desired; standard estimators of regression variance-covariance matrices may be used to estimate  $V_{\beta}$ ; a sample average of  $\partial \hat{d}_t / \partial \beta$  may be used to estimate  $D$ .

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Table 1

## Empirical Sizes of Nominal 5%-Level Tests for Forecast Encompassing

n	Test Statistic	$\frac{n}{R}$					
		2	1	.5	.25	.125	.0625
8	Eq'n (10a)	8.3	5.9	5.0	4.3	3.7	3.6
	Eq'n (10b)	9.8	6.4	5.4	5.3	6.3	7.7
16	Eq'n (10a)	15.5	10.8	7.8	5.9	5.1	4.8
	Eq'n (10b)	8.0	5.1	4.1	4.5	5.3	6.1
32	Eq'n (10a)	20.8	14.2	9.6	6.5	5.5	5.1
	Eq'n (10b)	6.5	5.0	4.2	4.3	5.0	5.5
64	Eq'n (10a)	23.5	15.5	10.3	7.9	6.6	
	Eq'n (10b)	5.5	4.7	4.8	5.2	5.4	
128	Eq'n (10a)	24.7	15.7	10.6	8.1		
	Eq'n (10b)	5.3	4.7	4.8	5.2		
256	Eq'n (10a)	25.2	16.7	10.8			
	Eq'n (10b)	5.0	4.7	4.8			

Notes:

1. This table presents empirical sizes of nominal .05 two-sided tests for  $H_0: Ed_t=0$ ,  $d_t \equiv E(e_{1t}^2 - e_{1t}e_{2t})$ . The model is given in (1), with  $\beta_1=1$ ,  $\beta_2=0$ ,  $(e_{1t}, X_{1t}, X_{2t})'$  i.i.d. normal with variance-covariance matrix =  $\text{diag}(1,1,2)$ .

2. " $n$ " is the number of one step ahead forecast errors used to compute  $\bar{d}$ ;  $\bar{d}$  is the sample average of  $e_{1t}^2 - e_{1t}e_{2t}$ , where  $e_{it}$  is the forecast error when the least squares estimate of  $\beta_i$  is used for forecasting (see (5));  $R$  is the sample size used to compute the least squares estimates of  $\beta_1$  and  $\beta_2$ . Thus in the row labeled "8," the values of  $R$  corresponding to the six values of  $\frac{n}{R}$  are 4, 8, 16, 32, 64 and 128.

3. Equation (10a) is a statistic that would be asymptotically valid as  $n \rightarrow \infty$  if the  $e_{it}$ 's were observed, rather than computed as regression residuals. Because regression residuals are used and  $0 < \pi \equiv \lim_{R, n \rightarrow \infty} \frac{n}{R}$ , equation (10a) will asymptotically have an actual size greater than .05. Equation (10b) is a statistic that is asymptotically valid as  $R, n \rightarrow \infty$ , and takes account of the fact that  $\bar{d}$  is constructed from regression residuals.

4. Equation (10a) uses critical values from a  $t(n-1)$  distribution, equation (10b) from a  $N(0,1)$  distribution. The entries "8.3" and "9.8" in row  $n=8$ , column  $\frac{n}{R}=2$ , for example, indicates that in about 830 of the 10,000 samples, the equation (10a) test statistic was greater than 2.365 in absolute value (2.365 is the critical value for a  $t(7)$  distribution); in about 980 of the 10,000 samples, the equation (10b) test statistic was greater than 1.96 in absolute value.