Value Factors Do Not Forecast Returns for S&P 500 Stocks

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Abstract

This paper investigates how effectively value factors can forecast future returns for stocks in the S&P 500.

Ranked portfolios and linear models are constructed from a set of quarterly value factor from 1998 to 2013. Portfolios are drawn from the quarterly S&P 500 stock universe to avoid survivor bias.

Over this time period, with a set of over 400 or more stocks per quarter, the returns from ranked portfolios or forecast by linear models produce at best weak performance compared to the S&P 500 index returns.

These results suggest that for this fifteen year time period, for the large capitalization S&P 500 stocks, the value factors examined here are not useful for constructing portfolios.

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Introduction

Investors will choose to buy stocks that they believe will increase in value. In doing this, the investor is making a forecast for the future return of the stock.

Value investing is based on the idea that a set of one or more value factors can be used to forecast future return. The literature on value investing is so large that it could easily consume a book length bibliography. In 1951 Benjamin Graham and David Dodd published their classic *Securities Analysis*, which described a value driven approach to investing. Benjamin Graham's most famous student, Warren Buffet, used value based portfolio analysis in his early days as a stock portfolio manager[12].

The actual process followed by a value investor may include human judgement about the future prospects of a company combined with a quantitative estimation of corporate value factors[14]. This paper focuses on computationally driven quantitative analysis of portfolios using value factors. These factors, like book value to price (B2P), are calculated from the information in quarterly annual reports.

Corporate Value Factors

A value investors looks for companies whose stock is under-priced relative to a set of value factors. There are a wide variety of factors that may drive stock prices and returns. Some of these factors may be macro-economic factors like the interest rate, the employment or construction indexes. The most commonly referenced value factor is the ratio of the stock price to the earnings per share (which is generally referred to as the price earnings ratio or P/E ratio). A low price earnings ratio may indicate that a company's stock is under-priced. The value investor hopes that when the "market" recognizes this mispricing, the stock price will rise.

Technology stocks and other growth companies can be a notable exception to corporate value metrics. At the time this paper was written Google had a price earnings ratio of about 30. Facebook had a P/E ratio of 141 and Amazon had a price earnings ratio of over 1,400. Twitter had no earnings, so the company had no P/E ratio.

The value factors that are investigated in this paper are calculated for the historical S&P 500 stocks, from 1998 through 2013. The S&P 500 is composed of stocks with large market capitalization.

The data to calculate these factors was obtained from the CRSP/Compustat Merged Database available from Wharton Research Data Service (WRDS).[1] For a detailed discussion of the Fundamentals Quarterly data set in WRDS see [11]. The value factors discussed in this paper are based on those discussed in Chapter 5 of *Quantitative Equity Portfolio Management*[4]. A description of how these value factors are calculated from the WRDS data set can be found in [11].

The value factors are summarized in Table 1:

MV	Market Value
EV	Enterprise Value
CF02EV	Cash Flow from Operations to Enterprise Value
RONA	Return On Net operating Assets
EBITDA2EV	Earnings Before Interest, Taxes, Depreciation and Amortization to Enterprise Value
E2PFY0	Trailing 12-month earnings to market capitalization
BB2P	Net buyback to market capitalization
BB2EV	Net external financing to enterprise value
B2P	Book to market capitalization
S2EV	Sales to Enterprise Value

Table 1: Value Factor Description

These value factors were chosen because they are frequently cited as indicators of future return (see Chapter 5 of [4]). For example, one popular factor is the the earnings to enterprise value factor (EBITDA2EV) factor, which is a ratio of earnings to the purchase price of the company. Larger values (closer to 1) suggest that a company is inexpensive relative to earnings, which in theory means that the stock is more likely to rise in value.

The stock universe used in this paper is drawn from the S&P 500 index for a given quarter. The constituents of the S&P 500 index change over time as stocks are added and removed from the index. When a portfolio from the

[1] Wharton Research Data Services (WRDS) was used in preparing this paper. This service and the data available thereon constitute valuable intellectual property and trade secrets of WRDS and/or its third-party suppliers.

S&P 500 universe is constructed, it is built from the S&P 500 constituents at that time to avoid survivor bias.

The value factors are constructed from the information obtained from the corporate quarterly reports that companies are required to file with the US Securities and Exchange Commission (SEC.) To match the quarterly factors, quarterly returns are constructed from the quarterly close price for each stock in the portfolio.

Corporate quarterly data is not immediately available. In many cases there is a lag of six months (two quarters). When constructing a linear model, the value factors are lagged by two quarters relative to the future return (constructed from the close price). This should reflect market reality, since the value factors for a given quarter are not available to "the market" for six months.

Ranked Portfolios and Linear Models

In this paper, the effectiveness of the value factors in Table 1 to forecast returns are investigated in two ways:

1. Portfolios are constructed by ranking the stocks on the basis of the value factors (one at a time).

2. Portfolios are constructed by ranking the stocks on the return predicted by a linear model constructed from the value factors.

In constructing a ranked portfolio, a long only, equally weighted portfolio is constructed from the top ten percent of the sorted stocks (on the basis of either a value factor or a linear model prediction.)

In some cases 50/50 long/short portfolios are also constructed. These portfolios consist of an equal number of stocks in a long position in the sorted top ten percent and a short position in the bottom ten percent. The positions in the portfolio are equally weighted.

Factor Correlation

In this section the correlations between the value factors are examined for all 891 stocks in the S&P 500 universe throughout the back test period.

Factor correlation is an important statistic because it shows the relationship between paired factors. If a pair of factors is highly correlated (correlation close to 1) two portfolios ranked on the factors will have similar performance.

In linear models, a factor may be omitted from the linear regression if it is highly correlated with another factor. Avoiding highly correlated factors may also help avoid multi-colinearity, which results in inaccurate ordinary least squares regression results.

Figure 1 shows the pairwise factor correlations for the 8 factors.

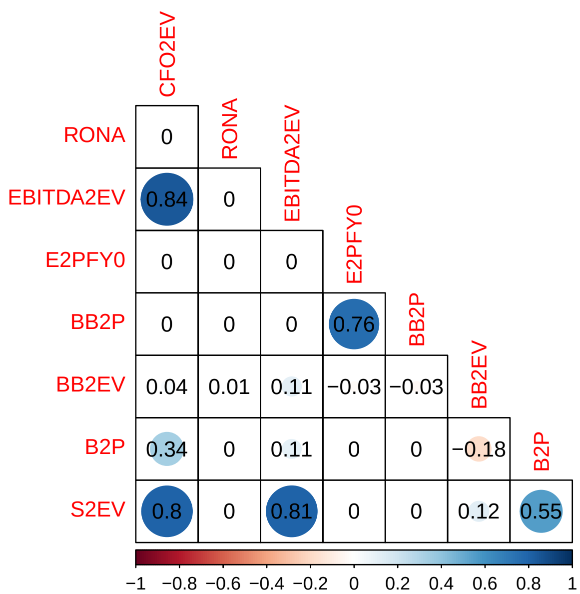

Figure 1: Factor Correlations

As Figure 2 shows, EBITDA2EV and S2EV are highly correlated with each other. Their correlations with the other factors are also similar. As a result, S2EV is omitted from this analysis in favor of the EBITDA2EV factor.

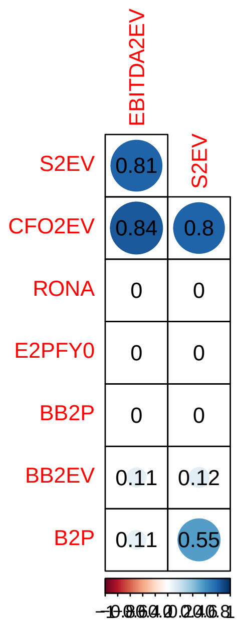

Figure 2: Correlation between EBITDA2EV and S2EV

Portfolio Back-testing

> *Whereof what's past is prologue*
> The Tempest
> William Shakespeare, 1611

The future outcome for a stock is unknown and unknowable in an exact sense. The only way to predict what *may* happen in the future is to use information from the past. By using past data to back-test portfolio models an imperfect estimate of future portfolio performance can be calculated.

In the back tests described here, the S&P 500 portfolio date range is from March 31, 1998 to September 30, 2013. This time period is chosen because many of the characteristics that are present in the current market, like low cost electronic trading, were present in this time period.

The Information Ratio

Portfolios are frequently evaluated relative to a benchmark like the S&P 500 (for a long only portfolio) or the "risk free rate", in the case of a long/short portfolio. A metric that can be used to compare the performance of a portfolio with the benchmark is the information ratio, IR:

$$IR = \frac{E[R_p - R_b]}{\sigma} = \frac{E[R_p - R_b]}{\sqrt{var(R_p - R_b)}} = \frac{\alpha}{\omega} \tag{1}$$

Here R_p is the quarterly portfolio return and R_b is the quarterly benchmark return (in this case the S&P 500).

To provide perspective on the information ratio (IR) measure, the table below shows the distribution of annual IR values for active portfolio managers [8] (e.g., a portfolio manager with a portfolio IR of 1.0 would be in the 90^{th} percentile of portfolio managers).

Percentile	Information Ratio
90	1.00
75	0.50
50	0.00
25	-0.50
10	-1.00

Table 2: IR Ranking

The information ratios quoted in this paper are quarterly information ratios. Information ratios are commonly quoted in annualized form. However, annualizing the quarterly information ratio adds inaccuracy, since this makes the assumption that the returns and variance are the same in each quarter.

Ranked Portfolios

One way to evaluate a factors effectiveness in selecting stocks for a portfolio is to rank the stocks on the basis of the factor [3, 5]. An equally weighted portfolio is constructed from the top ranked stocks (generally the top ten percent) in the case of a long only portfolio. For a long/short, market neutral portfolio, a long position is taken in the top ranked stocks and a short position is taken in the bottom ranked stocks.

To investigate the value factors, quarterly portfolios are constructed on the basis of each factor. Except for the RONA (return on assets) factor, all factors are divided by the market or enterprise value, which is calculated from the stock price. To adjust for the volatility of the factor values due to the volatility in the stock price, the value used in ranking is calculated by linear regression over the past 20 factor values (5 years). This regression is a time series regression over the factor values for each stock. An example is shown below in Figure 3.

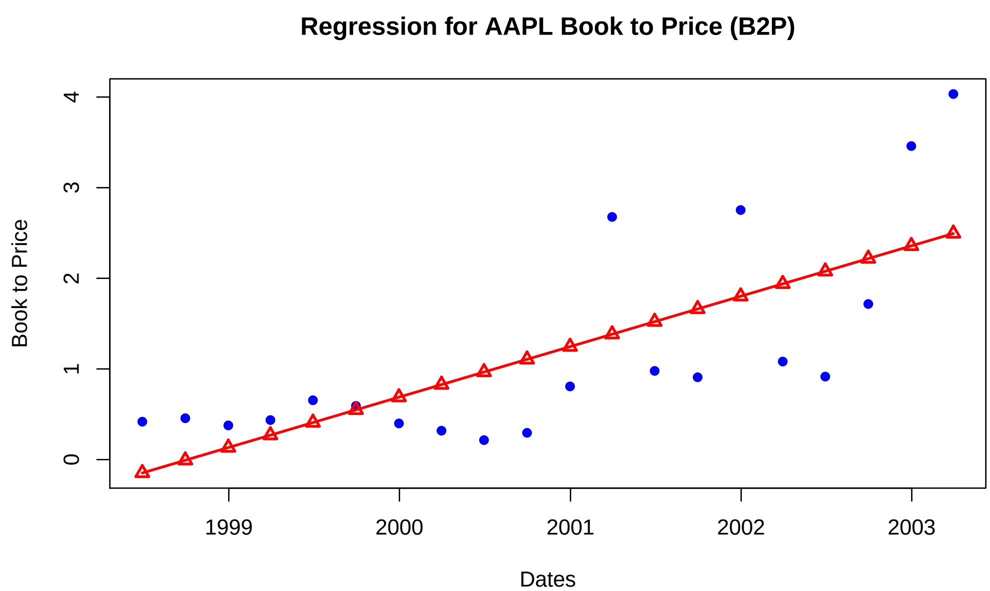

Figure 3: Time Series Regression for AAPL B2P

The factor value used in the ranking is the last value on the regression line.

The value calculated via regression lags the quarter in which the stock would be bought by six months to account for the reporting lag. The portfolio is rebalanced every quarter, so the stock is held one quarter and then sold. Transaction costs are ignored.

Once the factor value for each stock in the quarterly S&P 500 universe has been estimated by linear regression, the stocks are ranked by their associated factor value. An equally weighted portfolio is constructed from the top ten percent of the stocks.

Table 3 shows the information ratio for portfolios ranked on the basis of each of the seven factors. The quarterly S&P 500 close prices are obtained from `finance.yahoo.com` (ticker symbol $\wedge GSPC$.) Table 3 shows both the top and bottom deciles. All of these portfolios have a lower risk adjusted return than the S&P 500 index.

	CFO2EV	RONA	EBITDA2EV	E2PFY0	BB2P	BB2EV	B2P
Top Decile	-0.1362	-0.2924	-0.0754	-0.2424	-0.2625	-0.3082	-0.0408
Bottom Decile	-0.3538	-0.1028	-0.1965	-0.1153	-0.2141	-0.0939	-0.2850

Table 3: IR for Portfolios Selected by Sorted Factors

The factor that results in the portfolio with the best performance relative to the S&P 500 benchmark is the book to price (B2P) factor. The plot in Figure 4 shows the performance of the B2P ranked portfolio vs. the S&P 500 benchmark.

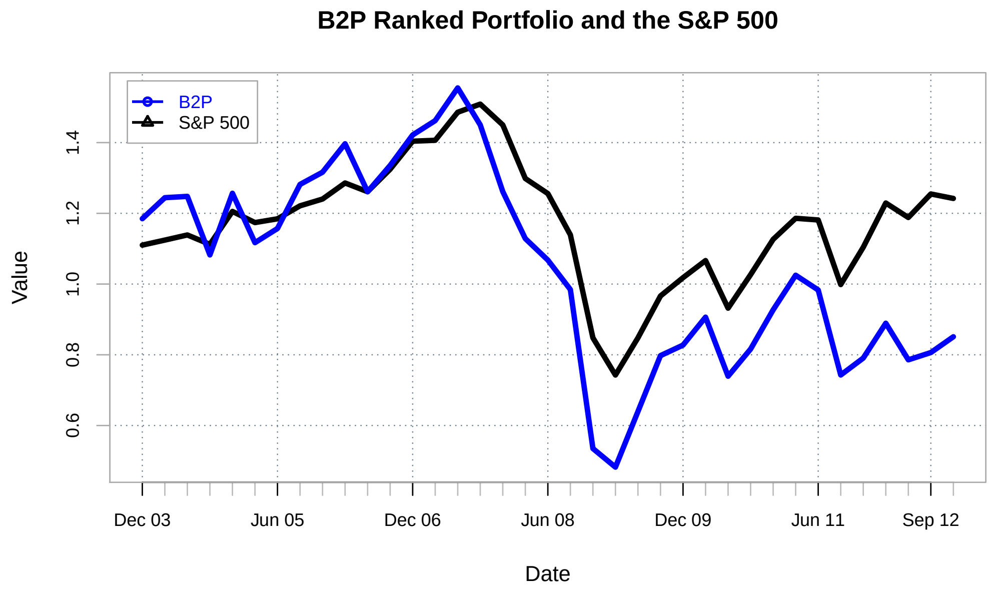

Figure 4: one dollar invested in the B2P and SP 500 Portfolios

Linear Value Factor Models

The financial performance of a company may depend on a wide variety of factors. This may be lost when a single factor is used to select portfolio assets. Ranking stocks on the basis of a linear model allows multiple factors to be combined to forecast future return.

Linear models, constructed from the time series of the factors associated with a stock, allows the forecasting strength of factors to be examined in isolation. Assessing factor performance can be more difficult when forecasting is aggregated by constructing a ranked portfolio of equally weighted stocks since there may be other factors, outside the model, that affect portfolio return.

The linear models that are constructed take into account the time lag between the quarterly date and the time the corporate information becomes available (e.g., the data from March 2013 may not be available until September 2013.)

A linear model at time t is used to estimate for the return at time $t + 1$. The linear model regresses the seven value factors against future returns. Since the factor data has a two quarter lag in availability, the factor data at time $t - 2$, is used to predict the return at $t + 1$, which is three quarters ahead. The model is constructed from factor data starting at time $t - 3$ back to $t - 3 - n$. These factors are regressed against returns from time $t - n \dots t$.

There are seven factors (CFO2EV, RONA, EBITDA2EV, E2PFY0, BB2P, BB2EV, B2P) over 20 past quarters used to build the linear model:

$$r_{t+1} = \beta_0 + \beta_1 f_{t,1} + \beta_2 f_{t,2} + ... + \beta_7 f_{t,7} + \epsilon_t \tag{2}$$

$$\begin{bmatrix} r_{t_2} \\ r_{t_3} \\ \vdots \\ r_{t_{21}} \end{bmatrix} = \begin{bmatrix} 1 & f_{t_1,1} & f_{t_1,2} & \dots & f_{t_1,7} \\ \vdots & \vdots & \vdots & & \vdots \\ 1 & f_{t_{20},1} & f_{t_{20},2} & \dots & f_{t_{20},7} \end{bmatrix} \cdot \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_7 \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_{20} \end{bmatrix} \tag{3}$$

From the past data we know $\boldsymbol{r}$ (the returns) and $\boldsymbol{f}$ (the factor values). The values of $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\epsilon}}$ are estimated via multiple linear regression.

$$\boldsymbol{r} = \boldsymbol{f}\hat{\boldsymbol{\beta}} + \hat{\boldsymbol{\epsilon}} \tag{4}$$

The data layout for the 20 quarters (5 year) of factor data regressed against 20 quarters of returns (where the returns are three quarters ahead) is shown below in figure 5.

Once the linear model is constructed, the linear model can be used to forecast the future return at time $t + 1$ from the factor values available at time t:

$$r_{t+1} = \beta_0 + \beta_1 f_{t,1} + \cdots + \beta_7 f_{t,7} \tag{5}$$

The accuracy of the linear model can be checked in back-testing, since the actual return at time $t + 1$ is known.

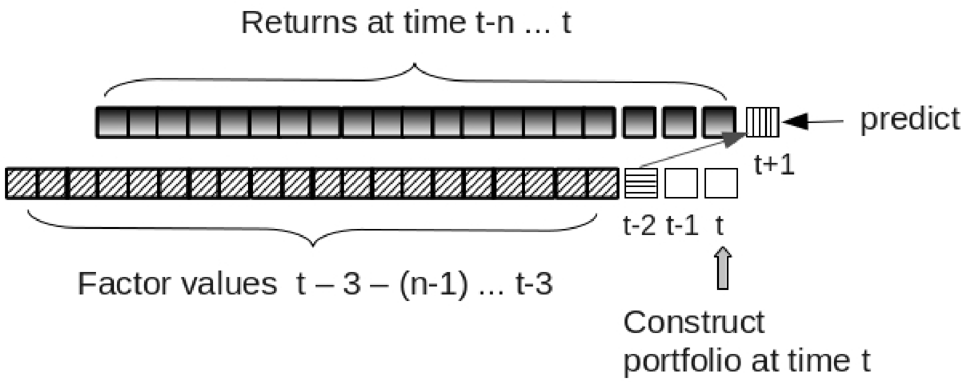

Figure 5: Factors and 3-quarter ahead returns

Five past years (20 quarters) are used to construct the linear model and a total of 21 quarters are needed (20 for the model, plus the "current" factor value used to forecast the future return). These quarters start two quarters back from time t (due to the lag in factor data availability). Twenty (three-quarter ahead) returns are needed to build the linear model. An extra return (the "actual" return) is used to check the prediction (and calculate the correlation between the predicted return and the actual return.)

The CRSP/Compustat data is downloaded for the entire set of stocks over the entire back test period. Not all stocks have 21 quarters of factor data and 23 quarters of return data available in the CRSP/Compustat database. These stocks are filtered out of the backtest set, leaving on average about 450 stocks per quarter (rather than the 500 S&P index stocks.)

In this study both ordinary least squares and robust regression are used. Robust regression does not produce results that are clearly better and sometimes produces results that seem to be worse.

Some authors [10, 13] have used weighted least squares regression. Weighted least squares relies on estimates of sample variance (see section 6.2 of [7]). Since there are only 20 quarterly values in the backtest data set, the standard error in the variance estimate will be relatively high, so weighted least squares was not used.

The time window used to build the linear model is "rolled" forward each quarter to estimate the forecasted return for that quarter.

The distribution of the ordinary least squares R^2 is shown below in Figure 6.

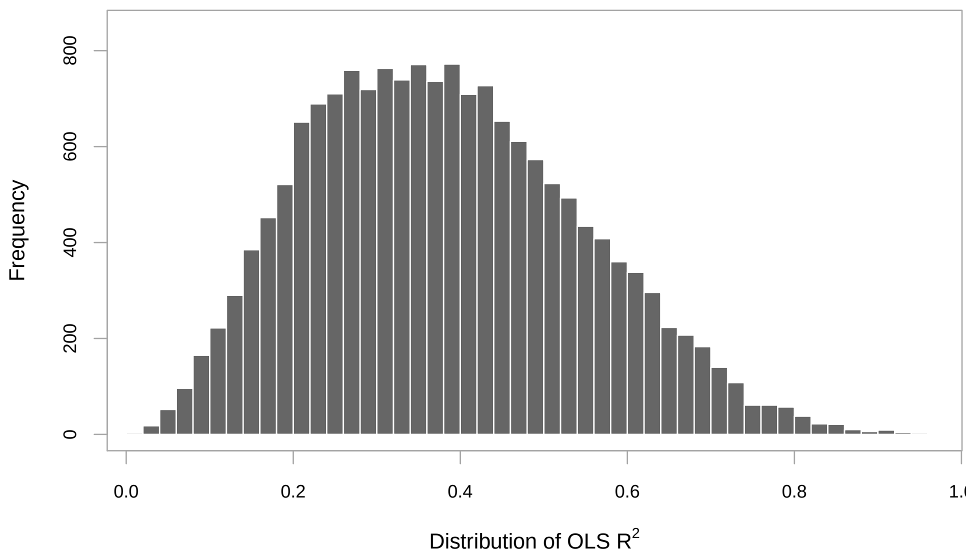

Figure 6: R^2 for OLS of Factors vs. 3-Quarter Ahead Returns

For each stock, the forecasting accuracy of the Ordinary Least Squares 7-factor model is compared to five other models. The models are listed below:

1. predict: the return at time $t + 1$ is forecast via an OLS model using the seven value factors, over a 20 quarter period.
2. robPredict: the same model as the OLS model, but using robust linear regression
3. retMu: the mean of the past 20 returns $(t - n \ldots t)$ is used as the value to forecast the return at time $t + 1$.
4. retEMA: the return at time $t + 1$ is forecasted by the Exponential Moving Average function with a window of 4, over 20 past returns.

5. retLinMu: OLS regression through the past 20 returns is used to forecast the return at time $t+1$.

6. random values with the same mean and standard deviation are correlated against the actual future return.

The box plot below in figure 7 shows distribution of the correlations between the predicted values for each stock at a given quarter t and the actual return at time $t+1$. For comparison, normal random values, with the same mean and standard deviation as the actual returns have been added (the yellow line). With the exception of the correlation of the random values with the actual return, all of the correlations are negative.

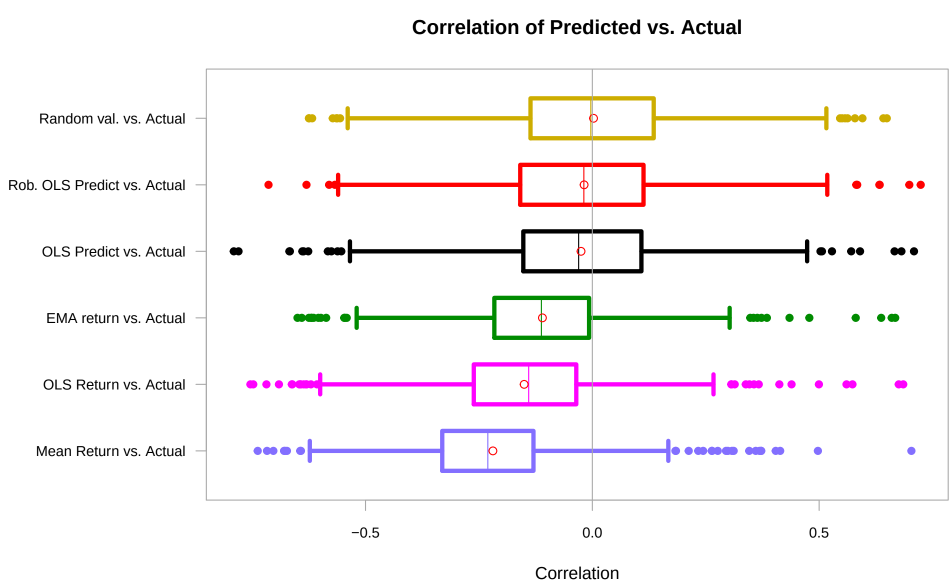

Figure 7: Predicted Return vs. Actual Return

The plot in figure 7 gives the following information:

1. Robust regression (red line) of the value factors with the future return is not much better than the random correlation.

2. The value factor based linear model (black line) has a higher

correlation with future returns than either the random factor or the robust regression. But the differences is relatively small.

3. In strength of correlation between the actual returns:
   (a) The mean return (over five years, or 20 quarters, of past data) has the strongest correlation
   (b) followed by the mean calculated via the exponential moving average
   (c) followed by the mean calculated by ordinary least squares regression through the past returns

The mean return, although negatively correlated, is a remarkably strong at forecasting future returns.

Model Selection for Value Factors

The linear models used to forecast future returns are multi-variate linear models that make use of all seven of the corporate value factors. In some cases adding more factors to a linear model can increase the model error. To investigate this possibility R's `leaps` package is used to choose optimal linear models (on the basis of Mallow's Cp information criteria).

To keep track of which factors are used in the linear models, the result from each `leaps` model selection includes a bit vector with one bit set for each factor. Examples of these bit vectors are shown in Table 4.

	CFO2EV	RONA	EBITDA2EV	E2PFY0	BB2P	BB2EV	B2P
1	0	0	1	0	0	0	0
2	1	0	1	0	0	0	1
3	1	1	0	0	0	0	1
4	0	0	0	1	0	0	0
5	0	0	0	0	1	0	0
6	0	0	1	0	0	0	0

Table 4: Linear Model Represented as a Bit Vector

Figure 8 shows the factor distributions in the models selected by `leaps`. Most models have more than one factor and the distribution of the factors in the models is relatively uniform.

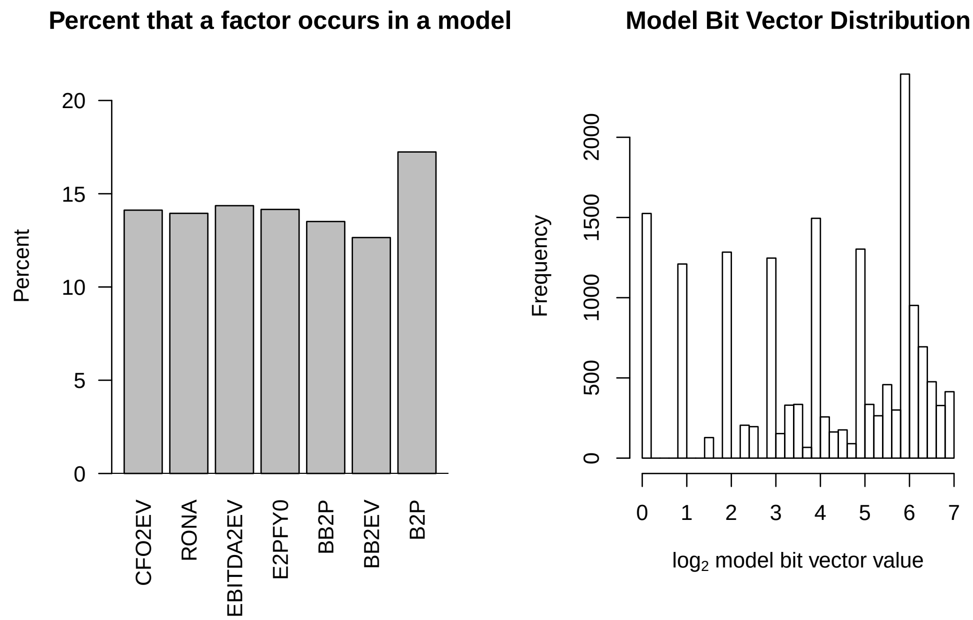

Figure 8: Factor Distribution in the Linear Models

The `leaps` optimized linear models do not result in better return forecasts. Figure 9 shows the correlation between the predicted and actual return for both the `leaps` optimized models and the full 7-factor model. The two distributions are almost exactly the same.

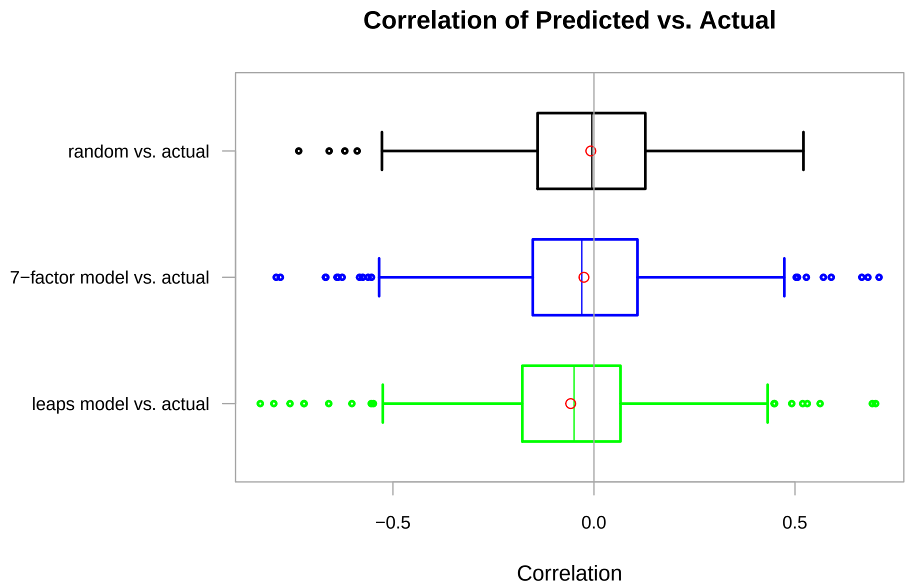

Figure 9: Correlation of predicted and actual values for leaps and 7-factor model

Monthly Factors

The linear models discussed above are constructed from five years of quarterly data. With relatively few quarterly data points, the linear model may have a high error (which is reflected in the low R^2 values for many models.) In this section the number of values in the linear model is increased by using monthly values (e.g., 60 values, rather than 20).

Value factors are reported in quarterly corporate reports submitted to the US Securities and Exchange Commission, so more frequent corporate data values are not available. Except for the return on assets (RONA) factor, all factors are scaled by either the enterprise value or the market value. The enterprise value and market value are derived from the number of shares outstanding and the current share price. The market and enterprise values change as rapidly as the stock values change in the market.

The quarterly data set used above is expanded to monthly values by using market and enterprise values that are calculated from the monthly close prices. This expands the linear model from twenty quarterly values to sixty two monthly values (two additional value are available by expanding the last corporate value). This is shown below in Figure 10.

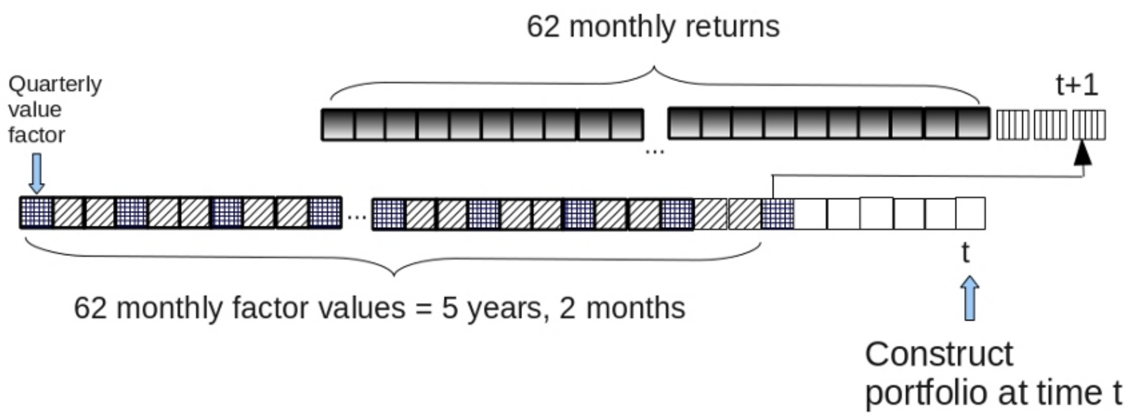

Figure 10: Monthly Factors and 9-month Ahead Return

The Figure 11 shows the density plots for the quarterly and monthly R^2 error for the ordinary least squares (OLS) linear regression models used to predict future returns. The R^2 error is much higher (e.g., a lower R^2 error value) for the monthly linear regressions.

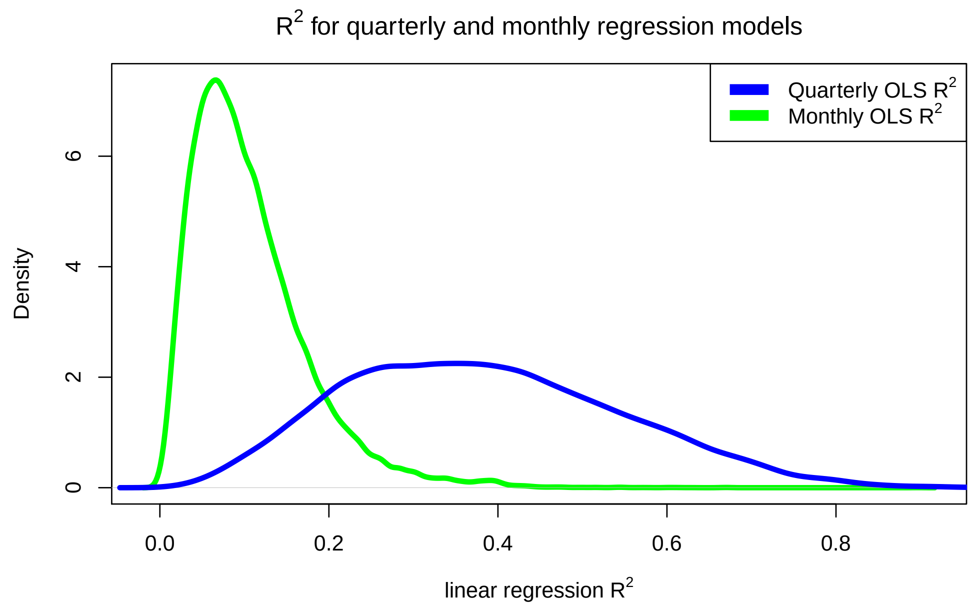

Figure 11: R^2 for Quarterly and Monthly Regression

Extending the factor data by using monthly close price information is probably adding volatility, which accounts for the increase in the linear model error (shown by the lower R^2 distribution).

Figure 12 shows the distributions for the monthly and quarterly correlations of the predicted returns vs. the actual returns. The correlation of the monthly values are slightly worse than the quarterly values, so no predictive advantage was gained by using monthly factor values.

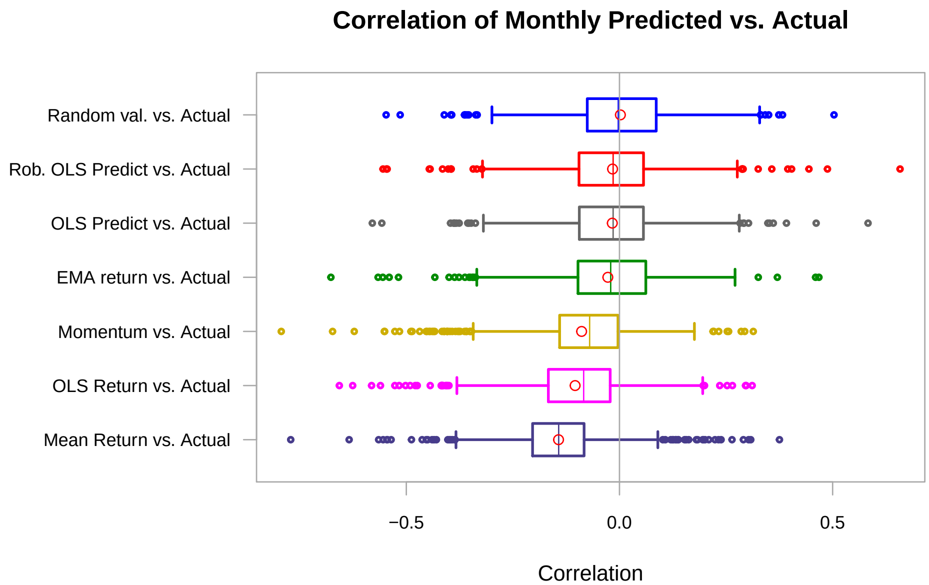

Figure 12: Correlation of Monthly Return Prediction

The correlation between a monthly return momentum factor and the actual return is included as well. This factor is discussed later in the paper. Note that the correlation of the momentum factor with the actual return is lower than the mean return factor.

Multi-Factor Portfolios

The results so far suggest that a linear model of seven value factors predicts future returns only slightly better than a random predictor. These results are derived from time series statistics.

The performance of portfolios based on the linear models described above is another view of the same information. Perhaps because portfolios are investment models, the results can be more stark that the statistics.

To investigate portfolio performance, a portfolio is constructed each quarter, from 2003-03-31 to 2012-03-31. The portfolio consists of the S&P 500 stocks that have sufficient history to construct the linear models. The history requirement reduced the number of stocks from 500 to an average of about 450.

Long Only Portfolios

Long only portfolios are created by ranking the stocks on the basis of a forecasting factor. The top ten percent of the stocks (45.) are chosen to create an equally weighted portfolio. The four forecasting factors are listed below:

1. Perfect portfolio: the stocks are sorted on actual return and the top 10 percent (45) are used to construct the long portfolio. The is a portfolio constructed with perfect foresight.
2. Portfolio based on the 7-factor least squares predictor: the least squares predictor is multiplied by -1 (since it is negatively correlated with actual returns - see Figure 7) and the stocks are sorted on this predictor. A equally weighted portfolio is formed from the top 10 percent (45 stocks).
3. Mean predictor portfolio: the mean return is multiplied by -1 and the stock are sorted on this predictor. An equally weighted portfolio is formed from the top 10 percent (45 stocks).
4. Random portfolio: 45 stocks are selected using a uniform random distribution over the number of stocks in the portfolio.

The portfolios results do not account for transaction costs.

The quarterly information ratio for the four portfolios is shown in table 5:

	IR
Perfect IR	1.3665
Mean Predict IR	-0.0340
OLS Predict IR	-0.0562
Random IR	-0.0670

Table 5: Portfolio IR

As suggested by Figure 7, the mean return is a stronger predictor than the value factor linear model.

A cumulative return plot is shown in 13 below. This plot shows the fate of one dollar invested in one of three portfolios: the S&P 500, the linear predictor and mean predictor portfolios.

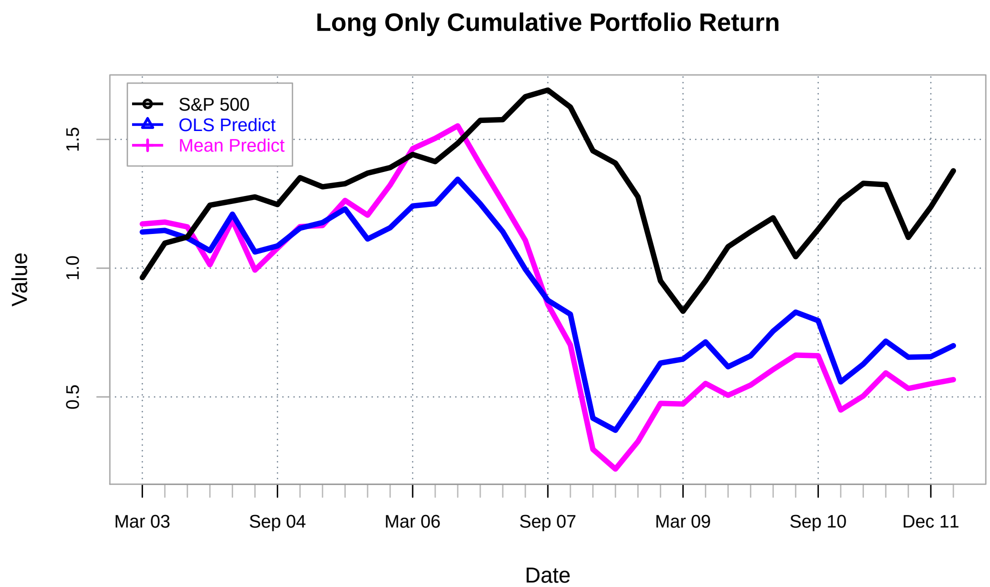

Figure 13: Return for one dollar invested in three portfolios

Market Neutral Portfolios

Three 50/50, long/short, market neutral, portfolios are constructed with an equal number of stocks in the long and short positions (this is not strictly a market neutral portfolio since the dollar values of the positions are not equalized.) The methods for constructing the portfolios are listed below:

1. Sort the stocks by the return predicted by the linear model, times -1. Construct a long position from the top 10 percent (45) of the stocks

and a short position from the bottom 10 percent.

2. Sort the stocks by the return predicted by the mean return times -1. Construct a long position from the top 10 percent (45) of the stocks and a short position from the bottom 10 percent.

3. Using a uniform random distribution, randomly select 45 stocks for a long position and 45 stocks for a short position.

The portfolios results do not account for transaction costs.

Market neutral portfolios are frequently compared to "cash" (the risk free rate, R_f). The calculation of the Sharpe ratio is the same as the information ratio, but the risk free rate is used as the benchmark.

$$\text{Sharpe Ratio}_{year} = \frac{4 \times E[R_p - R_f]}{\sqrt{4} \times \sigma} = \frac{4 \times E[R_p - R_f]}{\sqrt{4 \times var(R_p - R_f)}} \tag{6}$$

	Long/Short Annual SR
S&P 500 SR	0.1772
Mean Predict SR	0.1158
OLS Predict SR	-0.4101
Random SR	-0.7901

Table 6: Annual Sharpe Ratio for 50/50 long/short portfolio

The plot in Figure 14 shows the cumulative return of a dollar invested in long/short portfolios constructed from the linear predictor and the mean predictor. The cumulative return for the S&P 500 and the risk free rate is also shown.

The market neutral long/short portfolio constructed using the mean as a predictor for future return has a slightly higher return than the risk free rate, but the return is more volatile.

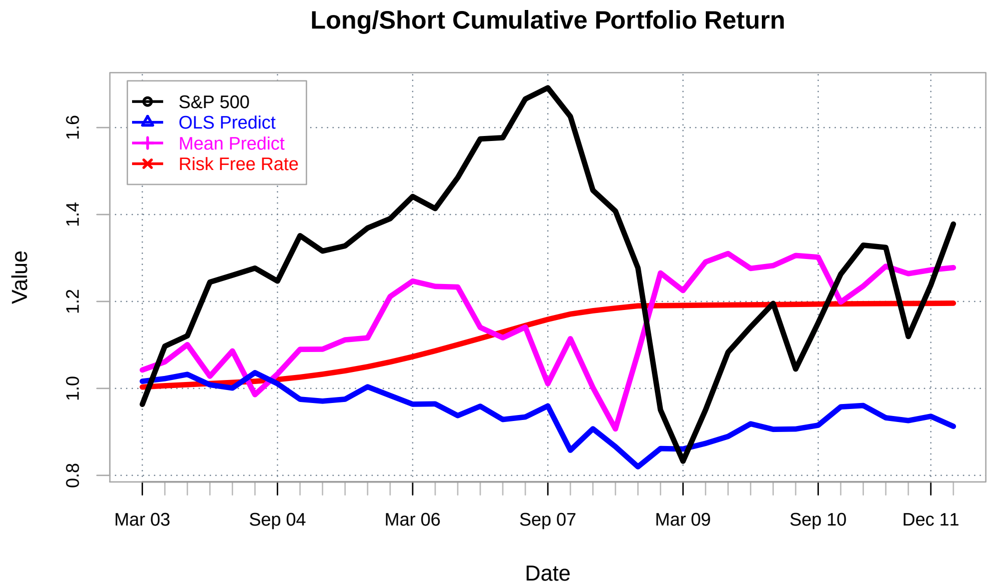

Figure 14: Return for one dollar invested in three Long/Short portfolios

Momentum

Momentum is a strategy that attempts to "buy the winners" (the stocks whose price is increasing) and sell the losers (the stocks whose price is decreasing) [9, 2]. In this section, value factor and return momentum are investigated.

The S&P 500 index tends to mirror the overall stock market, which in turn reflects the US (and world) economy. The back test period includes a number of significant events that may drive the stock market: the "dot-com" bubble and crash, the 9/11 terrorist attacks, wars in Afghanistan and Iraq, the financial crash of 2008 and the "great recession". The power of these events in effecting the stock market may drive momentum factors and suppress value factors. This section investigates value factor and return momentum factors.

Value Factor Momentum

The results above show that value factors, by themselves, are weak predictors of future return in the S&P 500. One value factor value would probably not be used as the basis for a buy or sell decision. Instead, a portfolio analyst might look at the trend in a value factor or set of value factors. Such a value factor trend can be quantified as value factor momentum. Value factor momentum has been used to forecast future returns in [10].

To calculate the quarterly value factor momentum, the quarterly ”return” for the value factors must be calculated:

$$R_t = \begin{cases} \frac{f_t - f_{t-1}}{f_{t-1}} & \text{if } f_{t-1} \neq 0 \\ 0 & \text{if } f_{t-1} = 0 \end{cases} \tag{7}$$

To calculate the quarterly factor momentum, the quarterly factor ”returns” are summed over the past year (e.g., four value factor returns).

Factor Momentum Correlation with Future Return

The distributions of the correlation between the quarterly factor momentum with the 3-quarter ahead return is shown below. The 3-quarter ahead return is used because of the lag in the availability of the corporate quarterly balance sheet data.

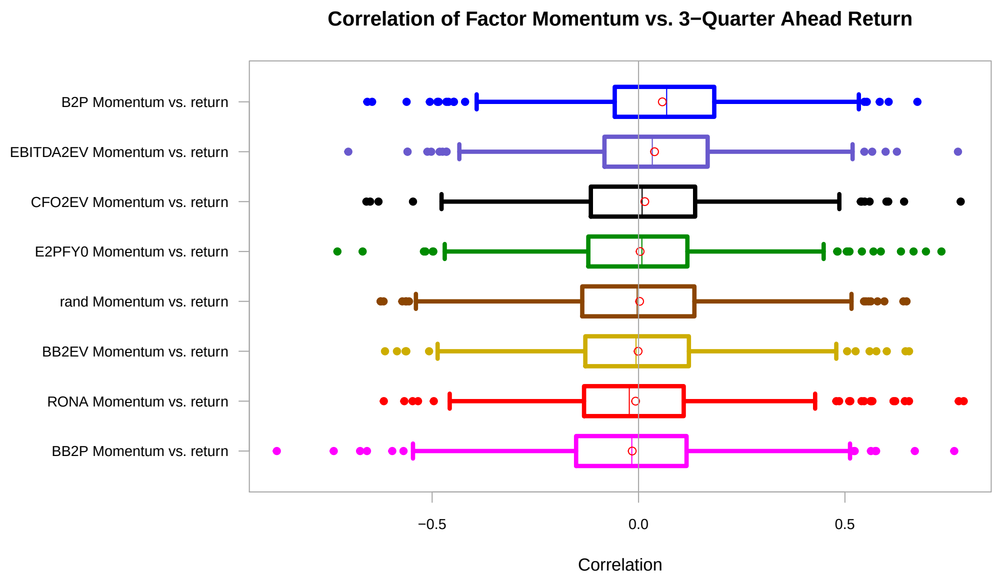

Figure 15: Correlation of Factor Momentum vs. 3-Quarter Ahead Return

Value Factor Momentum Portfolios

Long only portfolios are formed by sorting the stocks on the basis of the 1-year value factor momentum, for each of the seven value factors. The portfolio is constructed from the top decile of these sorted stocks. The quarterly portfolio IR (relative to the S&P 500 benchmark) for each of these portfolios is shown below in Table 7

Table 8 shows the Sharpe ratio for 50/50 equally weighted long/short factor momentum portfolios, where there is a long position in the top decile and a short position in the bottom decile.

As the quarterly IR and the annual Sharpe ratios indicate, the best performing market neutral portfolio uses the EBITDA2EV momentum factor. This factor indicates that the company has earnings momentum over the last year.

	Quarterly IR
EBITDA2EV	-0.0233
E2PFY0	-0.0417
RONA	-0.0627
BB2EV	-0.0675
BB2P	-0.0807
CFO2EV	-0.1068
B2P	-0.1080

Table 7: Value Factor Momentum Portfolio IR

	Annual Sharpe Ratio
EBITDA2EV	0.5688
B2P	-0.1191
E2PFY0	-0.1532
RONA	-0.4360
BB2EV	-0.4881
CFO2EV	-0.6548
BB2P	-0.8321

Table 8: 50/50 Long/Short Value Factor Momentum Portfolio Sharpe Ratio

A cumulative return plot of the EBITDA2EV momentum portfolio, the S&P 500 and the risk free rate is shown in Figure 16.

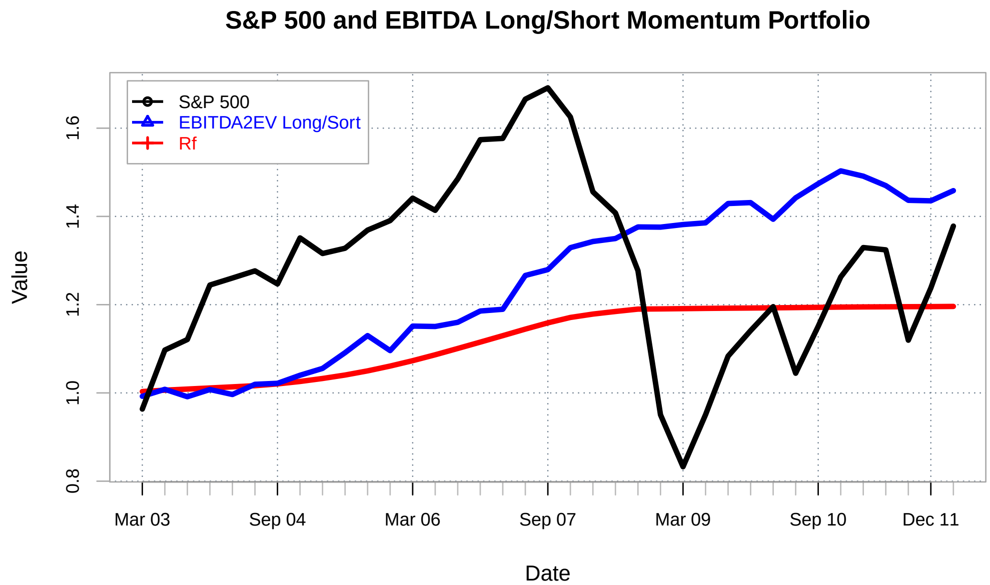

Figure 16: Return for one dollar invested in Long/Short momentum portfolios and SP 500

The market neutral EBITDA2EV momentum factor portfolio (shown in blue) has significantly better return than the risk free rate (shown in red), with very little draw down. However, transaction costs are ignored. The cost of shorting half of the portfolio and the bid/ask spread would reduce the portfolio return, in practice.

Of all portfolios examined in this paper, the market neutral EBITDA2EV momentum factor portfolio appears to have the best return and the lowest volatility. Figure 17 shows the drawdown plot for the market neutral EBITDA2EV momentum factor portfolio.

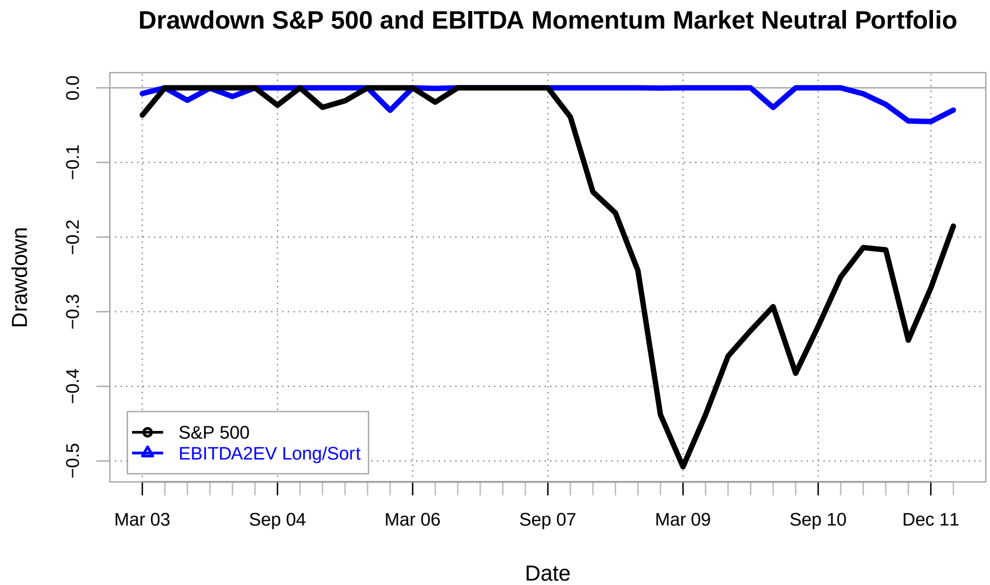

Figure 17: Drawdown for the market neutral EBITDA2EV momentum factor and the SP 500

The low volatility and drawdown for the market neutral EBITDA2EV portfolio may make it an attractive canidate for a leveraged portfolio (e.g., a portfolio that uses margin borrowing) to boost yield.

Return Momentum

To provide perspective on the factor momentum portfolios, return momentum is examined in this section. Return momentum has been reported to be negatively correlated with value factors [1]. In this section a 1-year monthly return momentum factor is examined.

The basic technique for calculating a 1-year return momentum factor is to sum the monthly returns within a 1-year period, from months $1 \ldots 11$ skipping the return for month 12. Figure 18 shows this calculation. In this case the stock is bought at the end of month 13 and sold at the end of month 16, yielding a quarterly return.

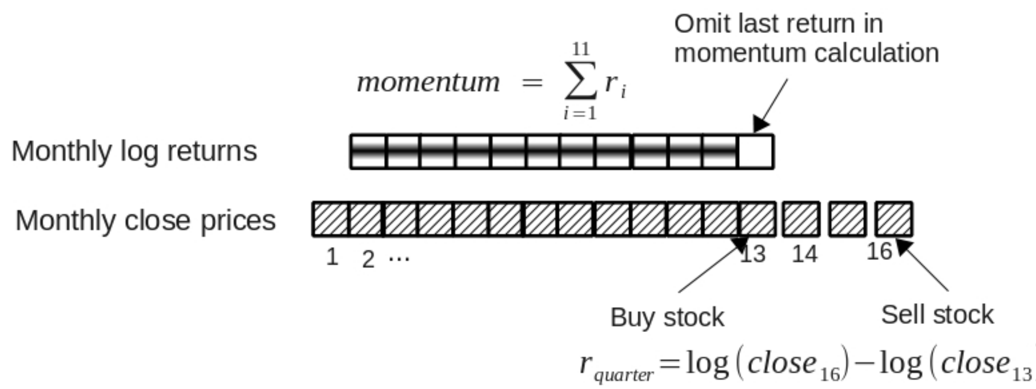

Figure 18: Momentum Calculation Based on Monthly Values

As Figure 19 shows, the quarterly return period is non-overlapping.

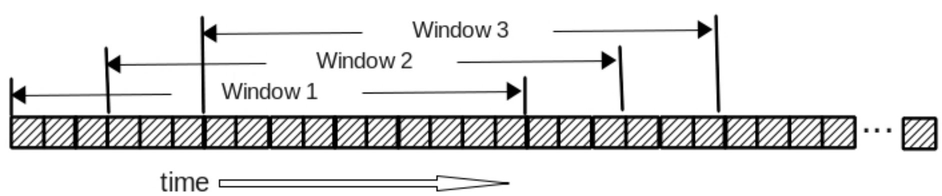

Figure 19: Sliding Windows Used to Calculate Momentum

To build a portfolio, the stock universe (in this case the S&P 500 stocks for that quarter) is sorted by the associated momentum factor. The top 10 percent decile portfolio consists of an equally weighted portfolio of the top 10 percent of the sorted stocks. The bottom 10 percent decile consists of the equally weighted portfolio of the bottom 10 percent of the stocks.

Table 9 shows that the bottom decile has a higher IR than the top decile, suggesting that there is a negative correlation between the momentum and the future return. This negative correlation can also be seen in Figure 12. As a result, the 50/50 long/short portfolio consists of a short position in the top ten percent of the momentum ordered stocks and a long position in the bottom ten percent.

Table 9 gives the quarterly information ratio for the top and bottom deciles of long only portfolios and the long/short portfolio.

	Momentum Portfolio
IR Top Decile (quarterly)	-0.2758
IR Bottom Decile (quarterly)	-0.0799
Long/Short Sharpe Ratio (annual)	0.1234

Table 9: Quarterly IR and Annual Sharpe Ratio for Momentum Portfolios

The plot in figure 20 shows the fate of one dollar invested in the S&P 500, the top and bottom decile momentum portfolio and the market neutral long/short momentum portfolio.

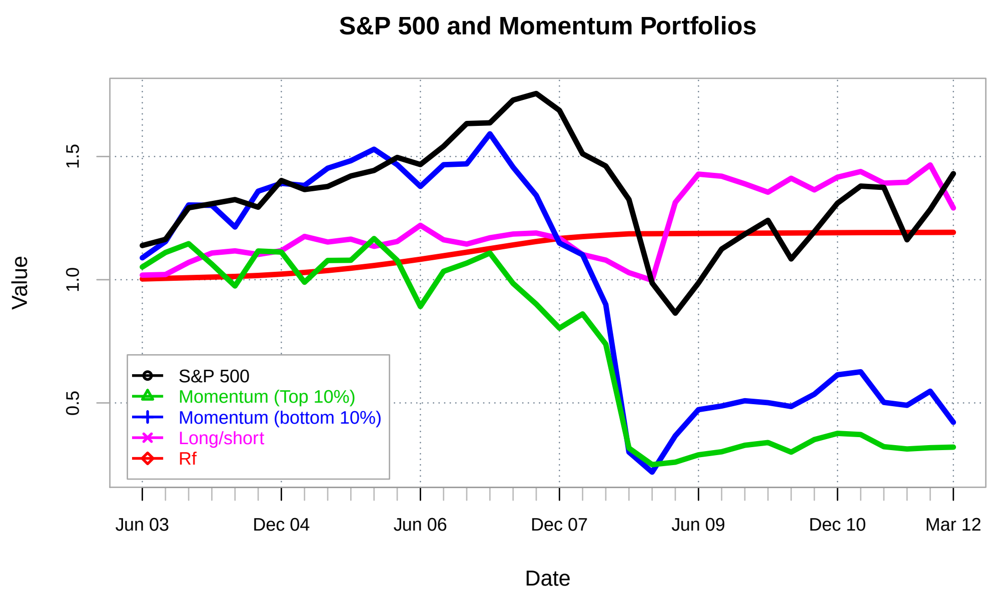

Figure 20: Return for one dollar invested in momentum portfolios and SP 500

Over the back test period, none of the return momentum portfolios out performs the S&P 500 and in most cases the portfolios do not out perform the risk free rate. In contrast, one of the value factor momentum portfolios, based on the EBITDA2EV factor, out performs both benchmarks (not taking into account transaction costs.)

Discussion

The evidence strongly suggests that value factors are not effective for forecasting future returns for the large market capitalization S&P 500 stocks. The only exception to this is the EBITDA2EV momentum factor in a market neutral portfolio (discussed above). The value factor results seem to contradict a large literature that reports that portfolios constructed on the basis of value factors do show return in excess of the benchmark.

There may be several reasons for these contradictory results. Most of the studies that report excess returns from value factors use larger stock universes that are not confined to large market capitalization stocks. For example, the work by Fama and French [6] on the value factor premium uses the entire investible stock universe. These larger stock universes may include stocks where value factors are stronger in forecasting returns. The value factor performance reported in Chapter 5 of citeQian2007 is based on the Russell 3000 stock universe.

The effectiveness of value investing relies on recognizing stocks that are under-priced relative to their value characteristics. Value factors may not show forecasting strength in the case of the S&P 500 stocks because these stocks are closely followed by a larger number of market analysts. A stock that is closely followed in the market may already have the value factors accounted for in the stock price.

The results that are reported here mirror those reported by others. Israel and Moskowitz[1] investigate the relationship between firm size and the effectiveness of value factors in forecasting returns. They find that as the firm size increases, the strength of value factors diminishes. The negative relation between firm size and return has been widely reported. In [5], Fama and French write

> In multivariate tests, the negative relation between size and average return is robust to the inclusion of other variables.

Value factors may be better predictors of future return for small and mid-cap stocks. An in-depth exploration of this hypothesis is beyond the scope of this paper. A brief examination of two Exchange Traded Funds (ETF) value funds does raise the question of whether value factors do actually yield excess return for small and mid-capitalization stocks.

These two funds are the Vanguard Small-Cap Value Fund and the Vanguard Mid-Cap Value Fund. Relative to the S&P 500, the quarterly IR for the Vanguard funds is shown in Table 10.

	Quarterly IR relative to the S&P 500
Vanguard Small-Cap Value (VBR)	0.0987
Vanguard Mid-Cap Value (VOE)	0.1169

Table 10: Quarterly IR for Vanguard Small and Mid-Cap Value Funds

As the IR values show, the value factors do provide some excess return over the S&P 500 benchmark. Cumulative investment plots are shown below in Figures 21 and 22. While there is a slight excess return over the S&P 500, transaction costs and ETF fees would reduce this advantage to the point where it might disappear. (Note that these funds have different inception dates.)

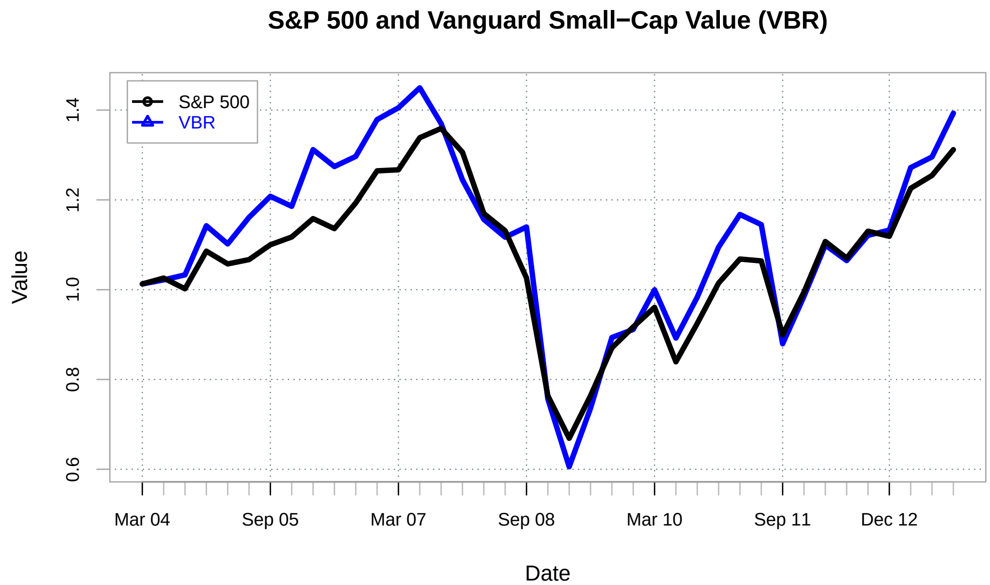

Figure 21: Return for one dollar invested in VBR and the SP 500

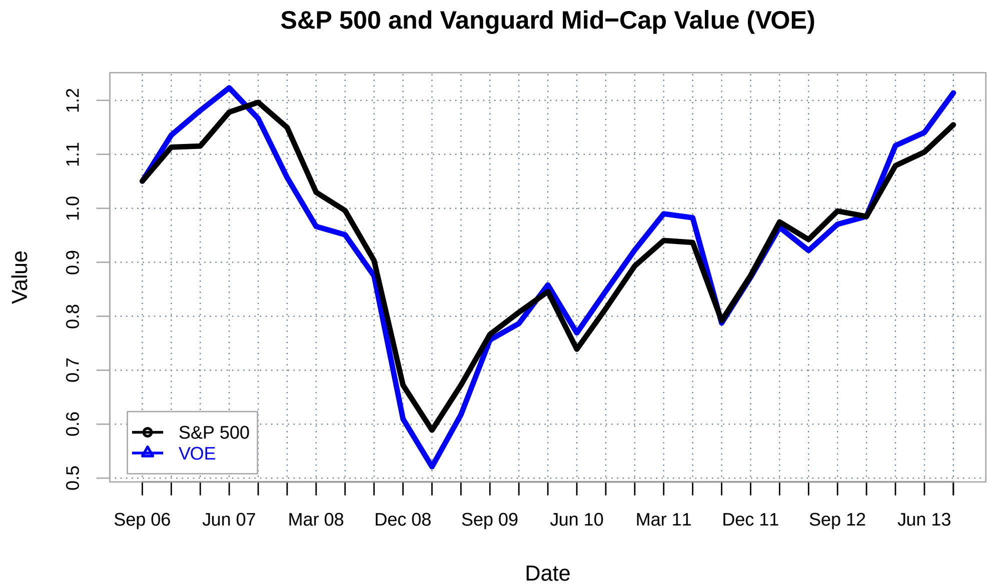

Figure 22: Return for one dollar invested in VOE and the SP 500

The Practice of Value Investing

A company's future prospects are not easily summarized in a few value factors. A portfolio manager will not only look at the current value factors, but how these factors are changing over time. For example, the EBITDA2EV momentum factor in a market neutral portfolio was the only factor that appeared to show excess return over risk free rate and the S&P 500 benchmark.

Successful value investing frequently relies on human judgement, in addition to the type of quantitative value factor analysis used here. When analyzing a company, a value portfolio manager will take into account factors like the competitive position of a company relative to other companies in the same market. The power of informed human judgement means that the results presented here do not necessarily condemn value investing. But these results may suggest one reason that the majority of value portfolio managers fail to beat their reference index.

Reproducible Research

This paper was written using Knitr[15]. Knitr combines text, formatted using $\LaTeX$, with the R code that generates the values, tables and plots in the document. In combination with the data, this paper can be completely regenerated from the Knitr source. The paper and the supporting R code are freely available without limitation (see `http://www.bearcave.com/finance/thesis_project/index.html`)

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