

## A Test of the Predictability of Sector Returns

## ABSTRACT

This paper tests four different models for their ability to predict the returns of equities in industrial sectors. Using Seemingly Unrelated Regression (SUR) to estimate out of sample returns, we find that a multi-factor model does not consistently improve the accuracy of predictions over other models in the sense of a reduction in the mean squared-error from actual returns. However, the factor model does provide a better indication of the direction of future returns.

## INTRODUCTION

This article examines the ability of four different models to forecast the returns of equities in various sectors. More specifically however, is that we aim to test factors that have garnered lofty reputations in the literature as good predictors of future asset returns. If these factors have predictive qualities, then a factor model employing them could perhaps yield more accurate predictions of future returns than other models on a consistent basis. In addition, we test sector returns instead of overall market returns because this may reveal that the sensitivity of returns to factors varies by sector. Because sector returns are highly correlated, the error terms from using OLS regressions on them will share similar components, thus resulting in our use of Seemingly Unrelated Regression (SUR) estimations.

We find that the use of a multi-factor model does not consistently reduce the mean squared-error (MSE) of predicted returns when compared to other models that were tested, such as a single factor model.

The ability to successfully predict the future returns of assets has taken on a reputation similar to the pot of gold at the end of the rainbow. The traditional approach to asset management assumes that prices follow random walks. This framework assumes that the rate of return required by investors on assets is constant and that future returns should be unforecastable. However, the literature is swamped with research refuting these implications of the random walk hypothesis. The focus of these papers has been on the predictive capabilities of various variables. Recent papers, such as Campbell and Schiller (2001), argue that some predictive power should lie in the fundamental valuation ratios of price/earnings and dividend/price. They were able to show that the reason these ratios display mean reversion over time was from future changes in asset prices, not from changes in dividends or earnings. Additionally, a tremendous body of literature has focused on the ability of various interest rates and credit spreads to predict future asset returns. Bernanke (1990) and Patelis (1993) motivate the background for this notion quite well. Bernanke showed that interest rate

variables could be useful in predicting the course of the economy while Patelis demonstrated that expected stock returns are positively correlated with expected macroeconomic conditions. In fact, the justifications that are given as to why some interest rate based variables have predictive capabilities predominantly focus on how they can be thought of as indicators of future macroeconomic conditions. To the extent that macroeconomic conditions “guide” asset returns, these variables should prove to be quite useful in predictor models.

More specifically, Estrella and Hardouvelis (1991) show that the term structure of interest rates, a significant predictor of future asset returns, can also act as a predictor of future real economic activity. Fama and French (1989) believe that the reason the term spread and dividend yield are predictors of future asset returns is because they reflect short-term business cycles and long-term business conditions, respectively. The inspiration for other variables that were incorporated in our analysis come from studies of a similar nature. Bernanke and Blinder (1992) report that the federal funds rate is a good measure of monetary policy actions because of its sensitivity to the supply of bank reserves. Additionally, Bernanke (1990) found that the spread between the yields of commercial paper and Treasury bills predicted future economic activity better than any other credit spread that was tested. It was hypothesized that this spread serves as an indicator of the stance of monetary. Research abounds on the dual role of credit spreads as predictors of both future asset returns and future macroeconomic conditions.

A note of interest: this dual role is of considerable interest to both the finance community and economic community. Macroeconomists have long wondered if monetary policy shocks have real effects. If they do, then it would be natural for asset prices to react accordingly, thereby providing an economic grounding for their use in explaining asset returns. This is the concept of the “credit channel” transmission of monetary policy.

## DATA

Monthly return data (from March 1980 to June 2001) was obtained for the following Standard & Poor's sectors from DataStream: financials, transportation, utilities, and industrials.

Other data that was obtained for use in the models were:

- Effective U.S. Federal Funds Rate (7 Day Average)
- Spread between Baa - Aaa bond indices (from Moody's)
- U.S. Year Treasury Bond yield

Additionally, the following fundamental variables were used:

- Dividend yield for each sector
- P/E ratio for the S&P Composite Index

The sectors that were analyzed and the short time horizon of observations that was used in our analysis were both dictated by the dearth of fundamental data available for indices. We did use the longest time horizon possible given the limited availability of data.

## METHODOLOGY

### Models

The first step in our horse race was to specify models that would be able to adequately test the random walk hypothesis. If future asset returns are not forecastable, then factor models that find their roots in the CAPM or APT should do no better than educated guesses in predicting future returns. This was the impetus behind the first two models: a mean of log returns based on the entire sample ( $\mu$ ), and a mean of log returns based on shorter sampling periods ( $\mu_t$ ):

$$\text{Model 1: } r_{t+1} = \mu$$

$$\text{Model 2: } r_{t+1} = \mu_t$$

The third model is a one-factor dividend yield (DY) model:

$$\text{Model 3: } r_{t+1} = \alpha + \beta(\log DY_t) + \varepsilon_{t+1}$$

Finally, the fourth model is a multi-factor model attempting to take advantage of the predictive powers of the factors used:

$$\text{Model 4: } r_{t+1} = \alpha + \beta_1(ES_t) + \beta_2(CS_t) + \beta_3(\log DY_t) + \beta_4(r_t) + \beta_5(\Delta FF) + \varepsilon_{t+1}$$

Factor	Representative Variable
earnings spread	ES = T-Bond yield - E/P ratio
credit spread	CS = Baa yield - Aaa yield
lagged log return	$r_t$
change in fed. funds	$\Delta FF = FF_t - FF_{t-1}$

For each of the above factors,  $r_{t+1} = \log(1 + R_{t+1}) = \log(P_{t+1}/P_t + D_{t+1}/P_t)$ .  $R_t$ 's,  $P_t$ 's,  $D_t$ 's and  $DY_t$ 's represent simple returns, prices, dividends, and dividend yields, respectively. These models were used for each of the four sectors.

## **Fundamental Factors**

The reason for using dividend yield as a fundamental variable in both the single and multi-factor models follows from the work of Campbell and Shiller (2001). They conclude that the dividend yield and P/E ratios do a poor job of forecasting future dividend growth and earnings growth, but appear to be useful in forecasting future stock price changes, lending weight to the theory that stock prices are mean reverting with respect to fundamental valuation ratios.

Additionally, the purpose of using lagged returns in the multi-factor model is for its potential use as an indicator of stock momentum or mean reversion. Of note is that, extracting from the random walk hypothesis, the best guess of tomorrow's stock price is today's observed price.

## **Economic Factors**

The monetary variables used have been the subject of much research, as mentioned previously. For example, Bernanke and Blinder (1992) demonstrate that the federal funds rate is a good proxy for monetary policy shocks. Furthermore, Thorbecke and Alami (1992) conclude that the federal funds rate is a priced factor in the arbitrage pricing theory model of stock returns.

The credit spread that is included in the multi-factor model serves as a forward-looking indicator of investor sentiment. Economic intuition would lead us to believe that during periods of high returns, investors are less risk averse, and so will tend to prefer Baa rated bonds over Aaa rated bonds. However, during periods of poor returns, investors are more risk averse and will flock to safety by investing in the higher rated bonds. The latter phenomenon will result in a widening of the yield spread. Unlike the spread between 10 year T-Bonds and 1 year T-bills (Stock and Watson 1989), this credit spread has not received a great deal of attention in the literature for its predictive ability. The above Stock and Watson spread, which measures the tilt of the term structure, was

not statistically significant in our factor model and data could not be found for monthly commercial paper rates, making impossible the use of the aforementioned credit spread studied by Bernanke. We did consider other spreads for which data was available, but found that this spread was the only one that proved to be statistically significant in our model.

A similar argument can be made for the use of the spread between T-Bond yields and the earnings/price ratio. The closer these two measures are, the more investors are effectively saying that they are so worried about the future earnings power of corporations that they prefer the predictable interest payments offered by T-bonds. However, the further they move apart, the more investors are in effect betting on profits staying high or going even higher, as represented by low E/P ratios.

## **Approach**

To develop a scorecard by which we would gauge the performance of the models, we turned to the mean squared-error (MSE). Whichever model yielded the smallest MSE of predicted values versus actual observed values was declared the victor. The models were first estimated over an initial observation period of fifteen years (1980 - 1995). Stock returns are regressed on one lag of the factor variables, providing a predicted value (of monthly log return). This predicted value would then be compared to the actual value that was realized, which is consequently an out of sample data point. The squared-error would then be calculated, and then the models would be estimated all over again, but now increasing the estimation period by one month to include the observed return that was used in the squared-error calculation. The process of comparing a predicted return to a realized return would then be repeated. We are in effect increasing the number of observations used in estimating the models incrementally. This would be done for all four models for each of the sectors. Of course, this applies to all but the first model that was estimated only once per sector as it is based on all the observations of the sample. Once the intervals of estimation reached the point to where no more out-of-sample data was available to calculate errors, the mean of the accumulated squared-errors was taken for each of the models in each of the sectors.

## Seemingly Unrelated Regression (SUR)

OLS provides a starting point to estimate models, however we had two models that had to be estimated for four different sectors that were assumed to be correlated. Thus, the cross-sectional error terms across the estimations will be correlated (see table 4). As such, since we were faced with estimating panel data, we used SUR. Under SUR, a set of equations is allowed to have cross-equation error correlations. Considering these conditions, we believe that SUR will yield more robust estimates than OLS. Smith and Kohn (1998) show that an advantage of estimating a SUR system of equations is that fewer observations are needed to obtain reliable estimates than if each of the regression equations was estimated separately and the correlations ignored.

## RESULTS

The multi-factor model did not consistently reduce the MSE of predictions over the other models, as table 1 below shows. This result is not surprising considering the poor explanatory power of the factor model, as evidenced by its low  $R^2$  across all sectors (see table 3). This low  $R^2$  can be explained in part by the high volatility of actual returns versus the lower volatility of predicted returns that are generated by the model.

However, the multi-factor model did produce the best MSE results for two sectors: transportation and industrials. The reason for this is not perfectly clear. An inspection of the t-statistics calculated from the total sample regression shows that some of the factors are relatively more significant for these two sectors than the others (see table 3). More specifically, the first factor (FS) is highly significant for both the transportation and industrial sectors. Furthermore, the second and third factors (CS, log DY) are also relatively more significant for the transportation sector than the others. One possible implication is that these factors are particularly important in explaining the returns of these sectors. It is not obvious if there exist any contemporaneous structural differences between these two sectors and the other two (financial and utility) that would justify this observation though.

Nonetheless, one potentially important advantage of the multi-factor model is that a regression of its predicted values against actual returns provides  $R^2$ 's that are more consistent than the other models across the four sectors (see table 2). Specifically, these are the out-of-sample returns predicted by the model for the years 1995-2001. (See figures 3-6). This out-of-sample  $R^2$  is also known as the information coefficient (IC) and is sometimes used to measure the forecasting skill of an asset manager or model. An IC of 1 indicates a perfect linear relationship between predicted and actual returns, while an IC of 0 indicates no linear relationship. Since the factor model yielded stable IC's across the sectors, it is providing better predictions than the other models regarding the *direction* of future returns.

Also of note is that the single-factor dividend yield model consistently produced the largest MSE. This is not too surprising a result. We would expect that a multi-factor model would improve estimates over a single-factor model if for no other reason than it incorporates more information in generating a prediction of return. Furthermore, the first model incorporates information about future returns, so its predicted values are in essence in-sample predictions.

The economic intuition behind the factors is affirmed by the betas of the regression (see table 3). We see that, as expected, the beta of dividend yield is positive. This implies that increases in the ratio indicate higher future returns, which will act to bring the ratio down in the future. This is the conclusion reached by Campbell and Shiller.

Additionally, the betas are negative for the credit spread factor, meaning that a widening of the credit spread would predict lower future returns. A widening of the credit spread could be a reflection of increased investor risk aversion. This sentiment would be embodied by investors rebalancing their portfolios away from relatively high risk assets towards relatively low risk assets. An example of this is shifting out of lower rated bonds for higher rated ones, or shifting out of stocks in favor of bonds. The pessimism indicated by a widening of the credit spread could possibly reveal information about lower expected future equity returns in this latter manner.

The beta for the earnings spread factor has a negative sign for similar reasons. The negative sign implies that a widening of the spread will predict lower future returns. The movement of the earnings/price ratio away from the yield on low risk Treasury bonds could be indicative of the appetite for risk of investors. If investors are confident about the potential future earnings growth of corporations, they will shift resources out of cash and into equity, and will pay a premium for the shares of those companies, lowering the earnings/price ratio. Holding the yield on T-Bonds constant, a drop in the earnings/price ratio will widen the spread. However, as the earnings/price ratio falls, future returns are expected to fall, restoring the mean reversion of this ratio

(Campbell and Shiller, 2001). To the extent that the earnings/price ratio is a forward-looking indicator of investor sentiment, this spread could aid in predicting future asset returns. An implication of our model is that this spread is not significantly important for the returns of utility stocks, in contrast to the other sectors. To further test this observation, we would need information on the earnings/price ratio specific to stocks in the utility sector. This data was not available.

Furthermore, the change in the federal funds rate is not a significant explanatory variable for any of the sectors. This is somewhat of a surprising result and may be explained in part by the observation that the effect of changes of the federal funds rate cannot be fully observed over a one month period and that short-term prices seem to react primarily to unexpected changes in the rate.

Intuition alone does not provide an obvious answer as to what the sign of the lagged return factor should be. If returns are high one period, we expect them to be high the next period as well, and vice versa. This type of analysis would lead one to believe that the beta should be positive. However, if returns are mean reverting, then one would expect a negative beta. But mean reversion depends on the relative level of returns. It is during times of very high or very low returns when the effects of mean reversion are believed to be the most pronounced. The beta for lagged returns in the model is negative, siding with the mean reversion hypothesis. However, the lagged returns factor is not significant for any of the sectors.

## CONCLUSION

The results of our analysis lead to the conclusion that although some variables may have some predictive capabilities, the functional use of them for strategic investing is severely limited. The best comparison that can be made is how the multi-factor model measured up against the sample mean model (model 2). The MSE of the factor model did not provide consistently better results when compared to model 2. It did improve the accuracy of estimates over a single factor model however, and any comparison to the first model (total sample mean) would not be fair as it takes into account future data.

The multi-factor model did provide better and more consistent results over the other models in terms of the information coefficient. This implies that although it may not provide more accurate estimates of future returns in an absolute sense, it does provide estimates that are more indicative of the direction of future returns. Furthermore, the multi-factor model reveals that the sensitivity of returns to factors varies by sector. The economic reasons as to why this occurs are not obvious and could be a source of future research.

The analysis that was performed was limited by the lack of data available. For sectors, dividend yield data was only available from 1980, and price/earnings ratio data was not available at all. Thus, we did not have full reign over the variables that were selected for the factor model and the time horizon was limited as well. Furthermore, we only assumed that the error-terms were correlated cross-sectionally, and not over time. This could be a source of future improvements.

## TABLES AND FIGURES

### Out-of-Sample Results

March 1995-June 2001 (N=78)

**Table 1: MSE**

	Model 1	Model 2	Model 3	Model 4
TRANSPORTATION	0.00277	0.00278	0.00292	0.00265
UTILITIES	0.00212	0.00213	0.00221	0.00218
FINANCIAL	0.00403	0.00406	0.00434	0.00414
INDUSTRIALS	0.00215	0.00216	0.00222	0.00209

**Table 2: R<sup>2</sup>**

	Model 1	Model 2	Model 3	Model 4
TRANSPORTATION	-0.0000	-0.1689	0.3211	0.2520
UTILITIES	-0.0000	-0.3140	0.2255	0.2024
FINANCIAL	-0.0000	-0.2779	0.0142	0.1105
INDUSTRIALS	-0.0000	-0.1860	0.0803	0.1641

### Entire-Sample Results

Data covers monthly observations from March 1980 through July 2001 (N=254 for each sector).

### Seemingly Unrelated Regression (SUR) Results for Sector Returns Against Explanatory Variables

**Table 3: Multi-Factor Model**

T-statistics reported in parenthesis. \*, \*\*, \*\*\*, denote significance at the 10, 5, and 1 percent levels, respectively.

	Alpha	$\beta_1$	$\beta_2$	$\beta_3$	$\beta_4$	$\beta_5$	R <sup>2</sup>
TRANSPORTATION	0.307*** (3.080)	-0.010*** (-3.027)	-0.028** (-2.337)	0.039*** (2.694)	-0.052 (-1.047)	-0.009* (-1.879)	0.070
UTILITIES	0.209*** (3.069)	-0.003 (-1.595)	-0.019** (-2.30)	0.0317*** (2.741)	-0.078 (-1.367)	-0.001 (-0.207)	0.040
FINANCIALS	0.212*** (2.713)	-0.007** (-2.139)	-0.022* (-1.919)	0.0273** (2.305)	-0.021 (-0.433)	-0.006 (-1.282)	0.017
INDUSTRIALS	0.132** (2.554)	-0.007*** (-2.732)	-0.014* (-1.754)	0.015** (1.982)	-0.046 (-0.977)	-0.004 (-1.062)	0.040

**Table 4: Cross-error term correlations for Multi-Factor Model by Sector**

Equation	Transportation	Utilities	Financials	Industrials
Transportation	1.0000			
Utilities	0.3677	1.0000		
Financials	0.6816	0.4961	1.0000	
Industrials	0.7207	0.3800	0.6800	1.0000

**Figure 1: Monthly Forecasted Return vs. Realized Return for each sector**

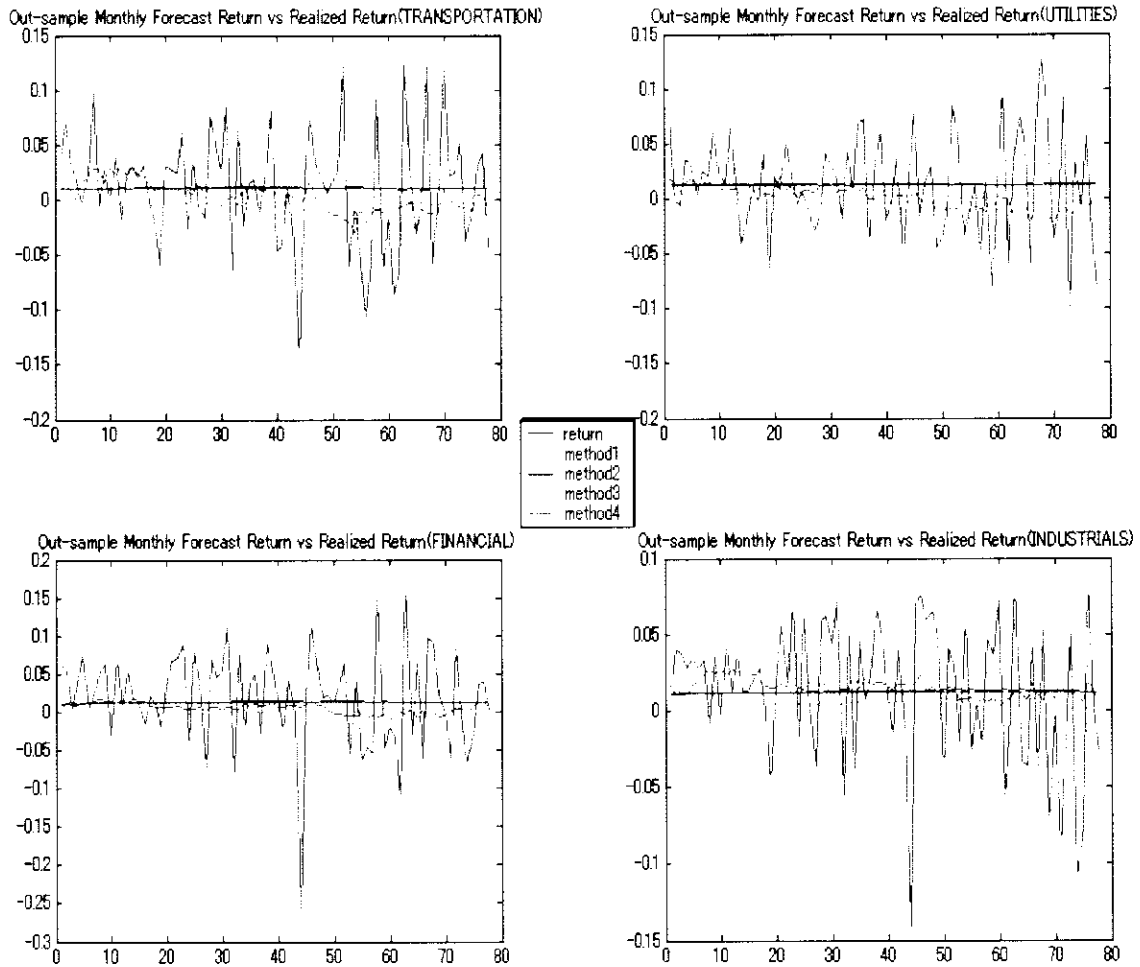


Figure 2: Bar Chart of MSE for each sector:

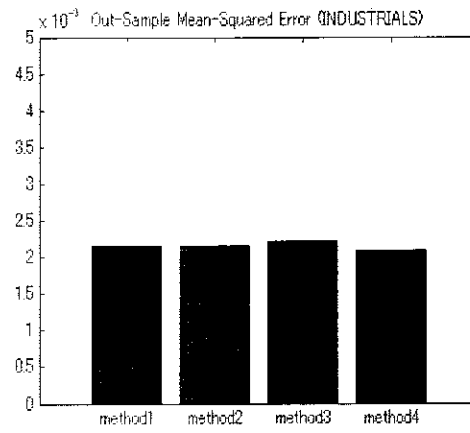
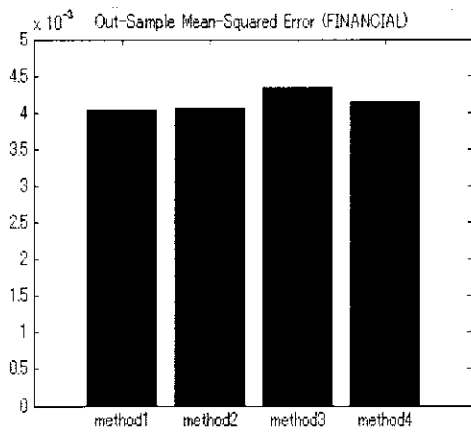
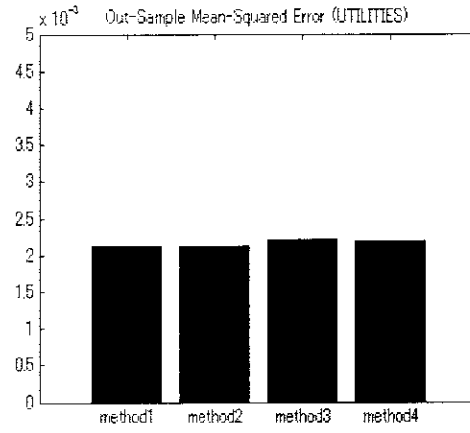
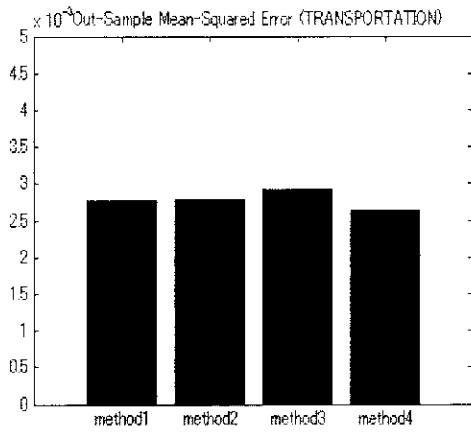


Figure 3: Forecasted Return vs. Realized Return (Transportation)

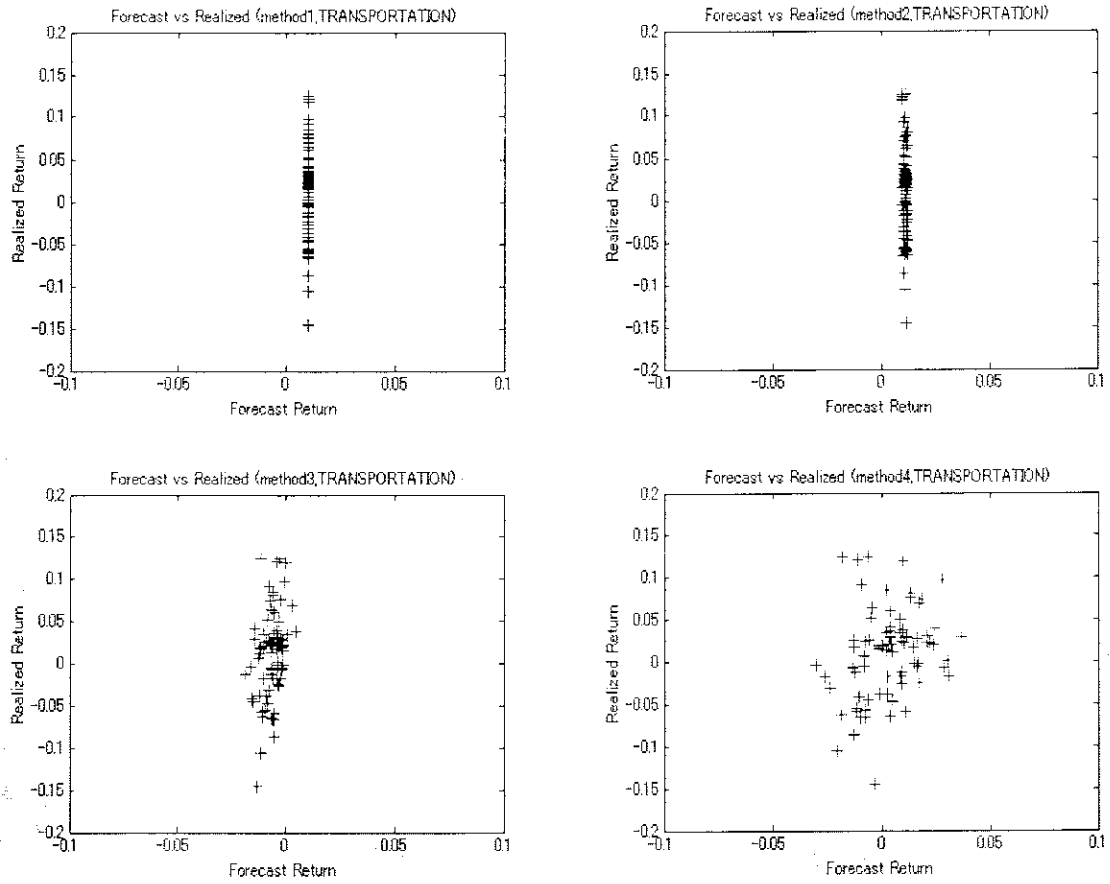


Figure 4: Forecasted Return vs. Realized Return (Utilities)

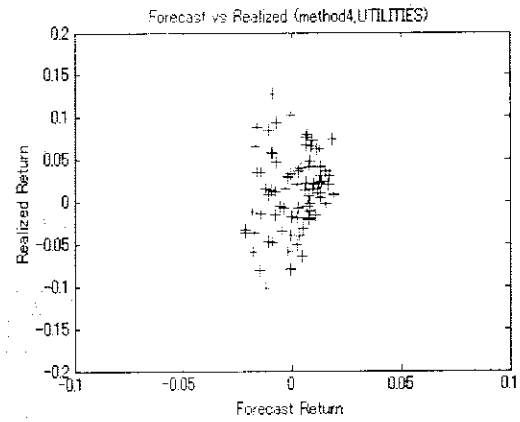
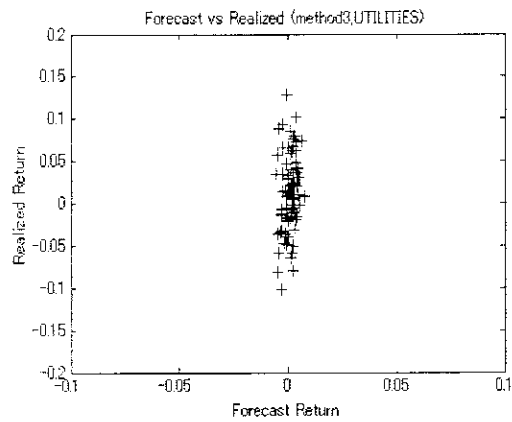
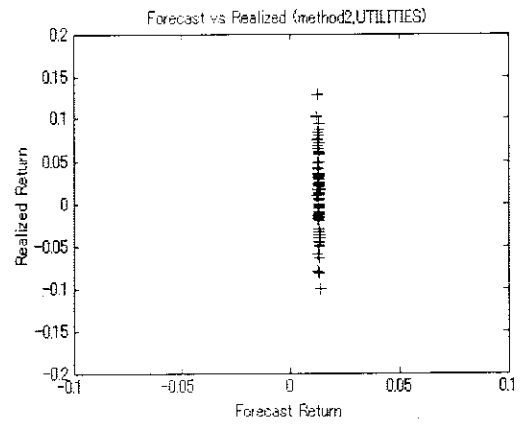
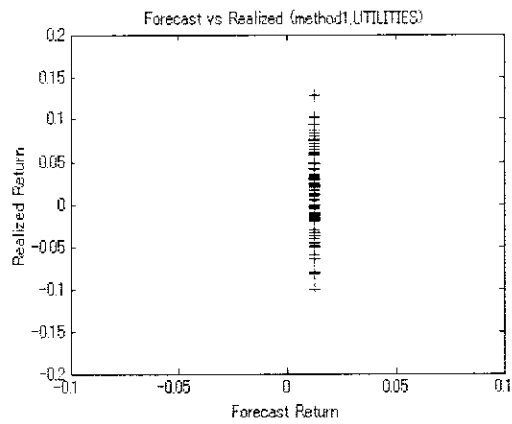


Figure 5: Forecasted Return vs. Realized Return (Financials)

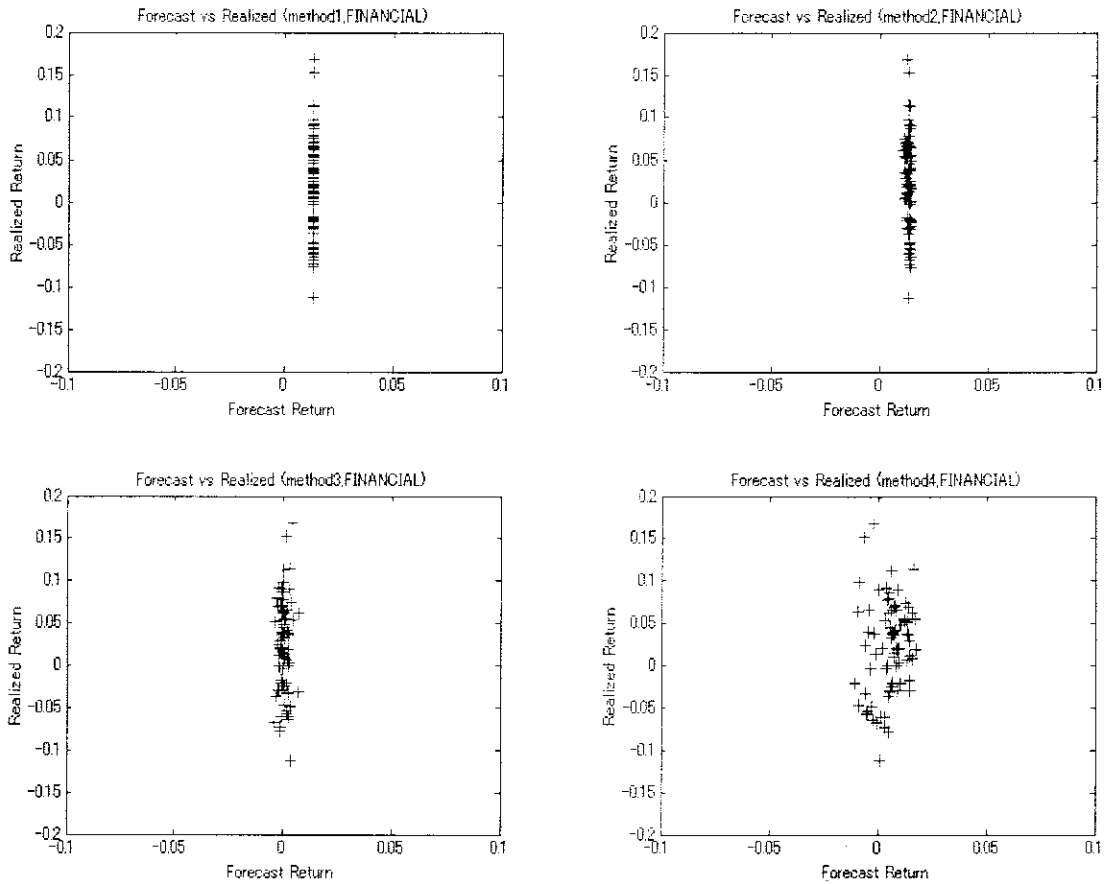
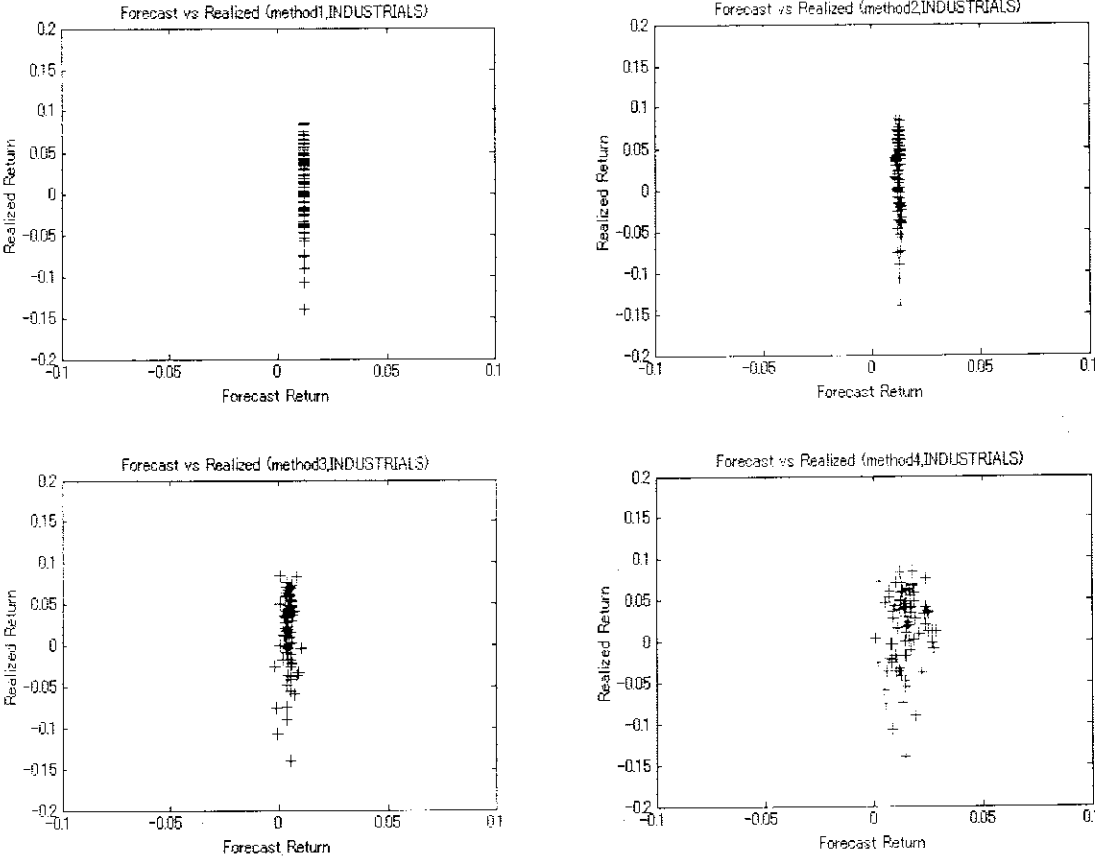


Figure 6: Forecasted Return vs. Realized Return (Industrials)



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