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Predictability of Bank Stock Returns: Evidence from the Endurance Index of Bank Investor Sentiment

Ling T. He[a]

a. Carmichael Professor of Finance, Department of Economics & Finance, University of Central Arkansas, Conway, Arkansas

Abstract

Applying the binomial probability distribution-based investor sentiment endurance model developed by He (2012) to the banking sector, this paper creates an endurance index of bank investor sentiment. The index reflects the probability of the high or low stock price being the closing price for the NASDAQ Bank Index. Results of this study reveal a considerable forecasting ability of the index. Both monthly and quarterly forecasts of bank stock returns demonstrate high accuracy. For example, the overall accuracy for the six-quarter rolling forecasts reaches 71.25%. The true forecasting model and accuracy ratio applied in this study provide investors and analysts of bank stocks, as well as banking professionals, with effective analytical tools.

Keywords: endurance index of bank investor sentiment; forecasting ability; rolling forecast; accuracy ratio

JEL: G17, G21

1. Introduction

Bank stocks constitute an important segment of the U.S. capital market. Returns and risk involved in banking operations create a remarkable dynamic for bank stock prices. Identifying determinants or predictors of bank stock returns has attracted a great amount of attention for both academics and banking professionals for decades. However, empirical results reported in the literature are still far from conclusive. Therefore, to improve the forecasting ability for bank stock returns by applying a new forecasting approach becomes the primary motivation of this study.

Many previous studies use market factors, such as changes in the overall stock market and interest rates, to explain changes in bank stock prices. These studies yield inconsistent results. The sensitivity of bank stock returns to changes in interest rates is found to be insignificant in some studies (Stone, 1974; Lloyd and Shick, 1977; Chance and Lane, 1980; and Sweeney and Warga, 1986), but significant in other studies (Lynge and Zumwalt, 1980; Booth and Officer, 1985; Scoott and Peterson, 1986; and Chaudry and Reichert, 1999). He, et. al. (1996) report that bank stock returns are very sensitive to changes in the real estate market, in addition to the stock market and interest rates. Employing the Flexible Least Squares method, He and Reichert (2003) provide empirical evidence that all three factors are important in explaining risk premiums included in financial institutions and bank stock returns; however, their explaining power changes over time.

In contrast, other studies find that some firm-specific fundamental variables have explaining or predicting power on the cross-section bank stock returns. These variables include earnings, loan-loss reserves, non-interest income, leverage, and more (Grammatikos and Saunders, 1990; Musumeci and Sinkey, 1990; Madura and Zarruk, 1992; Kim and Santomero, 1993; and Docking et al., 1997). Furthermore, Cooper et al (2003) point out that results of their out-of-sample forecasting suggest that the cross-sectional predictability of bank stock returns is not due to increased risk, but rather is a result of investor under-reaction to changes in banks' fundamental variables. Lu et al. (2012) report their empirical evidence that firm-specific information sentiment extracted from public news has considerable influence on the prediction of abnormal stock returns. Nevertheless, according to Howe and Haggard (2012), there is a shortcoming to using firm-specific variables in the banking industry, since banks are more opaque than industrial firms in terms of providing less firm-specific information regarding equity returns than industrial matching firms. Therefore, it is not uncommon that both micro and macro data are simultaneously used in banking analysis, such as predicting bank failures (Shen and Hsieh, 2011).

In order to integrate findings of past studies and improve on the prediction of bank stock returns, a comprehensive measure of investor reactions to all sorts of relevant information, macro or firm specific, should be developed. An endurance index of investor sentiment developed by He (2012) might be a good candidate in this regard. This binomial probability distribution model-based index demonstrates decent forecasting abilities on monthly and quarterly changes in the stock market and housing sector (He, 2014). This study applies the sentiment endurance model into the banking sector to examine predictability of bank stock returns.

Delong et al. (1990) defines investor sentiment as investor interpretations and reactions to news, which reflect investors' beliefs about future cash flows and investment risks, and therefore, stock valuations. Changes in investor sentiment, forming and correcting reactions to news, are a major driving force of stock market returns. Barberis et al. (1998) point out that investors may underreact to news when stock prices slowly reflect news. On the other hand, investors might consistently overreact to news in the same direction over long horizons and cause stocks to be overpriced. Only those substantial and persistent investor reactions, not short-lived ones or noises, can shape dynamics in the stock market.

The endurance index of investor sentiment can better measure persistence of investor sentiment and quantify its effect on stock prices, compared with many other investor sentiment indexes described in the literature, such as investor survey- or investor mood-based indexes, retail investor trades, mutual fund flows, trading volume, dividend premium, close-end fund discount, opinion implied volatility, IPO first-day returns, IPO volume, equity issues over total new issues, and insider trading (see Baker and Wurgler, 2007). Because of the following imbedded limitations as discussed by He (2012), few of the existing investor sentiment proxies can be used to forecast stock returns.

First, all time interval-based sentiment indexes, regardless of whether they are derived from a regular or irregular frequency, cannot effectively measure a continuous process that reflects stock price dynamics. The continuing changes in stock prices are simply the results of ongoing alterations in investor reactions to news; that is, investor reactions to news are always instantaneously quantified into stock prices, no matter whether the reactions are rational or irrational; optimistic or pessimistic. Second, short-lived sentiments, such as opinion- and mood-based ones, are instable and most of them cancel out each other during a trading day. The prices that reflect the long-lasting resilient sentiment cannot be offset and will sustain until the end of a trading day. Therefore, only the closing prices can evaluate investors' persistent reactions to all significant events and news during the entire trading day. Many other prices cancel out each other during the trading day, as many unreliable sentiments cancel out each other. Third, event-based sentiment indexes record investor reactions to a particular type of news, therefore, cannot effectively predict stock price dynamics, a mirror of all relevant important information.

During a trading day, the fact that stock prices keep fluctuating drives stock prices more or less inclining to the high or low price until the closure of the stock market. This dynamic process shows investor sentiment as well as resilience or endurance of the sentiment. Only long-lasting resilient sentiment will be built into the closing price. Therefore, the probability of the high or low price being the closing price becomes an effective measure of the endurance of investor sentiment. The sentiment endurance index essentially quantifies the probabilities of the most optimistic and pessimistic sentiments, represented by the high and low prices, respectively, being the closing price. The following binomial probability distribution model suggested by He (2012) can describe the process:

$$P_t \times H_t + (1 - P_t) \times L_t = C_t, \tag{1}$$

where P_t represents the probability of the high price (H_t) being the closing price (C_t) and takes a value of zero to unity; and $(1 - P_t)$ is the probability of the low price (L_t) being the closing price. When P_t=0.5, the overall investor sentiment is neutral; if $P_t > 0.5$, the overall sentiment is optimistic; and while $P_t < 0.5$ indicates the overall pessimistic sentiment. Therefore, the index of investor sentiment endurance (SE) at time t is revealed in

$$SE_t = (P_t - 0.5). \tag{2}$$

A positive SE indicates a bullish sentiment toward the closing price; while a negative SE represents a higher probability of the low price being the closing price. The sentiment endurance index is derived from stock price dynamics, therefore, can effectively quantify investor continuous momentous reactions to all important news. The persistence or endurance of these reactions, implied in closing prices, is the major driver of stock returns.

As an important sector of the U.S. economy, the banking industry and bank stocks deserve serious research attention. Regardless of numerous efforts committed in the past, there is no consensus on the driving force of bank stock dynamics and the predictability of bank stock returns. To push this line of research a step further, developing and applying a different forecasting method is necessary. The main purpose of this study is to create an endurance index of bank investor sentiment and use it to forecast bank stock returns. This study performs not only in-sample and out-of-sample forecasting, like many previous studies did, but also a true forecasting by using all lag terms of independent variables.

The endurance index of bank investor sentiment is easy to construct and use for forecasting bank stock returns. The demonstrated forecasting power of the index on banks stock returns in this study has broad implications on banking-related business practices through providing an effective forecasting tool to investors and analysts of bank stocks as well as banking risk management professionals.

The remainder of the paper is organized as the follow. Section 2 describes the data and methods used in this study. Section 3 discusses empirical results and Section 4 concludes major findings.

2. Data and Methods

The NASDAQ Bank Index, which contains 404 U.S. commercial bank stocks is analyzed in this study. The daily indexes are averaged into monthly and quarterly series. The index numbers include High, Low, and Closing prices. The index starts in November 1990 and the last month covered in this study is December 2012. Data availability dictates the sample period. The monthly and quarterly SE indexes are constructed based on equations (1) and (2).

The monthly and quarterly endurance indexes of bank investor sentiment and the lag terms of the indexes are used as independent variables to explain, respectively, variations in monthly and quarterly bank stock returns represented by percentage changes in the NASDAQ Bank Index, in order to examine the explanatory power of each independent variable. Regression results indicate that only the current term and one-period lagged term of SE have significant influence on bank stock returns. The result is in line with findings in previous studies. For example, He (2012) reports that both the SE and lagged SE can explain a significant portion of variation in the stock market, which is represented by the S&P 500 Stock Index, and Baker and Wurgler (2006) find that their lagged sentiment index has a negative impact on returns of some stock portfolios.

The rolling estimates of coefficients of SE and Lagged SE are obtained from the following regression model:

$$R_t = a_t + b_t SE_t + c_t SE_{t-1} + e_t, \qquad (3)$$

where R_t represents bank stock returns at time t. The rolling coefficient estimates of SE and one-period lagged SE, together with the rolling constant terms, are used to perform three different types of forecasting. First, the in-sample forecasting is used, which uses rolling coefficients at time t to predict bank stock returns at time t. There is no time lag between predicting variables and the variable to be predicted.

$$F_t = a_t + (b_t \times SE_t) + (c_t \times SE_{t-1}), \tag{4}$$

where F_t represents forecasts.

Second, different from Equation (4), the following equation (5) uses one-period lagged rolling coefficients and constant terms to forecast bank stock returns:

$$F_t = a_{t-1} + (b_{t-1} \times SE_t) + (c_{t-1} \times SE_{t-1}). \tag{5}$$

Although this out-of-sample forecasting can demonstrate some forecasting ability of rolling coefficients, there exists a potential problem that SE at time t is used in predicting of bank stock returns at time t. To overcome this drawback, the following true forecasting model is estimated:

$$F_t = a_{t-1} + (b_{t-1} \times SE_{t-1}) + (c_{t-1} \times SE_{t-1}). \tag{6}$$

In Equation (6) the one-period lagged term of SE replaces SE and multiplies with the one-period lagged coefficient of b. Equation (6) is not completely consistent with the rolling regression model, Equation (3), in which coefficient of b represents sensitivity of bank stock returns to SE not the one-period lagged SE. However, SE is stable at times of t and t-1 as evidenced by similar means and standard deviations for SE and lagged SE (Table 1). This result may warrant the feasibility of Equation (6).

In order to assess the quality of forecasting, the t-test, without the assumption of equal variances, an analysis of variance (ANOVA) is used to examine if the averages of rolling forecasts are statistically indifferent from the actual bank stock returns. An insignificant test statistic implies that the forecasts are statistically accurate, that is, there is no considerable difference, on average, between the rolling forecasts and the actual bank stock returns. There is an embedded problem in the method: extreme positive and negative inaccurate forecasts can cancel out each other and result in a mean of forecasts close to the mean of actual bank stock returns. A more rigorous measure of the forecasting quality is the accuracy ratio, which can effectively avoid the potential unreliable and misleading test results. The accuracy ratio is derived from the following procedure (He, 2012).

Both series of forecasts and actual bank stock returns are sorted by forecast errors (forecasts – actual returns) from the smallest to the largest, respectively. Forecasts with negative errors are called under-forecasts, while those with positive errors are referred as over-forecasts. Then, all observations associated with positive forecast errors (the lower part of the sample) are deleted. The remaining observations with negative forecast errors are already in an order of the smallest (most inaccurate, farthest from the zero error) to the largest (most accurate). The equality test for the forecasts and corresponding real bank stock returns is performed repeatedly in a loop that begins with all under-forecasts and corresponding stock returns. If the statistic of the first test is significant, observation one of both variables goes out. If the second test statistic remains significant, observation two is out. As more inaccurate forecasts are thrown out, the significance level of the test statistic keeps declining, from the 1%, 5%, to 10%. The loop stops only when the test statistic is not significant at the 10% level, that is, the null hypothesis of equal means of the forecasts and relevant bank stock returns cannot be rejected at the 10% level. Therefore, the remaining under-forecasts are considered accurate.

The above process is repeated one more time with variables sorted by forecast errors from the largest to the smallest to identify accurate over-forecasts. The total number of accurate forecasts is simply the sum of accurate over- and under-forecasts. The number divided by the total number of forecasts is the accurate ratio, which effectively eliminates the problem of cancellation between extreme under- and over-forecasts.

Compared with the absolute forecast error, a traditional measure of forecasting quality, the accuracy ratio provides additional insights into rolling forecasting quality through distinguishing under- and over-forecasts. Obviously, this additional information, accuracy ratios of under- and over-forecasts, is essential in assessing the overall forecasting quality.

3. Results

The descriptive statistics for the period of 1991 through August 2012 (Table 1) suggest an optimistic sentiment of bank investors as evidenced with positive monthly and quarterly average SE, the investor sentiment endurance index, and the one-period lagged terms (SEL). It is consistent with Figures 1 and 2 which illustrate an overall optimistic tone dominated in the most part of the sample period. If the investor sentiment endurance index can effectively capture the overall investor reactions to news, the positive investor sentiment should be reflected in high stock returns. The average monthly bank stock returns of 0.85% and quarterly returns of 2.47% over the sample period provide supportive evidence. The fact that both monthly and quarterly series of SE and SEL share sizable positive coefficients of correlation with bank stock returns indicates the relevance and importance of sentiment endurance index in driving bank stock prices. Results of regression Model (3) confirm that both the current term of the sentiment endurance index (SE) and one-period lagged index (SEL) have significant explanatory power on the bank stock returns based on either monthly or quarterly data. The two variables can explain about 46.5% of variation in the monthly bank stock returns and 58.5% in quarterly returns (Table 1).

Figures 1 and 2 and Table 1 indicate some differences between the monthly and quarterly series of SE. For instance, the quarterly SE and SEL are less volatile than the monthly SE and SEL. Furthermore, the correlations between bank stock returns and quarterly SE and SEL seem higher than that between the monthly SE and SEL and bank stock returns. Those differences can affect forecasting quality and make the quarterly SE and SEL more accurate predictors of future bank stock returns. The difference in volatility also determines different time variation paths for the monthly and quarterly series of SE and SEL. This might lead to different forecasting qualities based on the two series of SE and SEL in different periods.

The assessment of forecasting quality is based on three different rolling forecasts. The first one is in-sample forecasting. A set of coefficients of SE and SEL in Model (3) are estimated and then multiplied with SE and SEL, combined with the constant terms, to get in-sample forecasts (Equation (4)). All in-sample forecasts, 6- & 12-month and 4-, 6-, & 8-

quarter rolling forecasts, are statistically indifferent from the real bank stock returns (Table 2). The result is not surprising, because the in-sample forecasting is only about testing the goodness of fit for data. When one-period lagged coefficients and constant terms replace the current ones, out-of-sample forecasts are produced. Out-of-sample forecasts can be used to examine forecasting power of estimated rolling coefficients of SE and SEL. Although the averages of absolute errors for different kinds of out-of-sample forecasts are larger than that for the in-sample forecasts, t-statistics of the equality test without an assumption of equal variance once again fail to reject the null hypothesis of equal means of Forecast and Return for all rolling out-of-sample forecasts. The same results are obtained for the true forecasts that use not only lagged coefficients and intercepts but also one-period lagged independent variables, SEL. Overall, results reported in Table 2 suggest decent forecasting ability for SE. Nonetheless, the equality test possibly exaggerate forecasting quality, because it simply compares the mean of forecasts with the mean of actual returns, therefore, the test result may be skewed by the potential cancelations of under- and over-forecasts.

In order to strictly measure the forecasting ability of SE, this study calculates accuracy ratios for various kinds of rolling true forecasts. The calculation of accuracy ratios involves several steps. First, all true forecasts are divided into the under- or over-forecast subsets to remove the potential cancelation problems. For example, the total number of 6-month rolling true forecasts is 255 in which 129 are under-forecasts and 126 over-forecasts (Table 3). After large under- and over-forecasts are rejected by the equality test at the 10% level in separate testing loops, the retained under-forecasts (UF) are 57 while retained over-forecasts (OF) are 46. Those retained UF and OF are statistically indifferent from their corresponding actual bank stock returns. Therefore, the accuracy ratio for UF is 0.4419 (57/129) and for OF is 0.3651 (46/126). The accuracy ratio for the combination of UF and OF is 0.4039 (103/255). These three accuracy ratios (0.4553, 0.3968, and 0.4257) for 12-month rolling true forecasts are all higher than that for the 6-month rolling forecasts (Table 3). The result suggests that the 12-month rolling method has the better forecasting ability. But there is a similarity between 6- and 12-month forecasts, that is, both enjoy noticeably higher accuracy ratios for UF than that for OF, after the rejections of highly inaccurate forecasts.

Figures 3 and 4 graphically compare all 6- and 12-month rolling forecasts with actual bank stock returns, respectively. The graphs show that a few extremely inaccurate forecasts appear to be under-forecasts, especially for the 6-month rolling forecasts. The result suggests that the under-forecasts are highly volatile in the highly bearish stock market, when a shorter rolling estimation period, in this case, the 6-month period, is used. However, the extremely negative bank investor sentiment cannot last very long. When the estimation period extends to 12 months, there is a substantial reduction in the negative volatility (Figure 4). With a few exceptions, the negative volatility nearly disappears in all quarterly rolling forecasts (Figures 5, 6, and 7). It reflects that the quarterly data can effectively smooth out the comparatively short-lived extremely negative investor sentiment. As a result, the quarterly data can produce more accurate forecasts.

All 4-, 6-, and 8-quarterly rolling forecasts exhibit high accuracy. They have overall accuracy ratios of 0.6585, 0.7125, and 0.6282, respectively (Table 3). In fact, all three kinds of quarterly forecasts enjoy considerable higher accuracy ratios in every aspect than that for the monthly forecasts. The better forecasting ability of the quarterly forecasts is consistent with the lower standard deviation of quarterly SE and higher correlations between bank stock returns and quarterly SE and SEL, compared with monthly SE (Table 1).

Accuracy ratios for both OF and UF of quarterly rolling forecasts indicate that the length of the rolling estimation period can affect the accuracy of forecasting. Results in Table 3 suggest that a 6-quarter rolling estimation is appropriate to predict future changes in bank stock prices. The accuracy of both UF and OF for 6-quarter rolling forecasts are apparently higher than that for 4- and 8-quarter rolling forecasts, as a result, the overall accuracy ratio of 6-quarter rolling forecasts is the highest, 0.7125 vs. 0.6585 for 4-quarter and 0.6282 for 8-quarter rolling forecasts (Table 3). The quarterly forecasts demonstrate higher accuracy ratios for over-forecasts, that is, fewer inaccurate (large) over-forecasts, compared with under-forecasts. This result is inconsistent with the monthly rolling forecasts.

There are several additional interesting observations from the bottom part of Table 3 which contains distribution of the retained UF and OF over two sub-periods suggested by Figures 1 and 2: a more optimistic period of 1991-1999 and a more pessimistic period of 2000-2012. In fact, the size of SE in the first period is almost twice of that in the second period (Table 1). In the optimistic period both monthly and quarterly forecasts show higher accuracy, compared with the pessimistic period. The only exception is the 4-quarter rolling forecasts which display the same accuracy (Table 3). The second interesting observation is that the 12-month rolling forecasts are more accurate than the 6-month rolling forecasts in both periods. Third, among three types of quarterly forecasts, the 6-quarter rolling forecasts produce the highest accuracy ratios in both periods. Finally, quarterly forecasts outperform monthly forecasts in both periods.

4. Concluding Comments

In order to enhance the forecasting ability on bank stock returns, this study constructs a binomial probability distribution-based endurance index of bank investor sentiment to measures the probability of the high or low bank stock price being the closing price. This bank investor sentiment endurance index directly uses bank stock price differentials to quantify bank investor reactions to all relevant news. Empirical results in this study suggest that the index can not only play a significant role in explaining variations in bank stock returns, but also possess considerable forecasting ability on bank stock returns.

The quarterly endurance index produces more accurate rolling true forecasts, Forecasts derived from all lagged independent variables, than does the monthly endurance index. The 6-quarter rolling forecasts have an overall accuracy ratio as high as 71.12%; even the lowest overall accuracy ratio reaches 62.82% (the 8-quarter rolling forecasts), in contrast to the monthly rolling forecasts, which have accuracy ratios ranged from 40% to 43%.

Results of this study also indicate that forecasting ability of the endurance index is time varying. Both monthly and quarterly forecasts are more accurate in the optimistic period (1991-1999) than in the pessimistic period (2000-2012). Nonetheless, quarterly forecasts outperform monthly forecasts in both periods.

Findings of this study evidently suggest that the bank investor sentiment endurance index can be used to effectively predict future changes in the bank stock prices on a monthly or quarterly basis. The demonstrated predictability of bank stock returns has broad practical implications on banking-related business practices, such as analyzing and investing in bank stocks as well as conducting risk management in the banking industry.

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Table 1. Descriptive Statistics and Regression Coefficients of Sentiment Endurance Index

	Monthly Data (1991.01-2012.08)			Quarterly Data (1991.Q2-2012.Q2)		
	N	Mean	St. Deviation	N	Mean	St. Deviation
Return	260	0.0085	0.0431	85	0.0247	0.0772
SE	260	0.0622	0.1008	85	0.0602	0.0761
SEL	260	0.0627	0.1009	85	0.0617	0.0764

Coefficients of Correlation

Return	1.0000			1.0000		
SE	0.5764	1.0000		0.6531	1.0000	
SEL	0.5365	0.3356	1.0000	0.5524	0.2560	1.0000
	Return	SE	SEL	Return	SE	SEL

Coefficient estimates of Model (3) with the dependent variable of Return

	SE	SEL	Constant	R^2
Monthly regression	0.1912	0.1654	-0.0138	0.4649
	(9.221)	(7.982)	(-5.577)	
Quarterly regression	0.5555	0.4166	-0.0344	0.5854
	(7.445)	(5.603)	(-4.425)	

	Monthly Data (1991.01-1999.12)			(2000.01-2012.08)		
	N	Mean	St. Deviation	N	Mean	St. Deviation
Return	108	0.0185	0.0405	152	0.0014	0.0436
SE	108	0.0833	0.1153	152	0.0472	0.0864
SEL	108	0.0842	0.1153	152	0.0474	0.0864

Coefficients of Correlation

Return	1.0000			1.0000		
SE	0.5820	1.0000		0.5604	1.0000	
SEL	0.6016	0.3592	1.0000	0.4637	0.2561	1.0000
	Return	SE	SEL	Return	SE	SEL

	Quarterly Data (1991.Q1-1999.Q4)			(2000.Q1-2012.Q2)		
	N	Mean	St. Deviation	N	Mean	St. Deviation
Return	35	0.0558	0.0743	50	0.0030	0.0723
SE	35	0.0801	0.0890	50	0.0462	0.0629
SEL	35	0.0820	0.0896	50	0.0475	0.0627

Coefficients of Correlation

Return	1.0000			1.0000		
SE	0.6032	1.0000		0.6739	1.0000	
SEL	0.6463	0.2851	1.0000	0.4051	0.1225	1.0000
	Return	SE	SEL	Return	SE	SEL

Return = percentage changes of the Nasdaq Bank Indexes. SE = Sentiment Endurance Index from Equations (1) and (2). SEL = one term lagged SE. N= number of observations used in calculations. The first observation is excluded from calculations because of the use of SEL. The lagged SE.t-values are in parentheses.

Table 2. Results of Equality Test for Forecast and Return Based on Different Rolling Regressions on Model (3)

6-Month Rolling Regressions

	Forecast	Return	t-stat	P-value	AbsError	N
In-Sample	0.0077	0.0076	0.0253	0.9798	0.0144	255
Out-of-Sample	0.0097	0.0076	0.4983	0.6185	0.0318	255
True Forecasting	0.0079	0.0076	0.0734	0.9415	0.0358	255

12-Month Rolling Regressions

	Forecast	Return	t-stat	P-value	AbsError	N
In-Sample	0.0091	0.0078	0.3880	0.6982	0.0179	249
Out-of-Sample	0.0103	0.0078	0.7121	0.4768	0.0244	249
True Forecasting	0.0094	0.0078	0.4200	0.6747	0.0313	249

4-Quarter Rolling Regressions

	Forecast	Return	t-stat	P-value	AbsError	N
In-Sample	0.0222	0.0236	-0.1173	0.9067	0.0150	82
Out-of-Sample	0.0091	0.0236	-1.0571	0.2921	0.0635	82
True Forecasting	0.0144	0.0236	-0.7017	0.4839	0.0638	82

6-Quarter Rolling Regressions

	Forecast	Return	t-stat	P-value	AbsError	N
In-Sample	0.0199	0.0209	-0.0853	0.9321	0.0232	80
Out-of-Sample	0.0111	0.0209	-0.7694	0.4428	0.0515	80
True Forecasting	0.0146	0.0209	-0.4857	0.6279	0.0598	80

8-Quarter Rolling Regressions

	Forecast	Return	t-stat	P-value	AbsError	N
In-Sample	0.0181	0.0195	-0.1228	0.9024	0.0268	78
Out-of-Sample	0.0191	0.0195	-0.0322	0.9743	0.0482	78
True Forecasting	0.0170	0.0195	-0.1957	0.8451	0.0605	78

In-Sample forecasting=Constant + (Coefficient of SE*SE) + (Coefficient of SEL*SEL).
Out-of-Sample forecasting=Constant_{t-1} + [$(\text{Coefficient of SE})_{t-1}$*SE] + [$(\text{Coefficient of SEL})_{t-1}$*SEL].
True Forecasting=Constant_{t-1} + [$(\text{Coefficient of SE})_{t-1}$*SEL] + [$(\text{Coefficient of SEL})_{t-1}$*SEL].
SE = Sentiment Endurance Index from Equations (1) and (2).
SEL = one term lagged SE.
AbsError=Absolute value of (Forecast-Return).
N= number of observations used in calculations.
t-stat= statistic of the test for equal means (Forecast and Return) without an assumption of equal variance.

Table 3. Accuracy Ratios for Different Kinds of Rolling True Forecasts

	6-Month	12-Month	4-Quarter	6-Quarter	8-Quarter
Under Forecasts (UF)	129	123	43	43	42
Retained UF	57	56	28	29	24
Accuracy Ratio	0.4419	0.4553	0.6512	0.6744	0.5714
Average Error	-0.0092	-0.0099	-0.0365	-0.0281	-0.0249
Over Forecasts (OF)	126	126	39	37	36
Retained OF	46	50	26	28	25
Accuracy Ratio	0.3651	0.3968	0.6667	0.7568	0.6944
Average Error	0.0098	0.0094	0.0252	0.0315	0.0320
Retained UF&OF	103	106	54	57	49
Total Forecasts	255	249	82	80	78
Accuracy Ratio	0.4039	0.4257	0.6585	0.7125	0.6282

Distribution of Retained UF&OF over Sub-Periods

	6-Month	12-Month	4-Quarter	6-Quarter	8-Quarter
1991.09-1999.12					
Retained UF&OF	46	44	21	23	18
Total Forecasts	103	97	32	30	28
Accuracy Ratio	0.4466	0.4536	0.6563	0.7667	0.6429
2000.01-2012.08					
Retained UF&OF	57	62	33	34	31
Total Forecasts	152	152	50	50	50
Accuracy Ratio	0.3750	0.4079	0.6600	0.6800	0.6200

Under Forecasts (UF) =Number of forecasts that are smaller than actual returns.
Over Forecasts (OF) =Number of forecasts that are greater than actual returns.
Retained UF=Number of under forecasts that are statistically indifferent from actual returns, after excluding large under forecasts at the 10% significance level.
Retained OF=Number of over forecasts that are statistically indifferent from actual returns, after excluding large over forecasts at the 10% significance level.
UF Retain Ratio=Retained UF/UF.
OF Retain Ratio=Retained OF/OF.
Accuracy Ratio=Ratio of Retained UF or OF to the number of forecasts.
Average Error=Average of (forecast-return) for Retained UF or Retained OF.

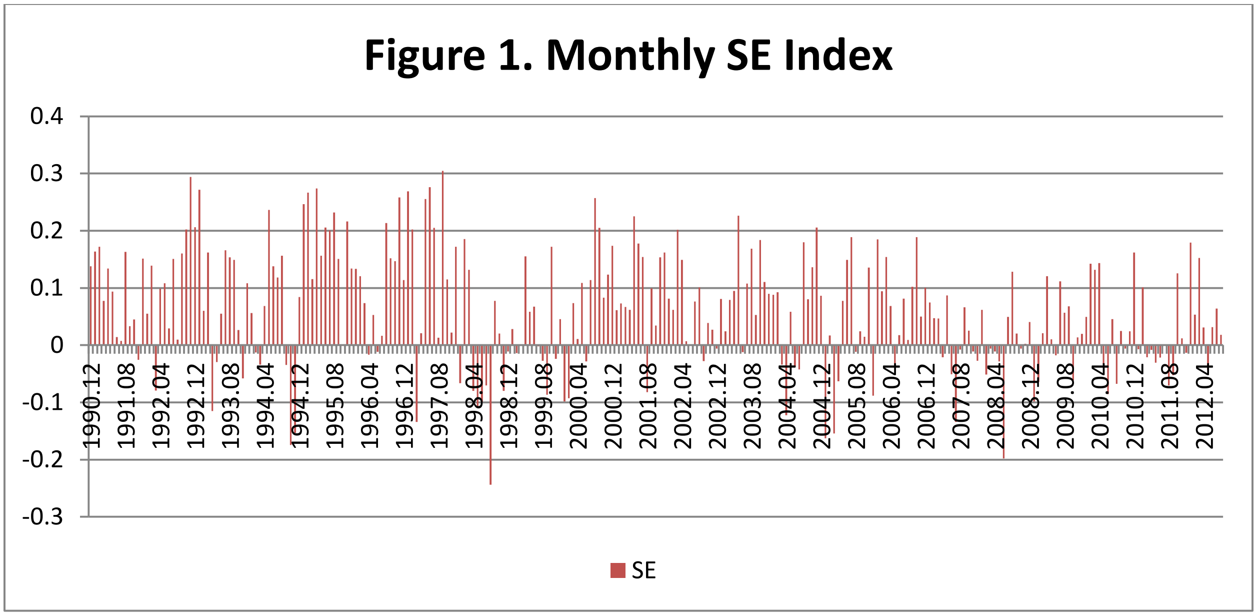


Figure 1. Monthly SE Index
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
1990.12
1991.08
1992.04
1992.12
1993.08
1994.04
1994.12
1995.08
1996.04
1996.12
1997.08
1998.04
1998.12
1999.08
2000.04
2000.12
2001.08
2002.04
2002.12
2003.08
2004.04
2004.12
2005.08
2006.04
2006.12
2007.08
2008.04
2008.12
2009.08
2010.04
2010.12
2011.08
2012.04
SE

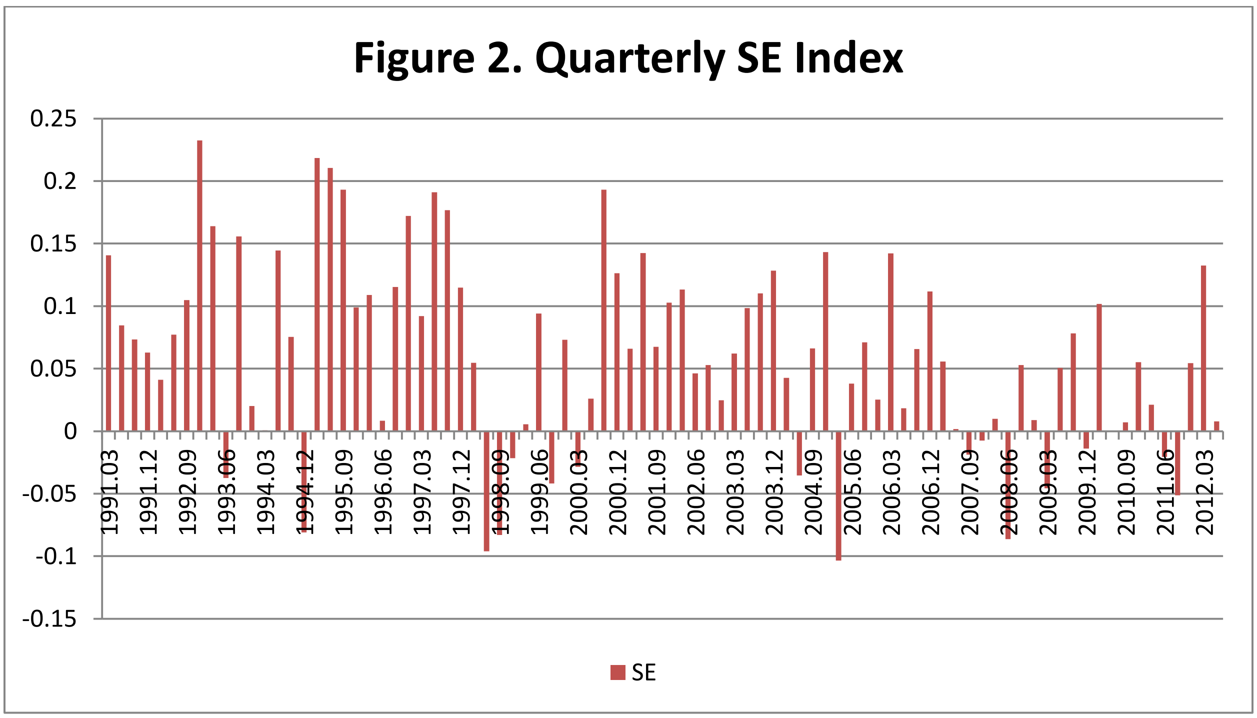


Figure 2. Quarterly SE Index
0.25
0.2
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
1991.03
1991.12
1992.09
1993.06
1994.03
1994.12
1995.09
1996.06
1997.03
1997.12
1998.09
1999.06
2000.03
2000.12
2001.09
2002.06
2003.03
2003.12
2004.09
2005.06
2006.03
2006.12
2007.09
2008.06
2009.03
2009.12
2010.09
2011.06
2012.03
SE

Figure 3. 6-Month Rolling True Forecasting

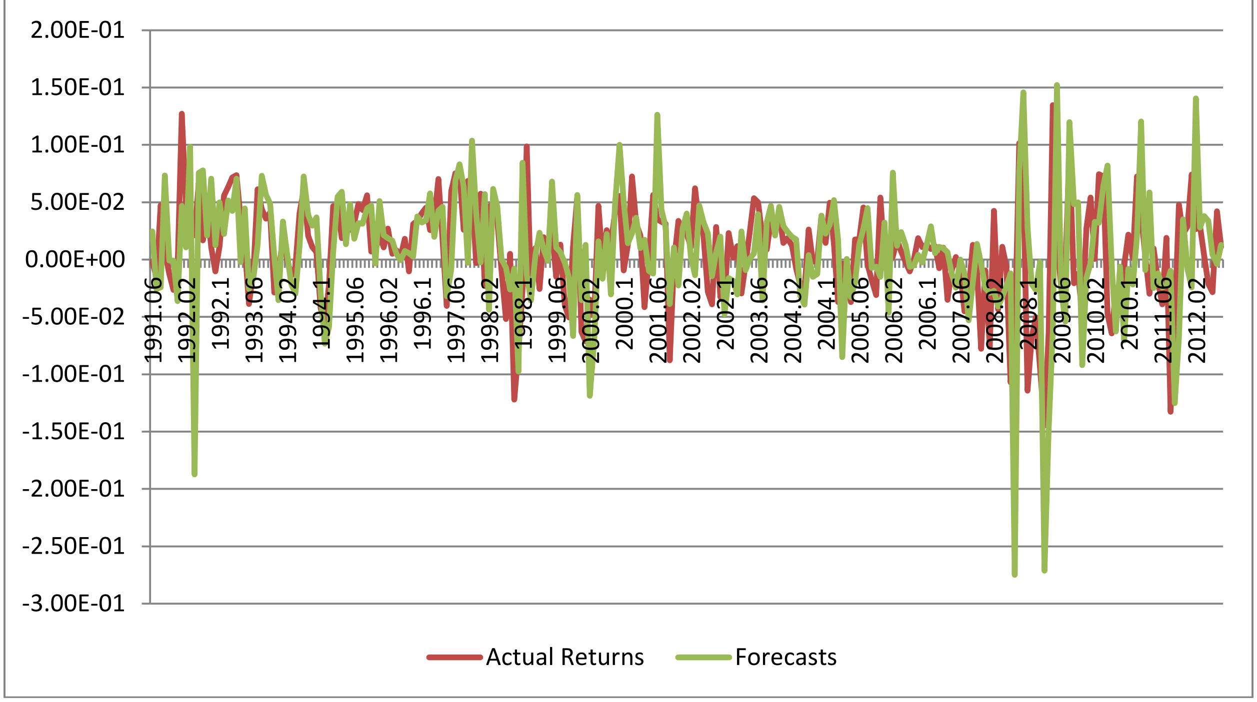
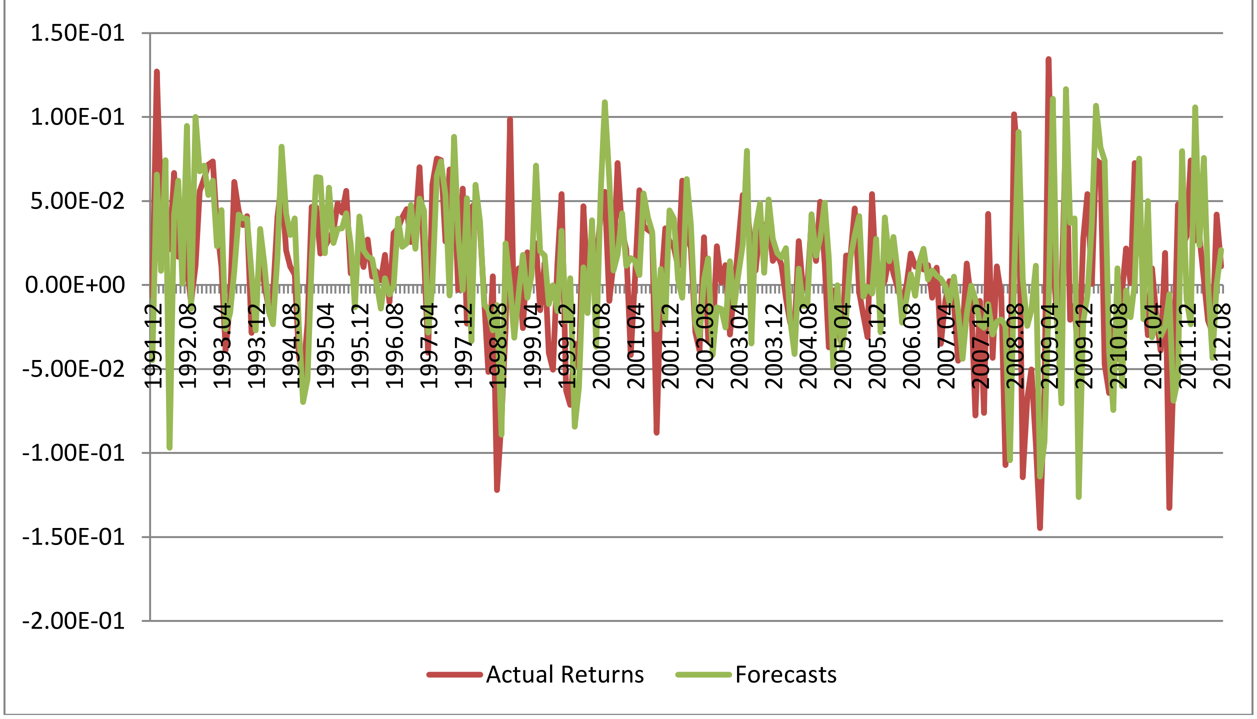


Figure 4. 12-Month Rolling True Forecasting



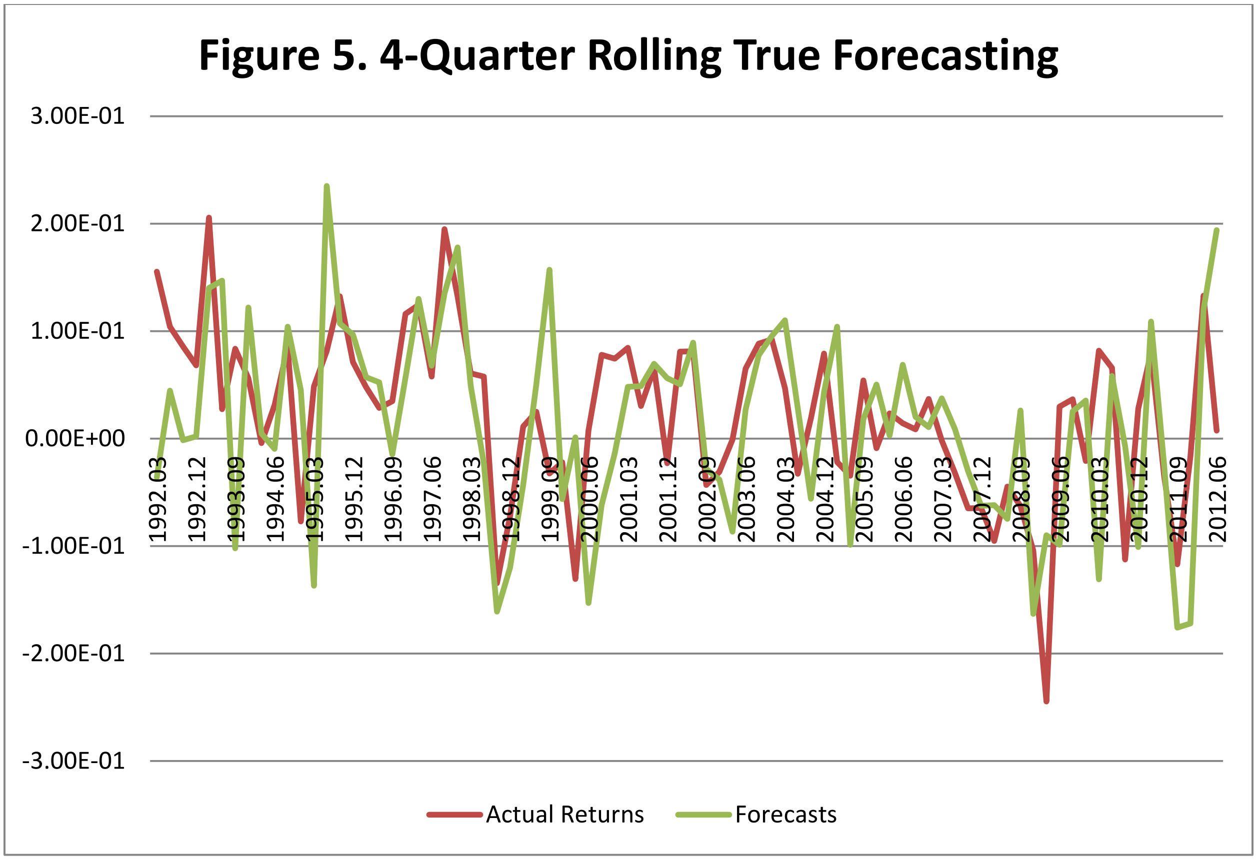


Figure 5. 4-Quarter Rolling True Forecasting
3.00E-01
2.00E-01
1.00E-01
0.00E+00
-1.00E-01
-2.00E-01
-3.00E-01
1992.03
1992.12
1993.09
1994.06
1995.03
1995.12
1996.09
1997.06
1998.03
1998.12
1999.09
2000.06
2001.03
2001.12
2002.09
2003.06
2004.03
2004.12
2005.09
2006.06
2007.03
2007.12
2008.09
2009.06
2010.03
2010.12
2011.09
2012.06
Actual Returns
Forecasts

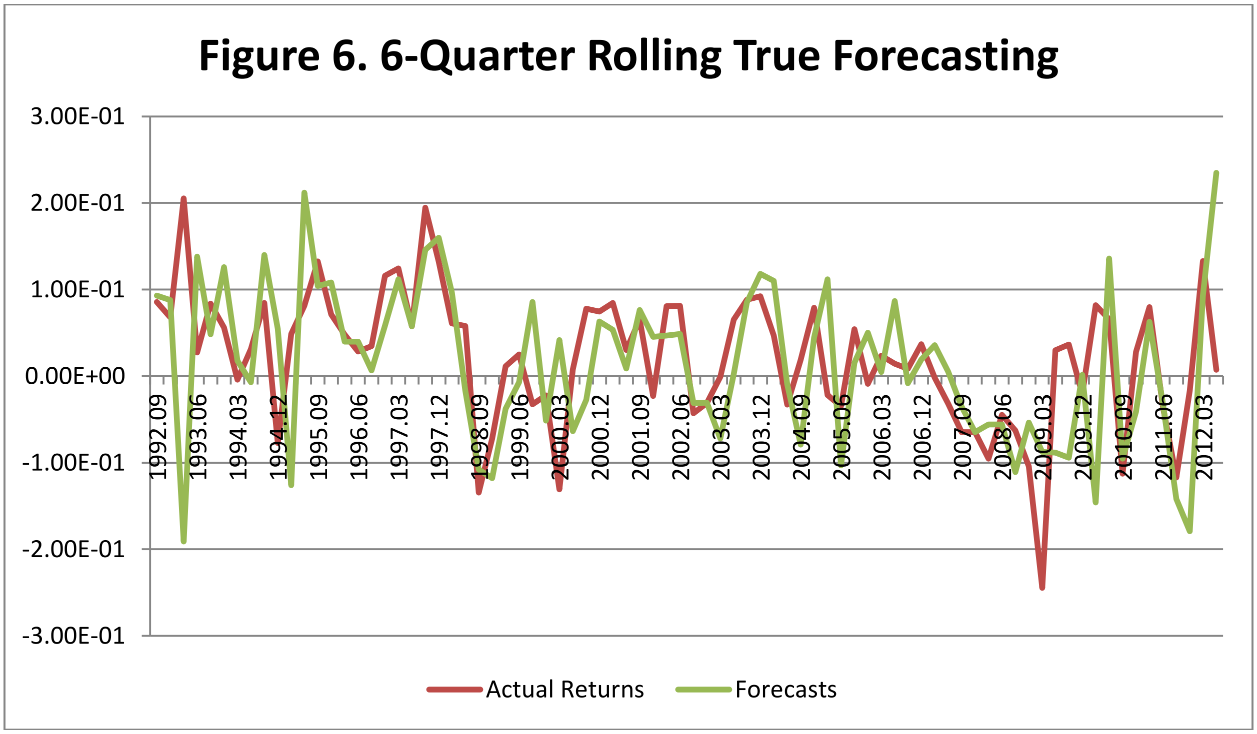


Figure 6. 6-Quarter Rolling True Forecasting
3.00E-01
2.00E-01
1.00E-01
0.00E+00
-1.00E-01
-2.00E-01
-3.00E-01
1992.09
1993.06
1994.03
1994.12
1995.09
1996.06
1997.03
1997.12
1998.09
1999.06
2000.03
2000.12
2001.09
2002.06
2003.03
2003.12
2004.09
2005.06
2006.03
2006.12
2007.09
2008.06
2009.03
2009.12
2010.09
2011.06
2012.03
Actual Returns
Forecasts

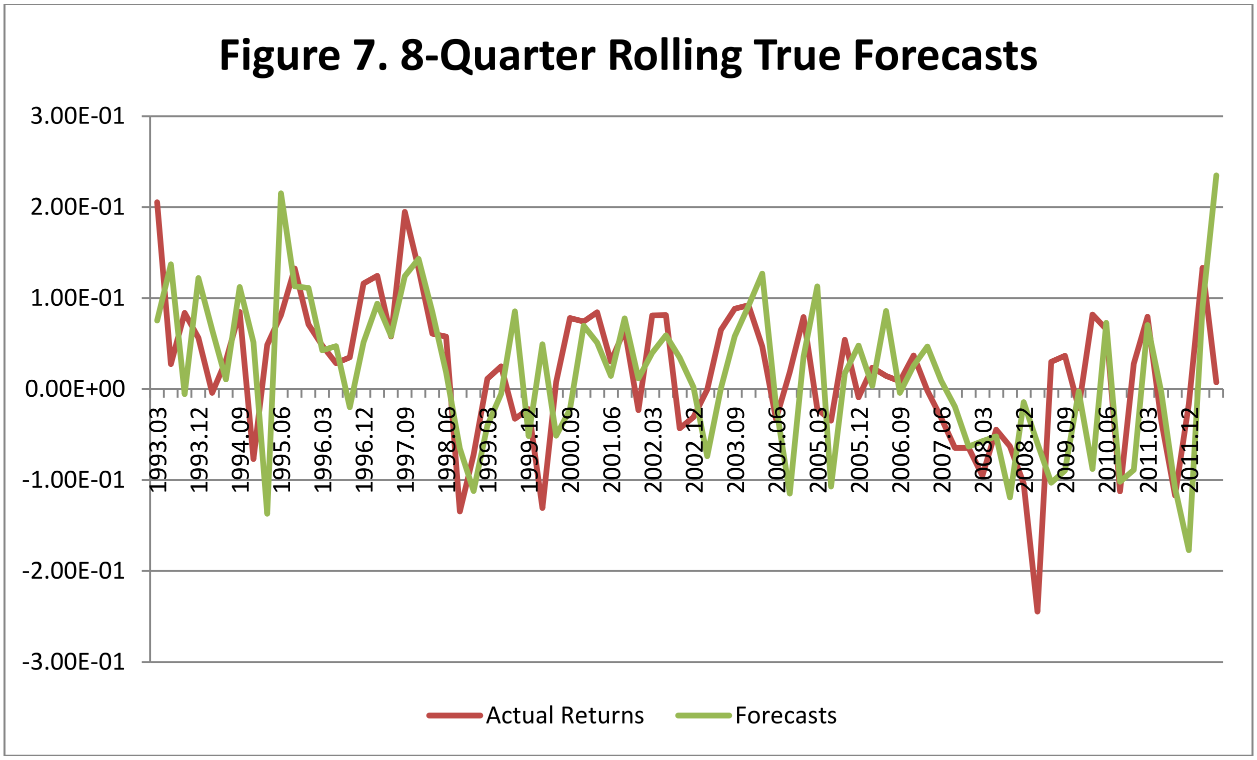


Figure 7. 8-Quarter Rolling True Forecasts
3.00E-01
2.00E-01
1.00E-01
0.00E+00
-1.00E-01
-2.00E-01
-3.00E-01
1993.03
1993.12
1994.09
1995.06
1996.03
1996.12
1997.09
1998.06
1999.03
1999.12
2000.09
2001.06
2002.03
2002.12
2003.09
2004.06
2005.03
2005.12
2006.09
2007.06
2008.03
2008.12
2009.09
2010.06
2011.03
2011.12
Actual Returns
Forecasts