ENHANCING FORECAST ACCURACY BY USING LONG ESTIMATION PERIODS

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ABSTRACT

A tradeoff between forecast accuracy and the length of an estimation period always exists in forecasting. Longer estimation periods are argued to be less efficient, however, using the forecast encompassing and accuracy test, this study discusses the importance of considering the overall usefulness of information in the in-sample period. The empirical results demonstrate that forecasts using the correct model have reduced measurement loss and the mean of forecast errors decrease with an increase in in-sample period. Moreover, for the forecast accuracy and encompassing tests, reducing the use of observations in making estimates leads to the wrong model being easily accepted. Additionally, these analytical results are also consistent with the application in hedge performance, that is, the hedge effectiveness is optimized when the estimation period is longest, particularly under the recursive scheme.

INTRODUCTION

Improving out-of-sample forecast accuracy is a key concern in numerous areas of economics and finance. Increasingly sophisticated economic models are being developed to fit real time series, but surprisingly a good in-sample fit does not necessarily translate into good out-of-sample performance. This surprising occurrence is due to model instability. Sample period length is one of the foundations of accurate in-sample estimates and out-of-sample forecasts. Forecasting agents often consider it necessary to estimate model parameters using only a partial window of the available observations, to avoid heterogeneity within the results. Some researches argue that a longer sample period achieves an increase in forecast bias and thus reduces efficiency. Shaffer (2003) notes that too large a sample may include older observations that may reflect different biases to those existing more recently. Harris and Shen (2003) proposed that a longer estimation period is associated with less efficient estimations when compared with short estimation periods. However, Clark and McCracken (2004) notes that reducing the sample, to lower the heterogeneity, also increases the variance of the parameter estimation, and increases forecast errors and mean square forecast errors (MSE). Therefore, the decision whether or not to use all available data when constructing a forecast is problematic and often results in a tradeoff. However, little attention has been given to addressing the problem of determining appropriate estimation periods.

LITERATURE REVIEW

The forecast approaches are also related to this point and two other common approaches. Both the rolling window approach and the recursive scheme, are considered here for one-step-ahead forecasting and provide evidence for the argument above. In the rolling scheme the forecasting model is estimated using a moving window of recent observations as the forecast progresses through time. "Rolling windows" is a commonly used concept in financial literature. Giacomini and White (2005) argue that a rolling window approach with limited memory estimators is appropriate in heterogeneous data environments. Many studies adopt a rolling window approach to forecast. Clements and Hendry (1988, 1999) propose that economic time series are often heterogeneous. However, this study argues that even in the rolling window scheme, the problem of estimate bias still exists, when the window size is too short to contain enough useful information. Otherwise, the recursive scheme indicates that estimating with more data as forecasting moves forward in time, and this expanding window approach is generally applied in the macroeconomic literature uses all available data (Stock and Watson, 2003). In a stationary environment, the recursive scheme is necessary since the limited memory estimators are inefficient (Giacomini and White, 2005). Therefore, as noted by Pesaran and Timmerman (2004), a forecasting approach that is based on the breakpoint risk must be inefficient as it does not fully use all available information. Regardless of the environment or forecast approach used, sufficient useful information should be contained in the estimation periods to reduce the bias parameter estimate and improve the out-of-sample forecast performance.

This study considers two sets of out-of-sample forecasts and analyses the relationship between spot and nearby futures of the West Texas Intermediate (WTI) crude oil price. The study encompasses both those with and without structural change. The spot price increased 51.93% from January to August, 2005[1]. Forecasting the relationship is not only relevant to oil market traders, but also to global economic activity and government policy. Bai and Perron (1998, 2003)[2] have already demonstrated that structural change exists in the time series data, and eliminating this structural change will bias the forecast results. Moreover, such biases can accumulate and produce larger mean square forecast errors (see, Clark and McCracken, 2004; Jardet, 2004; Inoue and Kilian, 2002; Chauvet and Potter, 2002; Krolzig, 2001; Koop and Potter, 2000; Clements and Hendry, 1999). Consequently, this study designates the model with a structural break as the correct model, and the model without such a structural break as the incorrect model. Intuitively one may hold the belief that the out-of-sample forecast error under the correct model will be lower than that under the incorrect model, but interestingly this study finds that the results are adverse given a shorter estimation period. Longer estimation periods including full information not only produce consistent parameter estimations, but also improve the forecast performance and hedge effectiveness.

Moreover, this investigation adopted a new test to assess the reliability of the out-of-sample forecast abilities regarding the usefulness of the information contained for forecasting, termed the forecast encompassing test[3] (Clark and McCracken, 2001, 2004). As previously stated, mean square forecast errors are the most widely used criterion for testing forecasting abilities (for example, Stock and Watson, 2003 and Hamilton, 2001). However, recently forecast encompassing tests have provided a possible means of complementing the MSE criterion (Rapach and Weber, 2004). The tests effectively reveal whether one variable can be used to predict another. Clark and McCracken (2001) propose that the encompassing tests are the most effective for post-sample testing. For intuitive forecasting results, the model with a structural break should have a smaller mean square forecasting error and should encompass another model based on the better use of forecasting information. However, the empirical results differ when the estimation periods are insufficiently long, and the situation is modified with increasing period length.

The remainder of this paper is organized as follows: Section 2 describes the empirical methodology, including the nested model-setting and the tests of forecast accuracy and encompassing. Section 3 presents data and the empirical model for considering structural change. The application in hedge effectiveness is also drawn upon in this section. Section 4 describes the empirical results. Section 5 draws conclusions on the evidence provided in the paper.

METHODOLOGY

This study uses a simple nested linear model, with or without structural change, to demonstrate that one-step-ahead forecasting[4] with longer estimation periods performs better when more useful information is contained. Both rolling window and recursive schemes are used to examine the forecast accuracy and the encompassing nature of different estimation periods. Additionally, hedge performance is also considered in this investigation.

Nested Model-Setting and Forecast Scheme

Following Clark and McCracken (2001, 2004), sample of observations $\{y_t, x'_{2,t}\}_{t=1}^{T+1}$ contains a random variable y_t to be forecast and a $(k_1 + k_2 = k \times 1)$ vector of predictors $x_{2,t} = (x'_{1,t}, x'_{22,t})'$. $x_{1,t}$ denotes the regressors in the restricted model (model 1) and $x_{2,t}$ represents the regressors in the unrestricted model (model 2) with k_2 variables. The in-sample observations span 1 to R, and the out-of-sample observations span $R+1$ to $R+P$, where P denotes the number of one-step ahead forecasts. The total number of observations in the sample is $T+1 = R+P$. Moreover, forecasts of y_{t+1}, $t = R, \cdots T$ are generated using two linear models with the form $x'_{i,t+1}\beta_i^*$, $i = 1,2$, each of which is estimated. Under the null hypothesis, model 2 nests model 1, and thus model 2 includes k_2 excess parameters. Under the alternative hypothesis, the restriction k_2 is not true and model 2 is correct.

The forecasting schemes are permitted to be both rolling and recursive one-step ahead predictions. Under the rolling scheme, forecasting models are estimated using a moving window of the most recent R observations as the forecast horizon moves further forward. Under the recursive scheme, forecasting models are estimated using more data as the forecast horizon moves further forward, and the maximum number of observations used for parameter estimation is $T = R + P - 1$.

Forecast Accuracy and Forecast Encompassing Tests

This study denotes the one-step ahead forecast errors as $\hat{u}_{1,t+1} = y_{t+1} - x'_{1,t}\hat{\beta}_{1,t}$ and $\hat{u}_{2,t+1} = y_{t+1} - x'_{2,t}\hat{\beta}_{2,t}$ for model 1 and model 2, respectively. Clark and McCracken (2001) treat the tests for equal MSE (MSE-T and MSE-F) and forecast encompassing (ENC-T and ENC-F) as one-sided tests. The asymptotic distributions of equal MSE tests are derived by McCracken (2004), an F-type test proposed by McCracken (2001) (MSE-F), and a T-test developed by Diebold and Mariano (1995) and West (1996) (MSE-T). The test of forecast encompassing is derived by Clark and McCracken (2001). The statistics on tests regarding MSE equality (also called the 'forecast accuracy test') are described simply as follows:

$$MSE - T = P^{1/2} \frac{P^{-1}\sum_{t=R}^{T}(\hat{u}_{1,t+1}^2 - \hat{u}_{2,t+1}^2)}{\sqrt{P^{-1}\sum_{t=R}^{T}(\hat{u}_{1,t+1}^2 - \hat{u}_{2,t+1}^2)^2}} \tag{1}$$

$$MSE - F = P \times \frac{P^{-1}\sum_{t=R}^{T}(\hat{u}_{1,t+1}^2 - \hat{u}_{2,t+1}^2)}{P^{-1}\sum_{t=R}^{T}\hat{u}_{2,t+1}^2} \tag{2}$$

The null hypothesis is that the MSE of model 1 is less than or equal to that of model 2, while the alternative hypothesis is that the MSE of model 1 exceeds that of model 2. Furthermore, in the test for forecast encompassing, the null hypothesis is that the forecast produced with model 1 encompasses model 2, the covariance in the numerator of the encompassing tests statistics will be less than or equal to 0. The alternative hypothesis is that model 2 includes more information and the covariance should be positive. The statistics are reported as follows:

$$ENC-T = P^{1/2}\frac{P^{-1}\sum_{t=R}^{T}(\hat{u}_{1,t+1}^{2}-\hat{u}_{1.t+1}\hat{u}_{2,t+1})}{\sqrt{P^{-1}\sum_{t=R}^{T}(\hat{u}_{1,t+1}^{2}-\hat{u}_{1.t+1}\hat{u}_{2,t+1})^{2}}} \quad (3)$$

$$ENC-F = P\times\frac{P^{-1}\sum_{t=R}^{T}(\hat{u}_{1,t+1}^{2}-\hat{u}_{1,t+1}\hat{u}_{2,t+1})}{P^{-1}\sum_{t=R}^{T}\hat{u}_{2,t+1}^{2}} \quad . \quad (4)$$

Data and the Empirical Model

This study developed a nested linear model for analyzing the relationship between spot and nearby futures of West Texas Intermediate (WTI) crude oil price. The available data, obtained from the U.S. Department of Energy, is for the period June 23, 1988 to June 28, 2005 and includes a total of 4,178 observations. The restricted (model 1) and unrestricted models (model 2) are constructed as Eqns. (5) and (6):

$$S_t = \alpha_0 + \beta_0 F_t + u_{1t} \quad (5)$$

$$S_t = (\alpha_0 + \alpha_1 D_t) + (\beta_0 + \beta_1 D_t)\times F_t + u_{2t} \quad (6)$$

Where S_t and F_t are the continuously compounded returns of the WTI crude oil spot and nearby futures prices. The variable D_t equals one when the date is after the break and otherwise equals zero. The variables u_{1t} and u_{2t} represent the error terms for models 1 and 2, respectively. According to Bai and Perron (2003), one structural break was obtained in March 21, 1997, indicating that the coefficient shifted over the break date.

The out-of-sample periods run from the break date to the end of the data (March 21, 1997 – June 28, 2005), and the in-sample periods differ depending on the observation period length. Taking 500 days as an example, the first in-sample period begins at 500 days before the structural break date is taken to be March 9, 1995 to March 20, 1997. The second round forecast starts at 499 days before the structural date, that is March 10, 1995 under the rolling window scheme, while the starting date of the estimation period is fixed at March 9, 1995 under the recursive scheme. This study considers three estimation periods; one-year (250 days), two-years (500 days) and five-years (1250 days) under the rolling scheme. For the recursive scheme the setting is different. Due to the increase in the number of observations as the time of the forecast moves forward, the start points of the estimation periods are only set to either 250 or 500 days before the break date and the number of observations considered in forecasting increases as the time moves forward.

Application in Hedge Effectiveness

Additionally this investigation assessed the hedge effectiveness to examine the improvement in effectiveness with increasing estimation periods. While facing an oil market characterized by high volatility, eliminating or lowering risk used to be a key objective of majority traders with futures contracts being the most widely used method of achieving this. Hedge effectiveness can be defined as the proportion of the variance that is eliminated by the hedge, with hedge effectiveness and performance increasing with the size of the reduction. The unhedged variance is expressed as

$$Var(U) = \sigma_u^2 = Var(S_t)\ , \tag{7}$$

where S_t denotes the continuously compounded spot price returns. Alternatively, the hedged variance is calculated from the hedged return, which can be written as follows:

$$X_t = S_t - hr_t F_t\ , \tag{8}$$

where F_t represents the continuously compounded futures price returns, the coefficient hr_t is the hedge ratio which is known as the coefficient β in equation (5) and (6), and X_t denotes the return of the hedge investment. Thus, the hedged variance of the hedge equation is expressed as

$$Var(H) = \sigma_h^2 = Var(X_t) \tag{9}$$

The hedge effectiveness (HE) can be assessed using Eqn. (10). Hedge performance improves with increasing HE.

$$HE = \frac{Var(U) - Var(H)}{Var(U)} = \frac{\sigma_u^2 - \sigma_h^2}{\sigma_u^2} \tag{10}$$

EMPIRICAL RESULTS

Under the Rolling Scheme

Table 1 lists the out-of-sample forecasts. Notably, the MSE decreases with an increasing in-sample period under the correct model in this study. However, when the observation period is short, the forecasting errors under the correct model are not lower than under the incorrect one. For example, during the 250 day estimation period, the MSE is found to be 1.5926 in model 1, which exceeds the 1.5943 in model 2. The test statistics for MSE equality are significantly negative under the 1% level, indicating that the forecast error in model 2 is significantly higher than in model 1, the relationship between spot and nearby futures of WTI crude oil price, that is, the real model performs worse in one-step-ahead forecasting. Nevertheless, the situation reverses when the estimate period is increased to either 500 or 1250 days, and the MSE in unrestricted. Model 2 becomes significantly smaller than in the restricted model 1. This indicates that more useful information during the estimate period will reduce the variance of parameter estimation, and increase the accuracy of the out-of-sample forecast. Obviously, reducing the sample increases the variance of the parameter estimation and may even obtain reverse results.

Stronger evidence comes from forecast encompassing tests. In both the 500 and 1250 day estimation periods, the null hypotheses of model 1 encompassing model 2 are significantly rejected at the 1% levels. This means that the model with structural change contains more information than the model without structural change. However, the results for the 250 day estimation period are not as clear as for longer periods, and the conclusions reached are inconsistent between the 250 day estimation period and the longer estimation periods. The statistics in ENC-T tests is 2.642, and is significant at the 1% level, and the statistics in ENC-F is 3.767, indicating that there is insufficient evidence to reject the assumption that the dummy variable is useful. According to Clark and McCracken (2001, 2004), ENC-F is the most powerful measure, followed by ENC-T and MSE-F, while the least powerful measure is MSE-T. Therefore, without the powerful support provided by ENC-F, it cannot be concluded that model 2 does have more useful information than model 1 in 250 day estimation periods. Obviously, this is inconsistent with the fact that the structural break already exists in this instance.

Table 1: Empirical Results under the Rolling Scheme

Model 1: $S_t = \alpha_0 + \beta_0 F_t + u_{1,t}$				Model 2: $S_t = \alpha_0 + \alpha_1 D_t + (\beta_0 + \beta_1 D_t) F_t + u_{2,t}$			
	250 days	500 days	1250 days		250 days	500 days	1250 days
MAE	0.6340	0.6403	0.6392	MAE	0.6335	0.6326	0.6283
RMSE	1.2620	1.2656	1.2635	RMSE	1.2626	1.2621	1.2606
MSE	1.5926	1.6017	1.5966	MSE	1.5943	1.5930	1.5893
Tests for equal MSE (Forecast accuracy test)							
	250 days	500 days	1250 days				
MSE-F	-2.154**	11.111**	9.344**				
MSE-T	-0.753*	1.133**	0.688*				
Forecast encompassing test							
	250 days	500 days	1250 days				
ENC-F	3.767	16.879**	17.827**				
ENC-T	2.642**	3.453**	2.655**				

*Notes: Model 1 and model 2 are restricted and unrestricted models, respectively. MAE is the mean of the absolute forecast error, MSE is the mean square error, and RMSE is the square root of MSE. The forecast accuracy test and forecast encompassing test statistics and the relative critical values are suggested by Clark and McCracken (2001, 2004). **, * represent significances under the 1% and 5% levels.*

Under the Recursive Scheme

Table 2 lists the outcomes achieved using the recursive scheme. The MSE of model 2 remains almost unchanged with an increasing estimation period. This pattern is different from the rolling scheme, the recursive scheme is characterized by increasing the information added as forecasting moves forward in time. Therefore, when the forecast horizon becomes far enough away, the forecast errors become almost identical owing to almost identical sized sets of information being used for the estimation. As shown in this study, the forecast horizon is from March 21, 1997 to June 28, 2005. The horizon contains a total of 2,023 forecast days, and the MSEs are almost fixed at 1.5885 in any in-sample period. Besides, in the correct model-setting, forecasting under the recursive scheme obtains smaller MSE than under the rolling scheme resulting from the overall information involved.

Regarding the forecast accuracy test, MSE in model 2 are significantly lower than in model 1 at the 1% level for the 500 estimation period. However, for the 250 day period, the results of the MSE-F and MSE-T tests are inconsistent. The value of MSE-F is 17.474 and does not provide enough evidence to reject the null hypothesis that MSE is identical in models 1 and 2, but the MSE-T test is significantly below the 1% level. Based on the suggestion by Clark and McCracken (2001, 2004), the forecast accuracy tests are less useful than the forecast encompassing tests, thus, this study more closely examines the ENC tests. As for the forecast encompassing tests, the results are consistent among estimation periods. All the statistics are significant under the 1% level, indicating that model 2 really contains more useful information than model 1. The dummy variable of structural change is necessary, and eliminating the feature of structural change would increase the forecasting error.

Hedge Effectiveness

The empirical results are listed in Table 3. Under either rolling or recursive schemes, the hedge effectiveness is higher in model 2 except for the short estimation period, 125 days. The hedge performance is said to be improved in the correct model, but the result is biased during the short estimation period. Furthermore, under the rolling scheme with the correct model, the values of hedge effectiveness are 0.77111 and 0.77144 for the 500 day and 1250 day estimation periods respectively. The hedge performance improves with increasing estimation period. Compared with the recursive scheme, the hedge effectiveness is around 0.7716, and all values are higher than for the rolling scheme in model 2. In summary, under the condition of the model with structural change, the hedge effectiveness is optimized when the estimation period is longest, particularly under the recursive scheme. These results are consistent with the above arguments; that is, the hedge performance is better under the recursive scheme owing to the consideration of all information.

Table 2: Empirical Results under the Recursive Scheme

Model 1: $S_t = \alpha_0 + \beta_0 F_t + u_{1,t}$			Model 2: $S_t = \alpha_0 + \alpha_1 D_t + (\beta_0 + \beta_1 D_t) F_t + u_{2,t}$		
	250 days	500 days		250 days	500 days
MAE	0.6454	0.6494	MAE	0.6271	0.6271
RMSE	1.2657	1.2671	RMSE	1.2604	1.2603
MSE	1.6022	1.6054	MSE	1.5885	1.5885
Tests for equal MSE (Forecast accuracy test)					
	250 days	500 days			
MSE-F	17.474	21.582**			
MSE-T	1.199**	1.317**			
Forecast encompassing test					
	250 days	500 days			
ENC-F	26.624**	31.714**			
ENC-T	3.637**	3.842**			

*Notes: Model 1 and model 2 are restricted and unrestricted models, respectively. MAE is the mean of the absolute forecast error, MSE is the mean square error, and RMSE is the square root of MSE. The forecast accuracy test and forecast encompassing test statistics and the relative critical values are suggested by Clark and McCracken (2001, 2004). **, * represent significances under the 5% and 1% levels.*

Table 3: Hedge Effectiveness

	Rolling scheme		Recursive scheme	
Estimation period	Model 1	Model 2	Model 1	Model 2
250 days	0.77132	0.77130	0.76926	0.77159
500 days	0.76954	0.77111	0.76874	0.77158
1250 days	0.76999	0.77144		

CONCLUSION

The length of estimation period is always a problem in forecasting. An excessively long in-sample period is charged with reducing forecast efficiency, while an excessively short sample period will increase the variance of the parameter estimates and bias the out-of-sample forecasts. Accordingly, this study uses a simple nested linear model to demonstrate that one-step-ahead forecasting with longer estimation periods performs better when more information is contained. Both rolling window and recursive schemes are used to examine the forecast accuracy and encompassing for different estimation periods. The empirical results show that forecasts under the correct model reduces measurement loss, and the mean square forecast errors decrease with increasing in-sample period. The inclusion of more information in the estimate period lowers the variance of parameter estimation, and increases the accuracy of the out-of-sample forecast. For the forecast accuracy and encompassing tests, the use of fewer observations in making an estimate could easily lead to wrong decisions and the acceptance of the wrong model. Finally, these results are also consistent with hedge effectiveness, namely that the effectiveness is better under the recursive scheme in terms of considering all useful information.

END NOTES

[1] The oil price was $43.96 per barrel on 4 January, 2005 and was $66.79 per barrel on August 15, 2005.

[2] Gabriel et al. (2003) note that testing for structural change is a means of testing the model specifications.

[3] The preferred forecasts, namely those with better performance, depend on the competing forecasts lacking information. Chong and Hendry (1986) and Clements and Hendry (1993) termed this situation the preferred forecasts encompassing the competing forecasts. Clark and McCracken (2001, 2004) developed and formulated the tests.

[4] Harvey et al. (1998) suggested that it is reasonable to assume that the forecast errors of one-step-ahead forecasts are not autocorrelated, so that the regression-base test is very straightforward to implement.

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