Trend Factor: A New Determinant of Cross-Section Stock Returns

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Abstract

In this paper, we propose a trend factor to capture cross-section stock price trends. A higher degree of trends are likely when firms are experiencing some persistent and fundamental changes. Following traders and investors in practice, we use simple moving averages to measure trends. Like the popular size or book-market or momentum factors, our trend factor is a spread portfolio of buying stocks with the highest expected returns as forecasted by trends minus those with the lowest forecasted returns. We find that the trend factor earns a risk-adjusted 3% return per month out-of-sample, doubling those of the size and book-market factors, and tripling that of the momentum factor. The abnormal return is also robust to different control variables including size, price, B/M, trading volume, idiosyncratic volatility, and liquidity. Moreover, the trend factor explains well the cross-section portfolio returns sorted by short-term reversal and E/P ratios, and performs much better than the momentum factor.

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1. Introduction

A fundamental problem in finance is to explain why different assets have different returns. There are two lines of research that are of great interest here. The first is to examine what firm or market characteristics determine the cross-section stock predictability and help to understand the sources of cross-section time-varying expected returns. For example, Fama and French (1992) forcefully show that the market size and book-to-market (B/M) ratio predict the cross-section stock returns. Haugen and Baker (1996), in their comprehensive study, find strong and stable cross-section predictability using a large combination of firm characteristics. More recently, Cooper, Gulen, and Schill (2008) find that a firm's annual asset growth rate is an economically and statistically significant predictor of the cross-section of U.S. stock returns, which appears even to have the most predictive power among various existing firm-level predictors, such as book-to-market ratios, firm capitalization, lagged returns, accruals, and other growth measures. A large number of predictors have been identified over the last several decades, and Jagannathan, Skoulakis, and Wang (2009), Subrahmanyam (2010), and Goyal (2012) provide the most recent surveys and reviews on the variables that predict cross-section stock returns. The second line of research is to construct factors that explain the cross-section stock returns contemporaneously and that pin down the risk exposures of the stocks. The capital asset pricing model (CAPM) (Sharpe, 1964; Lintner, 1965), the Fama-French three-factor model (Fama and French, 1993, 1996), asset pricing model with liquidity factor (Pástor and Stambaugh, 2003), and the Carhart four-factor model with the momentum factor (Carhart, 1997), are examples of this line of research.

In this paper, we make a contribution to both lines of research. We propose a trend factor to capture cross-section stock price trends. Empirically, there are periods in which the stock price have strong trends, which are likely caused by some persistent and fundamental changes. For example, Cooper et al. (2008) find that the asset expansion/contraction tends to be followed by periods of abnormally low/high returns. To capture these trends, we, following the practice of traders and investors in practice, use simple moving averages to measure them instead of complex econometric models. At each time t, we sort stocks into portfolios by the expected future returns forecasted by the trend signals. Then, following the formation method for the popular size or book-market or momentum factor, we define our trend factor as a spread portfolio between the portfolio with the highest forecasted expected return and the lowest one. From a cross-section predictability point of view, we find that the trend factor earns an abnormal return over 3% per month and about 3% in risk-adjusted abnormal return per month out-of-sample, doubling those of the size and book-to-market factors, and tripling that of the momentum factor.

The abnormal return of the trend factor is also very robust. It is robust to various ways of constructing the trend signals using the moving average prices, and is robust to both equal-weighting and value-weighting. More importantly, the abnormal return persists after controlling for a variety of variables that are also predictors of the cross-section stock returns in both portfolio sorts and the Fama-MacBeth regression. These control variables include market size, last month price, last month return, B/M, trading turnover rate, idiosyncratic volatility, liquidity, and momentum. The cross-section predictability of the trend signals is also distinct from the cross-section predictability using the combination of firm characteristics documented in Haugen and Baker (1996). Controlling for the expected returns forecasted by the combination of firm characteristics, the trend factor or the spread portfolio still yields highly statistically and more importantly economically significant abnormal returns.[1] In addition, the expected return forecasted by the trend signals is always significant in the Fama-MacBeth regression even in the presence of the expected return forecasted by the combination of firm characteristics, which loses its significance once the last-month return is included in the regression.

In terms of asset pricing, the trend factor explains well the industry portfolios, the cross-section portfolio returns sorted by the short-term reversal (last-month return) or by various price ratios such as earnings to price ratio (E/P), cash flow to price ratio (C/P), and dividend to price ratio (D/P). Often the momentum factor fails to explain away the significance of the abnormal returns. For example, the CAPM alpha of the lowest ranked portfolio in the 2×3 size and short-term reversal sorted portfolios is 1.15% per month and highly significant (t statistic is 6.27). In contrast, adding the trend factor reduces the alpha to -0.543% and insignificant (t statistic is -1.29). In addition, the short-term reversal factor yields a CAPM alpha of 0.696% per month and highly significant but fails to yield any significant abnormal

[1] The abnormal return relative to the Fama-French three-factor model is 1.780% per month after controlling for the expected returns forecasted by the combination of firm characteristics versus 2.215% per month without the control. The slightly lower abnormal return produced by the trend factor without the control is due to shorter period and fewer firms after merging with the expected returns forecasted by the combination of firm characteristics, which are obtained using Compustat.

return when the trend factor is included. In contrast, adding the momentum factor fails to explain any of the abnormal returns and even increases the magnitudes of the alphas. For example, the short-term reversal factor has an alpha of 0.786% (versus 0.696% in CAPM) per month in the presence of the momentum factor.

Our factor is related to the well known momentum factor, but differs from it substantially in terms of both out-of-sample abnormal returns (when measured by the CAPM and FF 3-factor models) and explanatory power on cross-section asset returns. The momentum factor is formed by buying stocks that have had high returns over the past three to twelve months and selling simultaneously those that have had poor returns over the same period. Jegadeesh and Titman (1993) show that this factor has average returns of 1% per month for the following 3–12 months. Carhart (1997) argues that the momentum factor is a useful addition to the widely used Fama-French three-factor model. If a firm's price rises persistently, the momentum factor is likely to pick it up. However, the momentum factor is not entirely about price trends. A firm's price can rise sharply and temporarily due to short term positive shocks such as merger or acquisitions without any price trends. Hence, our factor is a real attempt to capture the predictability and pricing power of genuine price trends in the stock market. Indeed, our factor has a negative correlation (-0.34) with the momentum factor. Moreover, as noted before, our factor has 3% return instead of 1%, and explains the cross-section portfolio returns sorted by the short-term return reversal and various price ratios, whereas the momentum factor cannot.

What economic forces contribute to the trends in the stock market? As is the case with the momentum, investors' under-reaction or over-reaction can induce price trends. Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999) both show that behavior biases can lead to price trend. Daniel et al. (1998) argue that investors are overconfident about their private information and over-react to confirming news (self-attribution bias). Hong and Stein (1999) argue that investors initially under-react and subsequently over-react to information if information diffuses gradually. Barberis, Shleifer, and Vishny (1998) argue that prices can trend slowly when investors underweight new information in making decisions. Furthermore, Zhang (2006) argues that price trend is caused by investors under-reaction to public information and that investors under-react even more when the information about the stock is more uncertain. Therefore, when information uncertainty is greater, we would expect that the abnormal returns are even higher. We find strong evidence supporting the argument.

We use a number of proxies for information uncertainty or noise-signal ratio, and find that the spread portfolio based on sorting the forecasted expected return using the trend signals yields abnormal returns that are monotonically increasing as the information uncertainty increases. For example, when we use the idiosyncratic volatility to proxy for information uncertainty and sort stocks first by idiosyncratic volatility into quintile groups, the abnormal return of the spread portfolio increases monotonically from 1.174% to 5.206% per month across the quintiles from the lowest idiosyncratic volatility (information uncertainty) stocks to the highest idiosyncratic volatility (information uncertainty). We obtain similar results using other information uncertainty proxies such as share turnover rates, income volatility, credit ratings, analyst coverage, and firm ages.

The rest of the paper is organized as follows. Section 2 discusses various data sources where we obtain monthly stock returns, daily stock prices, various firm characteristics and market variables used in this paper. We also discuss how to construct the trend signal using moving average prices and how to forecast expected returns using the trend signals. Section 3 provides evidence for the cross-sectional predictability and profitability of using the trend signals. Section 4 provides further evidence to demonstrate the robustness of the cross-sectional profitability in various dimensions. Section 5 demonstrates the enhanced profitability of the trend signals under information uncertainty. Section 6 compares the trend strategy with the momentum strategy and the predictability using combined firm characteristics. Section 7 further examines the trend factor formed as the spread (difference) between the highest quintile portfolio and the lowest quintile portfolio and explore and compare its pricing power to various sorted portfolios to that of the momentum factor. Section 8 concludes the paper.

2. Data

To calculate the moving average signals, we use CRSP daily stock returns from January 1926 to December 2010. We include all domestic common stocks listed on the NYSE, AMEX, and Nasdaq stock markets, and exclude closed-end funds, real estate investment trusts (REITs), unit trusts, American depository receipts (ADRs), and foreign stocks (or stocks that do not have a CRSP share code of 10 or 11).

To construct the monthly trend signals, we first calculate the moving average prices on the last trading day of each month. The moving average (MA) price at the last trading day of month t of lag L is defined as

$$A_{jt,L} = \frac{P^t_{jd-L-1} + P^t_{jd-L-2} + \cdots + P^t_{jd-1} + P^t_{jd}}{L}, \tag{1}$$

where P^t_{jd} is the closing price for stock j on the last trading day d of month t, and L is the lag length. Following, for example, Brock, Lakonishok, and LeBaron (1992), we consider 3-,5- 10-, 20-, 50-, 100-, and 200- day moving averages. We then normalize the moving average prices by the closing price on the last trading day of the month to reduce the undue influence of either very high or very low prices. We do not normalize $A_{jt,1}$ as $A_{jt,1} = P^t_{jd}$.

$$PA_{jt,L} = \frac{A_{jt,L}}{P^t_{jd}}. \tag{2}$$

To predict the monthly expected stock returns, we follow the procedure outlined in Haugen and Baker (1996). We first run cross-sectional regressions each month regressing monthly stock returns on the trend signals to obtain time-series of the coefficients of the trend signals.

$$r_{j,t} = \beta_{0,t} + \sum_i \beta_{i,t} PA_{jt-1,L_i} + \epsilon_{j,t}, \tag{3}$$

where

$$\begin{aligned}
r_{j,t} \quad &= \text{rate of return to stock } j \text{ in month } t,\\
PA_{jt-1,L_i} \quad &= \text{trend signals at the end of month } t-1 \text{ on stock } j \text{ with lag } L_i,\\
\beta_{i,t} \quad &= \text{coefficient of the moving average signal with lag } L_i \text{ in month } t,\\
\beta_{0,t} \quad &= \text{intercept in month } t.
\end{aligned}$$

We then estimate the expected return for month t using the moving averages of the coefficients in the 12 months prior to month t (month $t-12$ to month $t-1$) and the moving signals for month $t-1$.[2]

$$E[r_{j,t}] = \sum_i E[\beta_{i,t}] PA_{jt-1,L_i}, \tag{4}$$

where

$$\begin{aligned}
E[r_{j,t}] \quad &= \text{expected rate of return to stock } j \text{ in month } t,\\
E[\beta_{i,t}] \quad &= \text{expected coefficient of the moving average signal with lag } L_i \text{ in month } t\\
&\quad\ \text{(estimated as the average over the trailing 12 months).}
\end{aligned}$$

[2]We do not include the intercept as it is the same for stocks in the same cross-section and thus plays no role in ranking the stocks.

In most of the analysis, we use a specification that includes the short-term trend signals up to 20 days, but we examine various specifications that include various number of trend signals for robustness. For clarify, we state the default specification as

$$r_{j,t} = \beta_{0,t} + \beta_{1,t} PA_{jt-1,3} + \beta_{2,t} PA_{jt-1,5} + \beta_{3,t} PA_{jt-1,10} + \beta_{4,t} PA_{jt-1,20} + \epsilon_{j,t}. \tag{5}$$

We control for a variety of firm and market attributes. We use the percentage of zero returns (%Zero) in a month as a liquidity measure (Lesmond, Ogden, and Trzcinka, 1999). %Zero is measured as the percentage ratio of the number of zero returns over the total number of returns in a month. The six-month momentum (see, e.g., Jegadeesh and Titman, 1993) is estimated as the cumulative returns from month $t-2$ to month $t-7$. We define book-to-market ratio as the total common equity per share (CEQQ in quarterly COMPUSTAT) from last quarter divided by the current month-end price. To estimate cash-flow-to-price ratio (C/P), we first estimate cash flow per share, which is defined as the sum of quarterly net income per share (NIQ in quarterly COMPUSTAT) and total depreciation and amortization (DPQ in quarterly COMPUSTAT). The C/P ratio is then estimated as the last quarter cash flow per share divided by the current month-end price. To estimate earnings-to-price ratio (E/P), we divide the total earnings (IBQ in quarterly COMPUSTAT) from the trailing four quarters by the current month-end price. Similarly, to estimate dividend-to-price ratio (D/P) or sales-to-price ratio (S/P), we divide the total dividend (the product of DVPSPQ and CSHPRQ in quarterly COMPUSTAT) or total sales (SALEQ in quarterly COMPUSTAT) from the trailing four quarters by the current month-end price. Finally, we lag these ratios by one month in the analysis.

We use a number of variables to proxy for information uncertainty. First, we estimate the idiosyncratic volatility (Idio. Vol.) as the variance of the residuals from regressing the monthly excess returns in the past 60 months on the Fama-French three factors. Second, we estimate the trading turnover rate as the monthly trading volume normalized by the total shares outstanding. Third, following Berkman, Dimitrov, Jain, Koch, and Tice (2009), we estimate the operating income volatility as the standard deviation of the seasonally differenced ratio of quarterly operating income before depreciation (OIBDPQ in quarterly Compustat) divided by average total assets (ATQ in quarterly Compustat), measured over the 10 quarters prior to the current fiscal quarter. We require minimum of four quarterly observations. The fourth proxy we use is the credit rating. Following Avramov, Chordia, Jostova, and Philipov (2009), we assign larger numeric numbers to less creditable ratings (e.g., $AAA = 1,\ D = 22$). The fifth proxy we use is analyst coverage defined as the number of analysts following a stock in IBES[3]. We eliminate stocks with no analyst following. The last proxy is the firm age in years. In addition, we also treat firm size as another proxy for information uncertainty. All the proxies are used in the previous literature. For example, Zhang (2006) uses firm size, firm age, analyst coverage, analyst forecast dispersion, stock volatility, and cash flow volatility as proxies for information uncertainty. Berkman et al. (2009) use income volatility, stock volatility, analyst forecast dispersion and firm age to proxy for information uncertainty.

3. Performance of the Trend Forecasts

Following the literature in cross-section return predictability such as Jegadeesh and Titman (1993), Ang, Hodrick, Xing, and Zhang (2006, 2009), and Easley, Hvidkjaer, and O'Hara (2002), we sort stocks into portfolios by the trend signals. Specifically, we form quintile sorted portfolios using the expected returns forecasted by the trend signals. Specifically, each month stocks are sorted into five quintiles according to their forecasted expected returns, and then in each quintile group stock returns are equal-weighted to form the equal-weighted portfolio return. The sort procedure thus produces five quintile portfolios that rebalance every month. We then examine both the average returns and the risk-adjusted abnormal returns of the five quintile portfolios as well as the High-Low spread portfolio, which is constructed as a zero-cost arbitrage portfolio that takes a long position in the highest ranked quintile portfolio and takes a short position in the lowest ranked quintile portfolio. Significantly positive abnormal returns earned by the High-Low spread portfolio support the cross-section predictability and profitability.

3.1. Average returns of the quintile portfolios

Table 1 reports the average returns and characteristics of the equal-weighted quintile portfolios sorted by the expected returns forecasted using the trend signals. The average returns increase monotonically from the quintile with the lowest forecasted expected returns (Low) to the quintile with the highest forecasted expected returns (High). More specifically, stocks

[3]we also examine dispersions in analyst earnings forecasts and obtain similar results.

with the highest forecasted expected returns yield the highest returns on average in the subsequent month, about 3.025% per month, whereas stocks with the lowest forecasted expected returns yield the lowest returns on average in the subsequent month, only about -0.067% per month. As a results, the High-Low zero-cost portfolio which takes a long position in the highest quintile and a short position in the lowest quintile generates a striking 3.09% per month with a heteroscedasticity and autocorrelation (HAC) robust t-statistic of 13.69. Also worth noting are the large gaps in returns between the lowest quintile and the second quintile and the highest quintile and the fourth quintile - the average return increases by 0.927% and 1.486% per month, respectively.

The market size displays a hump shape across the quintiles - both quintile Low and High have much smaller market cap than the other quintiles, while the book-to-market ratio stays roughly constant across the quintiles. The prior month returns (R_{-1}) decrease monotonically across the quintiles, whereas the past six-month cumulative returns ($R_{-2,-7}$) increase monotonically across the quintiles. Clearly the abnormal returns are potentially related to short-term return reversal (DeBondt and Thaler, 1985) and momentum (Jegadeesh and Titman, 1993), and therefore we will control for both anomalies in the next section. Idiosyncratic volatility displays a U-shaped pattern across the quintiles - the two extreme quintiles have higher idiosyncratic volatility. We also report the percentage of zero returns (%Zero) and share turnover rate, both of which measure the liquidity of stocks (Lesmond et al., 1999), and both liquidity measures stay roughly constant across quintile. The last two columns in Table 1 report price ratios. While the cash flow to price ratio displays a hump shape pattern, the sales to price ratio increases monotonically across the quintiles.

3.2. Risk adjusted returns of the quintile portfolios

The abnormal returns reported in Table 1 could be due to more risk taking of the strategy. Therefore we also examine the risk-adjusted abnormal returns. Table 2 reports Jensen's alpha and risk loadings with respect to the CAPM and Fama-French three-factor model, respectively. Both alphas increase monotonically from the lowest quintile to the highest quintile, from -1.129% to 1.808% for the CAPM, and from -1.290% to 1.175% for the Fama-French three-factor model, respectively. As a result, the High-Low spread portfolio has a CAPM alpha of 2.927% per month, and a Fama-French alpha 2.814% per month, only slightly lower than the unadjusted abnormal return (3.025%) in Table 1.

The market beta and SMB beta are asymmetrically U-shaped across the quintile, and the HML beta increases monotonically across the quintiles. Therefore the highest quintile has the highest risk exposures to the market risk, and its SMB and HML betas are also the highest, indicating it contains more small stocks and value stocks. The lowest quintile also has the second highest SMB beta consistent with the findings in Table 1.

4. Robustness

In this section, we show that the superior performance of the trend forecasts is very robust. We examine the robustness in a number of dimensions including different specifications of trend signals and controlling for a variety of firm attributes. Robustness can also be demonstrated in the later section where we examine the subperiod performance of the trend factor (Table 10).

4.1. Robustness to various specifications of trend signals

Table 3 reports the performance of using various specifications of trend signals to forecast future returns. We also report the performance of the value-weighted quintile portfolios for the various specifications. In the table the performance is measured by the Fama-French alpha. In Panel A, the first alternative specification includes the longer lagged moving averages such as 50-day, 100-day and 200-day moving averages, and the performance is slightly better than what is reported in Table 2 which uses the moving averages up to 20 days (2.866% versus 2.814%). It is also worth noting that the 20-day moving average alone generates similar albeit slightly weaker performance - the Fama-French alpha is 2.435% per month. Eliminating the 1-day moving average slightly reduces the performance - the Fama-French alpha is reduced to 2.731% per month. Finally, using the raw signals instead of the normalized signals significantly reduces the performance, although the outperformance is still economically and statistically significant (the Fama-French alpha is 1.996% per month). Panel B reports the value-weighted results. The Fama-French alphas are about half of what are reported for the equal-weighted portfolios. Nevertheless, all the alphas are still statistically and economically significant. For example, the strategy using moving averages up to 20 days (default case) yields a Fama-French alpha of 1.259% per month compared to 2.814% per month reported in Table 2.

4.2. Robustness to various control variables

Table 4 reports the results of controlling for various firm attributes that are known to predict cross-section returns. Panel A reports the results of double sort on size and the forecasted expected return using trend signals. Double sort is achieved by sorting the size first and then the forecasted expected return. Specifically, stocks are sorted into five size groups, and within each size group stocks are further sorted into five quintiles by the forecasted expected returns. Finally, we form 5×5 equal-weighted quintile portfolios, and each size group has five quintile portfolios. Clearly, Panel A shows that the performance is much stronger for the small stocks. For the smallest stocks, the High-Low spread portfolio sorted on the forecasted expected return yields a Fama-French alpha of 6.062% per month. A close examination of the individual quintiles tells us that the bulk of the superior performance comes from shorting the quintile with the lowest forecasted expected returns (the alpha is -4.262% per month). Performance decreases as the size increases, and the decrease in performance is mainly due to the increased alpha of the quintile with the lowest forecasted expected returns. For example, the lowest quintile of the largest stocks has a statistically significant Fama-French alpha of 0.243% per month, and as a result, the High-Low spread portfolio of the largest stocks yields a Fama-French alpha of 0.993% per month, still very significant both statistically and economically nevertheless. T

Panel B reports the performance of sorting on the forecasted expected return after controlling for various firm attributes. To control for size, for example, we first double sort stocks into 5×5 quintile portfolios as described in the preceding paragraph. We then average over the five quintile portfolios of the same ranking by the forecasted expected returns across the size groups to form five quintiles ranked by the forecasted expected returns that supposedly have similar size across the quintiles. This procedure has been widely used in the literature to check the robustness of the cross-section pricing power of the predictor, Ang et al. (2006, 2009), Avramov et al. (2009), Yu (2011), and Wahal and Yavuz (2012), to name a few. We similarly control for book-to-market ratio, last month return, last month price, and percentage of zero returns. The superior performance generated from sorting on the forecasted expected return remains unchanged (slightly higher for many cases) regardless of the control used. For example, it is not surprising that controlling for size does not reduce the performance as the High-Low portfolio yields significant Fama-French alpha in each of the five size groups. So after controlling for size, the High-Low portfolio still yields a Fama-French alpha of 2.899% per month, similar to the performance reported in Table 2. Also of note is the control of last month returns, or the short-term return reversal. In Table 1, last month return monotonically decreases across the quintiles of the forecasted expected return. However, controlling for last month return does not reduce the performance - the High-Low portfolio still yields a Fama-French alpha of 2.390% per month. We also control for liquidity as measured by the percentage of zeros, and the performance remains unchanged. Similar results are observed when controlling for book-to-market ratio and last month price.

5. Performance of Trend Strategy under Information Uncertainty

When information about stocks is very uncertain, or when the noise-to-signal ratio is very high, fundamental signals, such as earnings and economic outlook, are likely to be imprecise, and hence investors tend to rely more heavily on technical signals. Therefore, trend signals will be more profitable for the high information uncertain stocks than for the low information uncertain stocks.

In this section, we examine the predictability performance of the expected returns forecasted by trend signals for different groups of stocks that have different degrees of information uncertainty. Clearly, information uncertainty is not observable. Size is often used as a proxy for information uncertainty, and in Table 4 the performance of the High-Low portfolio monotonically increases as the size (information uncertainty) decreases (increases). We also use a number of other proxies including idiosyncratic volatility, trading turnover rate, quarterly income volatility, credit rating, number of analysts following, and age to demonstrate the robustness of the results.

Table 5 reports the performance of the sort results after first sorting the stocks by one of the information uncertainty proxies and then within each group further sorting the stocks by the expected returns forecasted using the trend signals. We also examine the performance after averaging across all groups of the information uncertainty proxy as a way to control for the information uncertainty proxy.

The Fama-French alpha of the High-Low portfolio sorted on the forecasted expected return clearly monotonically increases as the idiosyncratic volatility (information uncertainty) increases in Panel A. When idiosyncratic volatility is at the lowest (highest) level, the High-Low portfolio has an alpha of 1.174% (5.206%) per month. The abnormal returns of both the lowest and the highest quintile change drastically as the information uncertainty (idiosyncratic volatility) increases, but in the opposite direction. The abnormal returns of the lowest quintile decreases as the information uncertainty increases, while the performance of the highest quintile increases at the same time. As a result, the alpha of the High-Low spread portfolio increases from 1.174% to 5.206% per month. The remaining quintiles are rather insensitive to the change in the information uncertainty. In addition, controlling for idiosyncratic volatility by averaging over the five quintiles of idiosyncratic volatility yields similar performance to the single sort in Table 2.

In Panel B a similar pattern is observed when trading turnover rate is used to proxy information uncertainty. The performance of the High-Low portfolio decreases monotonically as the turnover rate (information uncertainty) increases (decreases); the Fama-French alpha decreases from 3.409% per month to 1.669% per month. Again, the lowest quintile and the highest quintile move in the opposite directions, while other quintiles are rather insensitive to the change in the information uncertainty. Similarly, controlling for the trading turnover rate does not reduce the performance.

In Panel C, we use income volatility to proxy for information uncertainty. The higher the income volatility, the higher the information uncertainty, and the higher the performance of the High-Low spread portfolio. The Fama-French alpha increases monotonically from 1.859% per month to 4.346% per month. The alpha of the lowest quintile decreases from -0.988% to -1/425% per month, while the alpha of the highest quintile increases from 0.871% to 2.921% per month. Controlling for income volatility by averaging does not reduce the performance. In Panel D we use credit rating to proxy for the noise-signal ratio. Presumably, weaker credit rating suggests higher default risk and thus more information uncertainty. Performance of the High-Low spread portfolio monotonically increases from 0.852% to 2.002% as the credit rating (information uncertainty) decreases (increases) across the quintile. The generally lower performance in this panel is due to the smaller sample of firms having credit ratings, which tend to be larger firms.

In Panel E, we use the number of analysts following as a proxy for information uncertainty. Stocks that are followed by more analyst should have less information uncertainty. The performance of the High-Low spread portfolio monotonically decreases as the number of analysts following increases across the quintiles - the Fama-French alpha decreases from 3.308% per month to 1.140% per month. Controlling for the number of analysts following by averaging across the quintiles still yields similar abnormal returns. The slightly reduction is due to the elimination of small firms which are not followed by any analyst. Finally, We use age of the firm to proxy for the information uncertainty or noise-signal ratio. Younger firms are subject to higher information uncertainty. We observe a similar pattern - from the youngest age quintile (Young) to the oldest age quintile (Old), the abnormal returns (Fama-French alphas) decrease monotonically from 2.980% per month to 1.561% per month. Again, controlling for age still yields significant abnormal returns and the magnitude is similar to what is achieved in the single sort shown in Table 2.

6. Alternative Strategy Comparison

6.1. Compare with the momentum strategy

In Table 1, past six-month returns monotonically increase across the quintiles of the forecasted expected returns, suggesting that the abnormal returns may be related to momentum. In this subsection, we examine whether momentum can explain the abnormal returns generated from forecasting expected returns using trend signals.

Table 6 compares the moving average strategy with the momentum strategy. Panel A reports the alpha of the four-factor model including Fama-French three factors and the momentum factor. Panel B reports the sort results after controlling for the past six-month cumulative returns from $t-2$ to $t-7$.

In Panel A, the alpha after controlling for the exposure to the momentum factor still displays a monotonic relation with the forecasted expected returns. Low forecasted expected returns are associated with low alphas and high forecasted expected returns are associated with high alphas. The High-Low spread portfolio yields an alpha of 2.777% per month, which is comparable to the alphas under the CAPM and Fama-French models. All quintile portfolios have significant yet negative exposures to the momentum factor, but the High-Low spread portfolio does not have any risk exposure to the momentum factor.

In Panel B stocks are double sorted by the past six-month returns from $t-2$ to $t-7$ and the forecasted expected returns using the trend signals using the procedure described previously. In each group of past returns (momentum), the Fama-French alpha increases monotonically from the lowest quintile of the forecasted expected return to the highest quintile of the forecasted expected return, and thus the High-Low spread portfolio yields positive and significant abnormal return. The High-Low spread portfolio yields the highest Fama-French alpha with stocks that have the lowest past returns (losers). which is as high as 4.788% per month. The High-Low alphas generally decrease moving from the low past returns (losers) to high past returns (winners), but all remain highly statistically and economically significant. For example, the smallest alpha is about 2.113% per month. If the quintile portfolios across the five past return groups are averaged, the High-Low alpha is 2.871%, which is very closed to that of the single sort reported in Table 2, suggesting that momentum can not explain the abnormal returns generated from using the trend signals.

6.2. Compare with forecasts using firm characteristics

Haugen and Baker (1996) use a variety of fundamental variables including both market and accounting variables to predict returns and form deciles using the forecasts. They find that the spread between the highest decile portfolio and the lowest decile portfolio yields significant abnormal returns. In this subsection, we compares the performance of the moving average forecasts to forecasts using the fundamental variables following Haugen and Baker (1996).

Table 7 reports the results of double sorts by the forecasted expected returns using the trend signals (ER_{MA}) and fundamental variables (ER_{AC}). In Panel A, we control for ER_{AC} and examine the performance of ER_{MA}. The High-Low Fama-French alpha increases from the low ER_{AC} tercile to the high ER_{AC} tercile, and averaging across the terciles still yields a highly significant alpha. However, the magnitude of the abnormal performance is weakened, which is likely due to the much smaller sample of firms and much shorter period - many accounting variables used in Haugen and Baker (1996) are not available until 1980.

Panel B reports the results of controlling for ER_{MA}, the forecasted expected returns using the trend signals, and examine the performance of ER_{AC}, the forecasted expected returns using the fundamental variables. The High-Low portfolio of ER_{AC} yields a significant Fama-French alpha when ER_{MA} is either low or high, and an insignificant alpha in between. After averaging across the terciles of ER_{MA}, the High-Low alpha is about 1.273% per month, lower than what is reported in Panel A for ER_{MA}.

Table 7 shows that these two approaches of forecasting the expected returns, using either the trend signals or fundamental variables, are related, but are distinct from each other at the same time. This is indicated by all the significant High-Low alphas for ER_{MA} after sorting by ER_{AC} first, but some insignificant High-Low alphas for ER_{AC} after sorting by ER_{MA} first. In addition, if we form an arbitrage portfolio by taking a long position in the portfolio that has the highest ER_{AC} and ER_{MA} (HH) and a short position in the portfolio that has the lowest ER_{QC} and ER_{MA} (LL), the Fama-French alpha of the portfolio is 3.58% (1.689-(-1.889)) per month, significantly higher than 2.814% per month, the alpha of the High-Low portfolio of ER_{MA} with single sort reported in Table 2.

6.3. Fama-MacBeth regressions

Portfolio sorting, although powerful, often does not control for other variables, and it also focuses on extreme portfolios. Fama-MacBeth regression, on the other hand, can control for many variables and focuses on the average effect. Therefore we run Fama-MacBeth regression to further examine the robustness of the results. Shanken and Zhou (2007) argue that weighted least square (WLS) often generates better results than the OLS used in the first step of the Fama-MacBeth regression. For each stock, we estimate the stock variance using the whole sample period and use the inverse of the variance as the weight.

Table 8 reports the results of regressing the monthly returns on the forecasted expected return using either the trend signals (ER_{MA}) or the fundamental variables (ER_{AC}) and various control variables using the Fama-MacBeth cross-sectional regression framework. In the first set of results, we examine the predictability of ER_{MA} and ER_{AC} separately and also combined while controlling for the market beta, size and book-to-market ratio. Both ER_{MA} and ER_{AC} have significant and positive coefficients indicating both signals can predict future cross-section returns. This is true even when both variables are present in the regression. These results are consistent with the double sort results in Table 7. In the second set of results, we add last-month return (short-term reversal) and six-month cumulative return from $t-2$ to $t-7$ (momentum) as additional controls. Now ER_{AC} becomes insignificant, while the last-month return is highly significant. This suggests that predictability of the fundamental variables may capture short-term return reversal. In contrast, ER_{MA} remains highly significant and the coefficient is only slightly reduced despite the significant presence of the last-month return, which is consistent with the sort results in Table 4. The last set of results are very similar to the second set of results despite the additional control variables added. ER_{MA} remains significant while ER_{AC} becomes insignificant.

7. The Trend Factor - High-Low Quintile Portfolio

The High-Low spread portfolio yields very large abnormal returns even after adjusting for the market risk and other risks associated with Fama-French size and book-to-market factors. The alpha is about 2.814% per month, which is 33.77% per annum. In this section we further analyze the time-series property of the High-Low spread quintile portfolio and argue that we can use the High-Low spread portfolio as another factor - the trend factor.

Figure 1 plots the returns of the spread portfolio (trend factor) over the period from 1927 to 2010. Over the last 84 years, returns of the spread portfolio are largely positive; there are 853 months with positive returns out of the total 1007 months. There are only a few incidences of large negative returns corresponding to various market crashes. The biggest loss is -24.90% in September 1939, and the largest return is 58.75% in May 1933, both of which happen in the Great Depression and prewar period. We also observe very large variations during the era of internet bubble burst. Surprisingly, the so called "Great Recession" of the last recession does not witness as much variations as the other two periods.

7.1. Summary statistics

Table 9 reports the summary statistics of the trend factor as compared to those of the four factors including Fama-French three factors and the momentum factor. Also reported are the pairwise correlations among the trend factor and the four factors. The average monthly return of the trend factor from February 1927 to December 2010 is 3.09%, or 37.08% per annum, much higher than the average return of any of the other factors. All the four factors yield average returns that are much less than 1% per month.[4] In addition, the standard deviation of the trend factor is about 4.86%, which is comparable to those of the other factors. Therefore the Sharpe ratio of the trend factor is much higher than any of the four factors. For example, the trend factor has a Sharpe ratio of 0.64, whereas the next highest one is 0.14 generated by the momentum factor.[5] The trend factor also has much higher autocorrelation than the four factors. For example, the first order correlation coefficient is 0.31 for the trend factor, while the next one is 0.19 for the HML factor. The trend factor is also correlated with the four factors. The correlation is 0.30 with the market portfolio, 0.30 with the SMB factor, and 0.24 with the HML factor, but the correlation is -0.14 with the UMD momentum factor, all of which are similar to the correlations between the other factors. In particular, the momentum factor is always negatively correlated with the other factors.

7.2. Trend factor and macroeconomic variables

We further investigate if the trend factor can be explained by any economic variables. Table 10 reports the results of regressing the returns on the trend factor to the four factors including the momentum factor and other economic variables. We include the monthly S&P 500 volatility estimated each month using daily returns, a recession dummy, which indicates recessionary periods identified by NBER, the default spread defined as the yield spread between BAA and AAA bonds, the tradable liquidity factor by Pástor and Stambaugh (2003), and the sentiment index by Baker and Wurgler (2006). The market volatility can proxy for information uncertainty at the aggregate level. Finally, We examine various subperiod performance[6].

The first three regressions in Table 10 use the whole sample period from 1972:02 to 2010:12. The first regression adds the market volatility in addition to the four factors. The market (S&P 500) volatility has a positive and significant coefficient, suggesting that the trend factor yields higher returns when the market volatility is higher, or when the information about the market or economy is more uncertainty. The second regression adds

[4]One can argue that this is not a fair comparison because the trend factor is equal-weighted while the four factors are value-weighted. The value-weighted trend factor has an average return of 1.38% per month, still much higher than that of any of the four factors.

[5]The value-weighted trend factor has a Sharpe ratio of 0.30.

[6]The liquidity factor available from WRDS is from 1968:01; the sentiment index is available from 1965:07.

the recession dummy in addition to the market volatility. The recession dummy also has a positive and significant coefficient while the market volatility remains positive and significant. Hance the trend factor will perform better in the recessions than in expansions. The third regression adds the default spread in addition to the market volatility and recession dummy. The recession dummy loses its significance while the default spread is positive and significant. In addition, unlike in the previous two regressions, the alpha is no longer significant. It seems that default spread explains the abnormal returns of the trend factor. However, this result is due to the Great Depression as shown in the fourth regression in Table 10, which excludes the Great Depression period. During the Great Depression, many firms were out of business, and those who survived are also subject to much heightened default risk. It should be of no surprise that default spread is highly significant.Once the Great Depression period is excluded, the intercept is still positive and highly significant. Even though default spread remains significant, the coefficient is reduced to half. The coefficient remains positive, which suggests that the trend factor has exposure to the default risk. Perhaps the stocks that are long in the portfolio have higher default risks. Similar results are obtained when we exclude the last recession - the Great Recession, as shown in the fifth column of Table 10.

The sixth regression starts from 1965:07, another commonly used subperiod. The abnormal return (intercept) remains highly significant. So is the market volatility. The recession dummy becomes significant again, but the default spread becomes negative and significant. We add sentiment in the seventh and eighth regressions. The trend factor does not have any exposure to the sentiment, and we obtain similar results whether or not we include the last recession. The intercept is highly significant, and the market volatility and the recession dummy are positive and significant while the default spread is negative and significant. Similar results are shown in the last two regressions where the liquidity factor is included. The intercept, the market volatility and the recession dummy are all positive and significant. The default spread remains negative and significant while the liquidity factor is not significant.

7.3. Explain the short-term reversal and other anomalies

In this subsections, we examine whether the trend factor can explain other common anomalies and compare its pricing ability with that of the momentum factor. Table 11 uses the well-known short-term reversal anomalies. Six (2 size *times* 3 last month return) portfolios are regressed under either CAPM or the Fama-French three-factor model with either the trend factor or the momentum factor. In the last column, we include the short-term reversal factor, which is constructed as the difference between the average of the two (large and small) portfolios with the lowest last month returns and the average of the two (large and small) portfolios with the highest last month returns. Panel A reports the results for CAPM, and Panel B reports the results for Fama-French three-factor model. In Panel A, all six short-term reversal portfolios as well as the short-term reversal factor have highly significant Jensen's alpha under CAPM. The first portfolio (*STRev1*), which contains small stocks with the lowest last month returns, yields the highest abnormal returns (1.15% per month), whereas the third portfolio (*STRev3*), which contains small stocks with the highest last-month returns, yields the lowest abnormal returns (-0.674% per month). The short-term reversal factor has an abnormal return about 0.696% per month.

However, all but two large portfolios (*STRev3* and *STRev6*) no longer have any significant abnormal returns once the trend factor is included in the regression; the alphas become negative but insignificant. Neither is the short-term reversal factor. The alpha of the short-term reversal factor is about 0.231% and insignificant. All but the two large portfolios also have significant exposure to the trend factor. On the other hand, adding the momentum factor does not help to explain any of the abnormal returns; in fact, all the alphas are even larger and more significant. For example, the first portfolio (*STRev1*) now has an alpha about 1.560% versus 1.150% per month. The short-term reversal factor has an alpha of 0.786% versus 0.696% per month.

With the Fama-French three-factor model in Panel B, the results are similar. The trend factor explains the abnormal returns of all but the two large portfolios; it also explains the abnormal returns of the short-term reversal factor. In contrast, all the alphas are significant under the four-factor model that includes the momentum factor.

Table 12 reports the results using decile portfolios sorted by earnings-to-price ratio (E/P), cash-flow-to-price ratio (C/P), and dividend-to-price ratio (D/P), and ten industry portfolios. For each set of portfolios, we report the regression results of the trend factor or the momentum factor in the context of CAPM. The results for the Fama-French three-factor model are similar. In each case, the trend factor can explain most if not all the abnormal returns and thus the alphas are mostly insignificant. By contrast, the alphas of most of the portfolios remain significant even after including the momentum factor.

8. Conclusion

We use the moving average prices to construct the trend signals and to forecast the expected stock returns. Stocks that have high forecasted expected returns tend to yield higher future returns on average, and stocks that have low forecasted expected returns tend to yield lower future returns on average. The difference between the highest ranked and lowest ranked quintile portfolios sorted by the forecasted expected returns is around 3% per month, even after controlling for the market risk and risks associated with the SMB, HML, and momentum factors.

The cross-sectional predictability and profitability of the trend signals are robust to various firm and market characteristics, such as size, book-to-market ratio, past return, trading volume, etc. The strategy yields much higher profitability if information about the stocks are more uncertain, consistent with Zhang (2006) who argues that price continuation or trend is due to investors under-react to public information and investors under-react even more if information is more uncertain.

We argue that the high-low spread portfolio can be used as a trend factor and that it performs better than the momentum factor in capturing the trend in returns. Our analysis shows that the trend factor can explain several anomalies whereas the momentum factor cannot. Future research are called for to examine whether or not the trend factor can explain more anomalies. It is also of great interest to see whether the trend factor is of significance across countries.

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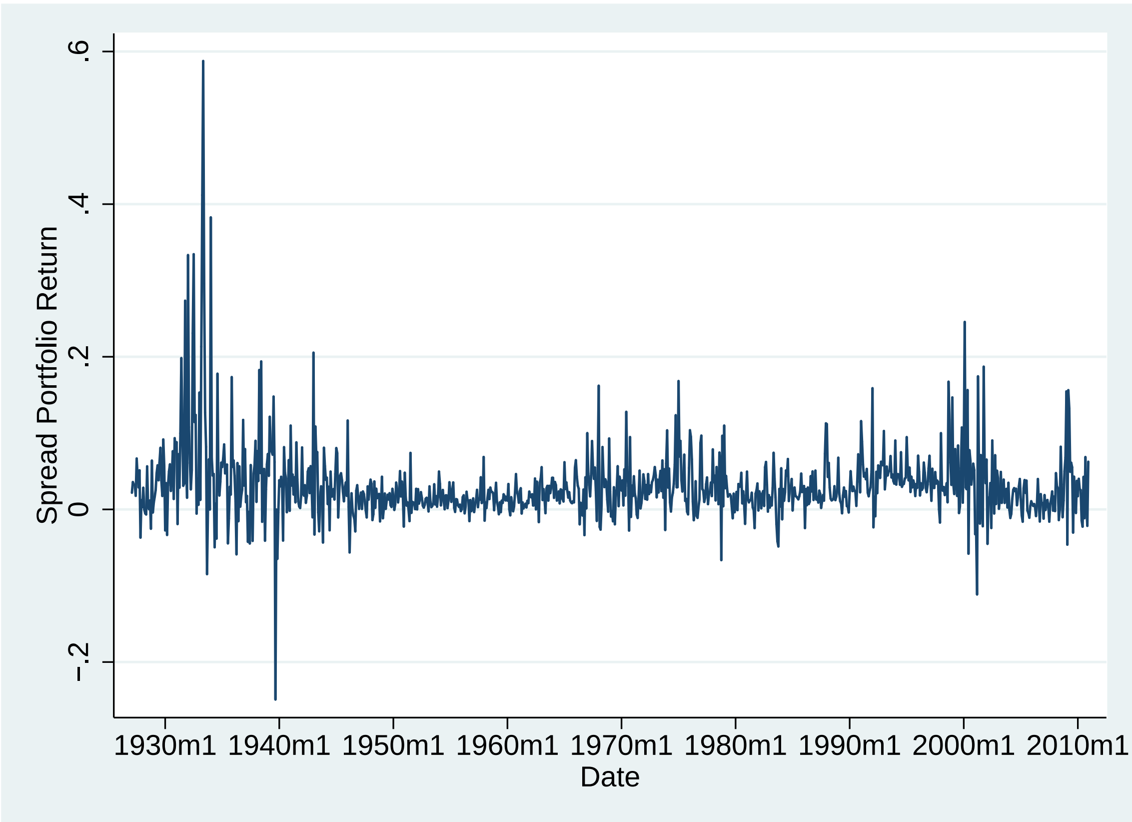

Figure 1: Time Series of Returns on the Trend Factor

Table 1: Average Returns and Other Summary Statistics

This table reports the average return and other characteristics of the equal-weighted quintile portfolios sorted by the expected returns forecasted from the moving average signals. Also reported are the characteristics of the spread between the quintile with the highest (High) forecasted returns and quintile with the lowest (Low) forecasted returns, the High-Low portfolio. The average returns and past returns are monthly returns and are reported in percentage. Market cap is in millions of dollars. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1926 to December 2010.

Rank	Return	Mkt Cap	logB/M	R_{-1}	$R_{-7,-2}$	Idio Vol(%)	%Zero	Turnover(%)	Cash/Price(%)	Sales/Price
Low	-0.067	387.9***	1.504***	9.418***	6.358***	2.022***	22.62***	7.060***	0.174	50.93***
	(-0.240)	(9.750)	(20.00)	(18.30)	(4.420)	(16.69)	(25.46)	(14.65)	(0.280)	(9.360)
2	0.860***	697.8***	1.729***	3.300***	7.462***	1.345***	23.10***	5.569***	2.528***	57.88***
	(3.640)	(7.630)	(22.34)	(11.19)	(6.140)	(19.26)	(23.76)	(14.22)	(7.430)	(10.82)
3	1.186***	804.7***	1.762***	0.893***	7.811***	1.258***	24.50***	5.141***	2.684***	63.23***
	(5.070)	(7.190)	(22.23)	(3.720)	(6.560)	(19.73)	(23.61)	(14.08)	(7.850)	(9.690)
4	1.539***	747.3***	1.739***	-1.332***	8.315***	1.424***	23.92***	5.360***	2.326***	65.67***
	(5.970)	(7.430)	(20.71)	(-5.640)	(6.520)	(18.71)	(23.31)	(14.33)	(5.600)	(9.880)
High	3.025***	405.8***	1.611***	-5.772***	8.825***	2.328***	24.63***	6.610***	-2.318**	71.52***
	(8.490)	(8.720)	(18.41)	(-15.22)	(5.440)	(16.73)	(24.53)	(13.70)	(-2.070)	(7.380)
High-Low	3.093***	17.92	0.108**	-15.19***	2.467***	0.305***	2.010***	-0.449***	-2.492***	20.59***
	(13.69)	(0.640)	(2.260)	(-22.61)	(4.000)	(4.160)	(3.360)	(-3.380)	(-4.020)	(3.780)

Table 2: CAPM and Fama-French Alphas

This table reports Jensen's alpha and risk loadings with respect to CAPM and Fama-French three-factor model, respectively, for the equal-weighted quintile portfolios and the spread between the quintile with the highest (High) forecasted returns and quintile with the lowest (Low) forecasted returns, the High-Low portfolio. The alphas are reported in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1926 to December 2010.

	Panel A: CAPM		**Panel B: FF**			
Rank	α	β_{mkt}	α	β_{mkt}	β_{smb}	β_{hml}
Low	-1.119***	1.214***	-1.290***	1.010***	0.880***	0.189***
	(-8.920)	(29.53)	(-13.44)	(37.49)	(10.06)	(2.740)
2	-0.153*	1.151***	-0.327***	0.967***	0.724***	0.267***
	(-1.710)	(31.85)	(-6.270)	(65.14)	(13.95)	(7.330)
3	0.171**	1.154***	-0.014	0.972***	0.669***	0.327***
	(1.970)	(28.22)	(-0.340)	(73.14)	(16.29)	(10.64)
4	0.467***	1.246***	0.271***	1.045***	0.764***	0.325***
	(4.670)	(26.75)	(5.660)	(61.48)	(12.67)	(8.300)
High	1.808***	1.480***	1.524***	1.175***	1.205***	0.426***
	(9.000)	(17.94)	(11.13)	(34.22)	(14.01)	(4.900)
High - Low	2.927***	0.266***	2.814***	0.165***	0.325**	0.237**
	(14.40)	(3.180)	(14.94)	(3.860)	(2.030)	(2.040)

Table 3: Robust Performance to Moving Average Specification

This table reports the performance of using various specifications of moving averages to predict future returns. As an additional robustness check, the table also reports the performance of value-weighted quintile portfolios. The performance is measured by Fama-French alphas reported in percentage. If not specified, we use the normalized moving average signals, and we use *Raw Signal* to denote the unnormalized signals. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1926 to December 2010.

	Low	2	3	4	High	High - Low
	Panel A: Equal-Weighted Results					
1-,3-,5-,10-,20-,50-,100-,200-day	-1.293***	-0.334***	-0.013	0.344***	1.574***	2.866***
	(-12.64)	(-7.092)	(-0.323)	(6.833)	(10.85)	(14.03)
20-day	-1.125***	-0.206***	0.023	0.162***	1.311***	2.435***
	(-11.26)	(-4.132)	(0.555)	(2.852)	(9.374)	(11.99)
3-,5-,10-,20-day	-1.304***	-0.214***	0.043	0.210***	1.427***	2.731***
	(-14.22)	(-4.269)	(0.996)	(4.137)	(10.60)	(14.50)
Raw Signal: 1-,3-,5-,10-,20-day	-0.869***	-0.465***	-0.041	0.411***	1.127***	1.996***
	(-9.855)	(-6.769)	(-0.630)	(5.137)	(8.861)	(11.10)
	Panel B: Value-Weighted Results					
1-,3-,5-,10-,20-day	-0.685***	-0.241***	0.012	0.282***	0.575***	1.259***
	(-8.885)	(-5.332)	(0.319)	(5.868)	(6.795)	(9.235)
1-,3-,5-,10-,20-,50-,100-,200-day	-0.728***	-0.227***	0.034	0.286***	0.583***	1.311***
	(-8.845)	(-5.101)	(0.904)	(6.206)	(7.145)	(9.315)
20-day	-0.496***	-0.071*	0.112***	0.190***	0.312***	0.808***
	(-6.394)	(-1.730)	(3.265)	(3.395)	(3.721)	(5.976)
3-,5-,10-,20-day	-0.727***	-0.127***	0.107***	0.230***	0.473***	1.200***
	(-9.039)	(-2.897)	(3.195)	(5.170)	(6.203)	(8.828)
Raw Signal: 1-,3-,5-,10-,20-day	-0.440***	-0.255***	-0.023	0.169***	0.525***	0.964***
	(-6.169)	(-4.397)	(-0.447)	(3.055)	(6.035)	(7.547)

Table 4: Robust Performance after Controlling for Firm and Market Characteristics

This table reports the sort results of controlling for various firm or market characteristics. In Panel A, stocks are first sorted by their market cap into five quintiles, and then in each quintile, stocks are further sorted into five quintiles by the expected returns forecasted from the moving average signals. The Fama-French alphas of the 5 × 5 equal-weighted quintile portfolios and the spread between the quintiles with the highest (High) and lowest (Low) forecasted expected returns are reported in percentage. In Panel B, the five quintile portfolios with the same rank from each of the market cap quintiles are averaged so that five new quintile portfolios that have the same average market cap are constructed. The Fama-French alphas in percentage are reported for the new quintile portfolios and the spread between the quintile with the highest (High) forecasted returns and quintile with the lowest (Low) forecasted returns, the High-Low portfolio. Similar procedure is used to control for other variables. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1926 to December 2010.

Market Cap	Low	2	3	4	High	High - Low
	Panel A: Double Sort with Market Cap					
Low	-4.282***	-2.058***	-1.385***	-1.116***	1.779***	6.062***
	(-20.11)	(-14.28)	(-11.40)	(-6.984)	(6.654)	(16.23)
2	-1.500***	-0.592***	-0.166**	0.168**	1.981***	3.480***
	(-12.37)	(-6.416)	(-2.098)	(2.088)	(11.45)	(14.93)
3	-0.574***	-0.039	0.253***	0.556***	1.808***	2.383***
	(-5.432)	(-0.566)	(3.823)	(8.932)	(12.75)	(12.52)
4	-0.009	0.250***	0.435***	0.792***	1.567***	1.576***
	(-0.116)	(4.333)	(7.621)	(11.00)	(13.89)	(11.36)
High	0.243***	0.322***	0.438***	0.702***	1.236***	0.993***
	(3.154)	(6.892)	(8.903)	(11.54)	(12.26)	(8.565)
	Panel B: Controlling for Firm Specific Variables					
Average over Market Cap	-1.224***	-0.423***	-0.085*	0.221***	1.674***	2.899***
	(-13.79)	(-7.437)	(-1.766)	(4.081)	(22.00)	(23.93)
Average over B/M	-1.331***	-0.242***	-0.029	0.319***	1.610***	2.940***
	(-17.39)	(-3.724)	(-0.508)	(4.529)	(17.11)	(26.47)
Average over Last Month Return	-1.142***	-0.298***	0.011	0.325***	1.248***	2.390***
	(-19.20)	(-7.221)	(0.276)	(7.226)	(13.86)	(24.41)
Average over Last Month Price	-1.338***	-0.329***	0.004	0.380***	1.452***	2.790***
	(-19.36)	(-6.257)	(0.081)	(7.051)	(16.47)	(23.24)
Average over %Zeros	-1.291***	-0.264***	-0.041	0.289***	1.601***	2.892***
	(-21.29)	(-7.050)	(-1.328)	(7.634)	(19.15)	(26.29)

Table 5: Performance under Information Uncertainty

This table reports the performance of using the moving average based forecasts under information uncertainty proxied by idiosyncratic volatility (Panel A), share monthly turnover rate (Panel B), income volatility (Panel C), and credit rating (Panel D). Stocks are double sorted by the information uncertainty proxies and the forecast expected return as described in Table 4. The alphas are reported in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1926 to December 2010.

	Low	2	3	4	High	High - Low
	Panel A: Controlling for Idiosyncratic Volatility					
Low	-0.390***	-0.006	0.187***	0.355***	0.785***	1.174***
	(-5.305)	(-0.090)	(2.777)	(5.401)	(9.244)	(13.11)
2	-0.687***	-0.163**	0.060	0.332***	0.898***	1.585***
	(-8.852)	(-2.575)	(0.915)	(5.027)	(10.93)	(14.10)
3	-1.058***	-0.256***	0.043	0.270***	1.083***	2.141***
	(-11.98)	(-3.930)	(0.664)	(4.265)	(11.19)	(15.14)
4	-1.335***	-0.458***	-0.147*	0.376***	1.605***	2.940***
	(-14.26)	(-6.587)	(-1.821)	(4.567)	(9.289)	(13.37)
High	-2.311***	-0.947***	-0.133	0.377***	2.895***	5.206***
	(-12.10)	(-7.536)	(-1.067)	(2.677)	(9.404)	(12.77)
Average over Idio. Vol.	-1.156***	-0.366***	0.002	0.342***	1.453***	2.609***
	(-17.20)	(-7.053)	(0.042)	(6.867)	(17.44)	(23.57)
	Panel B: Controlling for Turnover Rate					
Low	-1.417***	-0.385***	-0.096	0.200**	1.992***	3.409***
	(-9.611)	(-4.084)	(-1.097)	(2.020)	(9.886)	(12.60)
2	-1.398***	-0.212***	0.062	0.280***	1.846***	3.244***
	(-11.25)	(-2.596)	(0.875)	(3.996)	(10.68)	(13.63)
3	-1.338***	-0.256***	0.057	0.423***	1.725***	3.063***
	(-12.18)	(-4.415)	(1.048)	(6.729)	(11.72)	(15.65)
4	-1.281***	-0.332***	-0.003	0.380***	1.350***	2.631***
	(-12.15)	(-4.833)	(-0.056)	(5.289)	(9.744)	(14.64)
High	-1.095***	-0.371***	-0.102	-0.040	0.604***	1.699***
	(-9.803)	(-4.445)	(-1.218)	(-0.434)	(4.219)	(11.21)
Average over Turnover	-1.306***	-0.311***	-0.017	0.249***	1.503***	2.809***
	(-24.08)	(-8.368)	(-0.476)	(6.366)	(19.96)	(29.11)

	Low	2	3	4	High	High-Low
	Panel C: Controlling for Income Volatility					
Low	-0.988***	-0.203*	0.095	0.323***	0.871***	1.859***
	(-6.821)	(-1.789)	(0.792)	(2.664)	(6.217)	(11.88)
2	-1.121***	-0.161*	0.092	0.343***	1.210***	2.331***
	(-8.754)	(-1.800)	(0.890)	(3.821)	(8.780)	(12.04)
3	-0.941***	-0.159	0.107	0.417***	1.514***	2.456***
	(-6.587)	(-1.507)	(0.930)	(3.904)	(8.785)	(10.51)
4	-1.384***	-0.324**	0.077	0.453***	2.023***	3.407***
	(-7.934)	(-2.459)	(0.680)	(3.572)	(8.730)	(11.92)
High	-1.425***	-0.325	0.076	0.412*	2.921***	4.346***
	(-5.514)	(-1.617)	(0.433)	(1.906)	(7.809)	(11.48)
Average over Income Vol.	-1.151***	-0.235***	0.092	0.389***	1.713***	2.864***
	(-9.280)	(-2.868)	(1.186)	(4.795)	(9.931)	(13.32)
	Panel D: Controlling for Credit Rating					
High	-0.433***	-0.272**	0.121	0.284***	0.419***	0.852***
	(-3.868)	(-2.580)	(1.217)	(3.007)	(3.551)	(5.470)
2	-0.591***	-0.173*	-0.115	0.258**	0.536***	1.127***
	(-4.714)	(-1.657)	(-1.042)	(2.114)	(4.467)	(6.945)
3	-0.740***	-0.186	-0.027	0.321**	0.458***	1.198***
	(-4.343)	(-1.363)	(-0.222)	(2.373)	(2.708)	(5.428)
4	-0.926***	-0.368**	-0.024	0.249	0.397*	1.323***
	(-4.981)	(-2.164)	(-0.137)	(1.221)	(1.817)	(4.928)
Low	-0.946***	-0.585**	-0.373*	0.086	1.056***	2.002***
	(-3.056)	(-2.556)	(-1.736)	(0.343)	(3.445)	(5.465)
Average over Credit Rating	-0.710***	-0.319***	-0.101	0.244**	0.608***	1.318***
	(-5.690)	(-3.285)	(-1.047)	(2.148)	(4.460)	(7.884)

	Low	2	3	4	High	High-Low
	Panel E: Controlling for Number of Analysts					
Low	-1.269***	-0.084	0.192	0.498***	2.039***	3.308***
	(-6.463)	(-0.611)	(1.576)	(4.262)	(7.279)	(10.06)
2	-1.414***	-0.357***	-0.082	0.252**	1.065***	2.478***
	(-9.063)	(-3.369)	(-0.784)	(2.345)	(5.708)	(9.519)
3	-1.205***	-0.337***	-0.022	0.292***	0.935***	2.139***
	(-10.38)	(-4.107)	(-0.248)	(3.671)	(6.018)	(9.910)
4	-0.841***	-0.225**	0.001	0.309***	0.716***	1.556***
	(-7.564)	(-2.422)	(0.017)	(3.109)	(5.077)	(8.543)
High	-0.597***	-0.219***	0.013	0.194**	0.543***	1.140***
	(-4.966)	(-2.875)	(0.164)	(2.091)	(3.868)	(6.192)
Average over # of Analysts	-1.065***	-0.245***	0.020	0.309***	1.059***	2.124***
	(-9.634)	(-3.253)	(0.270)	(4.069)	(7.047)	(10.61)
	Panel F: Controlling for Age					
Young	-1.319***	-0.270***	0.093	0.362***	1.661***	2.980***
	(-11.74)	(-3.671)	(1.431)	(4.700)	(10.06)	(13.31)
2	-1.211***	-0.195***	0.025	0.476***	1.748***	2.960***
	(-9.948)	(-2.711)	(0.387)	(6.928)	(9.997)	(12.86)
3	-1.017***	-0.240***	0.013	0.358***	1.484***	2.501***
	(-9.882)	(-3.400)	(0.204)	(5.656)	(10.46)	(12.96)
4	-0.988***	-0.198***	0.056	0.357***	1.164***	2.152***
	(-11.08)	(-3.236)	(0.924)	(5.816)	(8.618)	(11.96)
Old	-0.793***	-0.259***	0.052	0.220***	0.768***	1.561***
	(-8.011)	(-3.783)	(0.669)	(2.826)	(7.314)	(10.75)
Average over Age	-1.157***	-0.255***	0.042	0.351***	1.518***	2.674***
	(-13.28)	(-5.291)	(1.013)	(7.624)	(10.53)	(13.43)

Table 6: Robust Performance after Controlling for Momentum

This table compares the moving average strategy with the momentum strategy. Panel A reports the alpha and risk loadings with respect to the four-factor model that includes the Fama-French three factors and the momentum factor. Panel B reports the sort results after controlling for the past six-month cumulative return from month $t-2$ to month $t-7$ using the double sort procedure described in Table 4. The alphas are reported in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1926 to December 2010.

Panel A: Measure Performance with Momentum Factor

Rank	α	β_{mkt}	β_{smb}	β_{hml}	β_{umd}
Low	-1.066***	0.962***	0.865***	0.090	-0.218***
	(-9.800)	(35.94)	(11.07)	(1.420)	(-4.530)
2	-0.197***	0.939***	0.716***	0.209***	-0.128***
	(-3.270)	(63.39)	(16.16)	(6.690)	(-5.090)
3	0.070	0.954***	0.663***	0.290***	-0.082***
	(1.610)	(69.17)	(17.78)	(9.680)	(-3.840)
4	0.335***	1.031***	0.760***	0.297***	-0.062**
	(5.760)	(59.17)	(12.62)	(7.530)	(-2.040)
High	1.711***	1.135***	1.193***	0.344***	-0.182***
	(11.36)	(36.87)	(13.13)	(3.870)	(-3.100)
High - Low	2.777***	0.173***	0.328**	0.253**	0.037
	(13.84)	(3.720)	(2.050)	(2.160)	(0.560)

Panel B: Control with Past 2 to 7-Month Return						
$R_{-7,-2}$						
	Low	2	3	4	High	High - Low
Low	-2.440***	-0.966***	-0.349***	0.104	2.348***	4.788***
	(-14.39)	(-7.607)	(-2.767)	(0.715)	(9.367)	(16.14)
2	-1.493***	-0.502***	-0.103	0.105	1.299***	2.792***
	(-14.19)	(-6.229)	(-1.431)	(1.343)	(9.650)	(14.82)
3	-1.012***	-0.206***	0.037	0.306***	1.164***	2.176***
	(-10.69)	(-3.340)	(0.654)	(5.098)	(10.31)	(12.32)
4	-0.778***	-0.140**	0.075	0.388***	1.335***	2.113***
	(-7.077)	(-2.199)	(1.228)	(6.121)	(12.42)	(11.52)
High	-0.760***	0.033	0.324***	0.614***	1.726***	2.486***
	(-5.349)	(0.296)	(3.669)	(5.979)	(11.02)	(10.81)
Average over $R_{-7,-2}$	-1.297***	-0.356***	-0.003	0.303***	1.575***	2.871***
	(-21.34)	(-8.242)	(-0.085)	(7.208)	(21.60)	(27.43)

Table 7: Moving Average Forecasts versus Fundamentals Forecasts

This table compares the performance of using the moving average based forecasts to using forecasts based on a variety of accounting as well as market variables (fundamentals) proposed by Haugen and Baker (1996). In Panel A, stocks are first sorted into five quintiles by their expected returns forecasted from the fundamental variables (ER_{AC}), and then further sorted into five quintiles by their expected returns forecasted from the moving average signals (ER_{MA}). The last row reports the results of the new quintile portfolios after controlling for ER_{AC} as described in Table 4. In Panel B, stocks are first sorted by the expected returns forecasted from the moving average signals, and then further sorted by the expected returns forecasted from the fundamentals. The alphas are reported in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1926 to December 2010.

ER_{MA}	Low	2	3	4	High	High - Low
			Panel A: Controlling for ER_{AC}			
Low	-1.889***	-0.630**	-1.008***	-0.601**	-0.272	1.617***
	(-5.117)	(-2.342)	(-3.889)	(-2.452)	(-0.888)	(3.812)
2	-1.084***	-0.432**	-0.090	-0.227	0.601**	1.685***
	(-4.319)	(-2.106)	(-0.466)	(-1.134)	(2.250)	(5.571)
High	-0.349	-0.564**	-0.044	-0.064	1.689***	2.038***
	(-0.848)	(-2.104)	(-0.174)	(-0.236)	(3.900)	(4.146)
Average over ER_{AC}	-1.107***	-0.542***	-0.381**	-0.297*	0.673***	1.780***
	(-5.244)	(-3.337)	(-2.342)	(-1.856)	(2.882)	(6.725)
			Panel B: Controlling for ER_{MA}			
Low	-1.637***	-0.949***	-0.882***	-0.672***	-0.327	1.310*
	(-3.927)	(-3.863)	(-3.791)	(-2.896)	(-0.730)	(1.902)
2	-0.658**	-0.384**	-0.169	-0.591***	-0.168	0.489
	(-2.342)	(-2.054)	(-0.827)	(-2.895)	(-0.481)	(1.254)
High	-0.703**	-0.011	0.092	0.829***	1.318***	2.020***
	(-2.043)	(-0.049)	(0.397)	(2.820)	(3.390)	(4.640)
Average over ER_{MA}	-0.999***	-0.448***	-0.320**	-0.145	0.274	1.273***
	(-4.414)	(-3.000)	(-1.992)	(-0.856)	(0.967)	(3.592)

Table 8: Fama-MacBeth Regression

This table reports the results of regressing monthly returns on the expected returns forecasted by the moving average signals (ER_{MA}), the expected returns forecasted by fundamentals (ER_{AC}) and other firm-specific variables. The regression is a modified Fama-MacBeth cross-sectional regression with weighted least square (WLS) in the first step. The weights are the inverse of the stock variance estimated from the whole sample period. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1926 to December 2010.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Intercept	-0.145***	0.008***	-0.149***	-0.124***	0.007**	-0.128***	-0.121***	0.011**	-0.128***
	(-6.73)	(2.69)	(-6.84)	(-5.48)	(2.38)	(-5.67)	(-4.85)	(2.41)	(-5.25)
ER_{MA}	0.439***		0.431***	0.361***		0.357***	0.345***		0.351***
	(7.50)		(7.29)	(5.87)		(5.85)	(5.07)		(5.22)
ER_{AC}		0.861**	0.826**		0.482	0.522		0.548	0.618
		(2.15)	(2.00)		(1.21)	(1.29)		(1.01)	(1.11)
β_m	-0.968	-0.671	-0.918	-1.100	-0.976	-1.260	0.640	0.476	0.135
	(-0.44)	(-0.31)	(-0.41)	(-0.47)	(-0.41)	(-0.53)	(0.29)	(0.21)	(0.06)
Log(Size)	0.327	0.093	0.256	0.570	0.619	0.464	-0.116	-0.187	-0.022
	(0.58)	(0.15)	(0.44)	(1.00)	(1.04)	(0.81)	(-0.16)	(-0.24)	(-0.03)
log(B/M)	0.043	0.212	0.217	-0.504	-0.707	-0.311	-0.228	-0.453	-0.106
	(0.05)	(0.24)	(0.26)	(-0.65)	(-0.81)	(-0.39)	(-0.25)	(-0.42)	(-0.11)
R_{-1}				-0.044***	-0.058***	-0.045***	-0.046***	-0.060***	-0.048***
				(-5.74)	(-7.98)	(-5.73)	(-5.36)	(-7.72)	(-5.65)
$R_{-7,-2}$				0.145	0.037	0.189	-0.051	-0.288	-0.127
				(0.43)	(0.11)	(0.54)	(-0.14)	(-0.77)	(-0.34)
Idio. Vol							-0.212*	-0.307**	-0.205*
							(-1.90)	(-2.41)	(-1.71)
%Zero							-0.024	0.327	0.259
							(-1.19)	(0.99)	(0.99)
Turnover							0.117	0.208	0.098
							(0.79)	(1.13)	(0.66)
E/P							-0.146	-0.369	-0.271
							(-0.45)	(-0.80)	(-0.87)
C/P							0.059***	0.067***	0.063***
							(3.51)	(3.92)	(3.64)
S/P							-0.399	0.085	-0.336
							(-0.60)	(0.11)	(-0.51)
D/P							-0.166	-0.424	-0.192
							(-0.21)	(-0.35)	(-0.24)

Table 9: The Trend Factor and Correlations with Fama-French Factors

This table reports the summary statistics of the High-Low spread quintile portfolio and the four factors including Fama-French three factors and the momentum factor. The summary statistics reported are sample mean, sample standard deviation, Sharpe ratio, first- and second-order autocorrelation coefficients. Also reported are the pairwise correlation matrix of the spread portfolio and the four factors. The sample period is from January 1926 to December 2010.

Variable	Mean (%)	Std Dev (%)	Sharpe Ratio	ρ_1	ρ_2	Correlation				
						Trend	Market	SMB	HML	UMD
Trend	3.09	4.86	0.64	0.31	0.23	1	0.30	0.30	0.24	-0.14
Market	0.62	5.48	0.11	0.12	-0.02	0.30	1	0.33	0.23	-0.34
SMB	0.25	3.34	0.08	0.07	0.06	0.30	0.33	1	0.10	-0.16
HML	0.39	3.59	0.11	0.19	-0.01	0.24	0.23	0.10	1	-0.40
UMD	0.70	4.82	0.14	0.08	-0.08	-0.14	-0.34	-0.16	-0.40	1

Table 10: The Trend Factor and Other Economic Variables

This table reports the results of regressing the returns on the spread portfolio to the four factors including the momentum factor and other economic variables including a recession dummy indicating the recessionary periods of NBER, default spread, sentiment, and Pastor and Stambaugh (2003) tradable liquidity factor. The intercept is in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively.

	1	2	3	4	5	6	7	8	9	10
	1927:02 to 2010:12	1927:02 to 2010:12	1927:02 to 2010:12	1933:07 to 2010:12	1933:07 to 2007:12	1965:07 to 2010:12	1965:07 to 2010:12	1965:07 to 2007:12	1968:01 to 2010:12	1968:01 to 2007:12
Intercept($\times$100)	2.420***	2.010***	-0.251	0.835***	0.812**	2.410***	2.320***	2.560***	2.560***	2.930***
	(9.39)	(9.44)	(-0.59)	(2.61)	(2.39)	(5.06)	(4.75)	(5.02)	(4.86)	(5.66)
Market Factor	0.186***	0.204***	0.212***	0.179***	0.166***	0.218***	0.216***	0.210***	0.217***	0.212***
	(4.04)	(4.49)	(5.16)	(4.98)	(4.28)	(5.15)	(5.16)	(4.78)	(5.03)	(4.50)
SMB Factor	0.334**	0.336**	0.289**	0.221**	0.231**	0.280***	0.275***	0.290***	0.253**	0.269**
	(2.07)	(2.09)	(1.97)	(2.12)	(2.20)	(2.91)	(2.81)	(2.89)	(2.43)	(2.50)
HML Factor	0.254**	0.263**	0.268***	0.112	0.120	0.100	0.104	0.134	0.089	0.129
	(2.29)	(2.42)	(2.78)	(1.02)	(1.04)	(1.23)	(1.29)	(1.62)	(1.06)	(1.49)
UMD Factor	0.046	0.059	0.090	0.060	0.085	-0.056	-0.054	-0.032	-0.064	-0.043
	(0.71)	(0.94)	(1.44)	(0.83)	(1.02)	(-0.95)	(-0.94)	(-0.47)	(-1.06)	(-0.61)
Market Vol	0.675**	0.629**	0.632**	0.982***	1.139***	1.693***	1.678***	1.815***	1.682***	1.776***
	(2.07)	(2.00)	(2.15)	(3.39)	(3.63)	(3.81)	(3.73)	(3.41)	(3.72)	(3.35)
Recession		0.020***	0.006	0.003	0.003	0.011**	0.012***	0.012**	0.011**	0.011**
		(3.77)	(1.59)	(0.95)	(0.93)	(2.49)	(2.65)	(2.49)	(2.57)	(2.46)
Default Spread			0.022***	0.010***	0.010***	-0.012***	-0.011**	-0.014***	-0.012***	-0.016***
			(5.76)	(2.92)	(2.73)	(-2.65)	(-2.35)	(-3.35)	(-2.67)	(-4.04)
Sentiment							-0.002	-0.002		
							(-1.39)	(-1.18)		
Liquidity									-0.021	-0.064
									(-0.35)	(-1.12)
N	1007	1007	1007	930	894	546	546	510	516	480
adj. R^2	0.168	0.194	0.285	0.134	0.128	0.159	0.162	0.154	0.151	0.146

Table 11: The Short-Term Reversal

This table compares the pricing ability of the trend factor and the momentum factor using the 2×3 size and short-term reversal portfolios. The last column is the result of the short-term reversal factor. Panel A includes the market portfolio whereas Panel B includes the Fama-French three factors. In each panel we include either the trend factor (r_{trd}) or the momentum factor (r_{umd}), respectively. The intercept is in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1926 to December 2010.

	STRev1	STRev2	STRev3	STRev4	STRev5	STRev6	FacSTRev
Panel A: CAPM Model plus Trend Factor or Momentum Factor							
$\alpha(\%)$	1.150***	0.280**	-0.674***	0.291***	0.137***	-0.281***	0.696***
	(6.27)	(2.24)	(-4.86)	(3.78)	(3.22)	(-4.68)	(6.58)
r_{mkt}	1.513***	1.252***	1.286***	1.253***	1.060***	1.128***	0.117**
	(17.09)	(17.14)	(19.71)	(44.58)	(66.56)	(23.66)	(2.19)
$\alpha(\%)$	-0.543	-0.584	-1.040***	-0.150	-0.043	-0.362***	0.231
	(-1.29)	(-1.51)	(-2.75)	(-1.02)	(-0.56)	(-2.65)	(1.06)
r_{mkt}	1.359***	1.174***	1.253***	1.213***	1.044***	1.121***	0.075
	(16.20)	(19.94)	(19.32)	(35.80)	(71.32)	(26.11)	(1.32)
r_{trd}	0.578***	0.295**	0.124	0.151***	0.061**	0.028	0.159**
	(4.33)	(2.20)	(0.95)	(3.38)	(2.58)	(0.57)	(2.23)
$\alpha(\%)$	1.560***	0.523***	-0.451***	0.398***	0.197***	-0.239***	0.786***
	(7.52)	(3.92)	(-3.02)	(4.32)	(4.42)	(-2.94)	(5.92)
r_{mkt}	1.373***	1.170***	1.210***	1.217***	1.040***	1.114***	0.087**
	(19.90)	(19.12)	(24.00)	(48.04)	(70.16)	(32.84)	(1.98)
r_{umd}	-0.468***	-0.274***	-0.252***	-0.121**	-0.068***	-0.048	-0.101
	(-6.15)	(-4.95)	(-3.50)	(-2.24)	(-3.60)	(-0.78)	(-1.17)

	STRev1	STRev2	STRev3	STRev4	STRev5	STRev6	FacSTRev
Panel B: Fama-French Model plus Trend Factor or Momentum Factor							
$\alpha(\%)$	-0.080	-0.203	-0.622***	-0.069	0.026	-0.250**	0.239
	(-0.43)	(-1.43)	(-4.99)	(-0.46)	(0.62)	(-2.00)	(1.03)
r_{mkt}	1.098***	0.954***	1.016***	1.168***	1.000***	1.057***	0.074
	(33.31)	(50.18)	(50.93)	(42.52)	(87.53)	(37.40)	(1.61)
r_{smb}	1.287***	1.035***	1.149***	0.236***	0.160***	0.306***	0.041
	(13.88)	(12.68)	(23.63)	(3.63)	(6.47)	(5.57)	(0.45)
r_{hml}	0.496***	0.485***	0.472***	0.060	0.166***	0.140**	-0.046
	(6.01)	(11.64)	(10.39)	(1.10)	(7.32)	(2.10)	(-0.48)
r_{trd}	0.312***	0.070	-0.117***	0.106**	0.014	-0.038	0.159**
	(5.23)	(1.41)	(-2.72)	(2.08)	(1.03)	(-0.90)	(2.02)
$\alpha(\%)$	1.100***	0.109**	-0.846***	0.333***	0.084**	-0.356***	0.804***
	(8.95)	(1.98)	(-9.99)	(4.34)	(2.20)	(-5.34)	(6.72)
r_{mkt}	1.085***	0.941***	0.975***	1.164***	0.998***	1.050***	0.075*
	(41.95)	(59.00)	(55.55)	(50.25)	(97.27)	(45.99)	(1.87)
r_{smb}	1.368***	1.050***	1.104***	0.264***	0.163***	0.293***	0.085
	(15.23)	(10.81)	(26.07)	(5.08)	(6.88)	(6.21)	(1.21)
r_{hml}	0.435***	0.450***	0.398***	0.040	0.161***	0.129***	-0.060
	(6.45)	(11.74)	(11.57)	(0.93)	(7.23)	(2.85)	(-0.85)
r_{umd}	-0.298***	-0.113***	-0.103***	-0.100**	-0.019	-0.002	-0.114
	(-5.59)	(-3.91)	(-3.27)	(-2.03)	(-0.95)	(-0.05)	(-1.51)

Table 12: Price Ratio Decile Portfolios

This table compares the pricing ability of the trend factor and the momentum factor using the 10 decile portfolios sorted by various price ratios and industry portfolios. In each panel we include either the trend factor (r_{trd}) or the momentum factor (r_{umd}), respectively. The intercept is in percentage. Newey and West (1987) robust t-statistics are in parentheses and significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from January 1926 to December 2010.

Panel A: E/P Decile Portfolios										
α(%)	-0.721**	-0.366*	-0.254	-0.121	-0.063	0.034	0.088	0.095	0.190	0.015
	(-3.78)	(-2.44)	(-1.67)	(-0.83)	(-0.43)	(0.22)	(0.56)	(0.58)	(1.06)	(0.07)
r_{mkt}	1.244**	1.123**	1.056**	0.995**	0.970**	0.934**	0.906**	0.909**	0.935**	1.016**
	(35.31)	(40.26)	(37.25)	(33.35)	(30.31)	(30.40)	(29.06)	(28.26)	(27.38)	(26.49)
r_{trd}	0.221**	0.165**	0.147**	0.133**	0.136**	0.125*	0.136*	0.163**	0.159**	0.265**
	(3.45)	(3.75)	(3.30)	(2.89)	(2.79)	(2.47)	(2.52)	(2.89)	(2.66)	(3.89)
α(%)	-0.047	0.157	0.236*	0.336**	0.402**	0.465**	0.562**	0.645**	0.734**	0.863**
	(-0.32)	(1.41)	(2.25)	(3.40)	(3.99)	(4.77)	(5.60)	(6.08)	(6.37)	(6.10)
r_{mkt}	1.266**	1.137**	1.065**	1.002**	0.978**	0.940**	0.913**	0.919**	0.944**	1.038**
	(38.44)	(39.96)	(35.58)	(31.48)	(28.85)	(28.34)	(26.96)	(26.77)	(25.79)	(25.29)
r_{umd}	-0.119	-0.114**	-0.131**	-0.135**	-0.134**	-0.129**	-0.146**	-0.151**	-0.159**	-0.191**
	(-1.77)	(-2.86)	(-3.60)	(-3.81)	(-3.62)	(-3.65)	(-3.79)	(-3.56)	(-3.48)	(-3.84)
Panel B: C/P Decile Portfolios										
α(%)	-0.711***	-0.391**	-0.224	-0.089	-0.081	0.015	0.097	0.059	0.085	0.074
	(-3.80)	(-2.50)	(-1.42)	(-0.58)	(-0.51)	(0.10)	(0.59)	(0.37)	(0.47)	(0.35)
r_{mkt}	1.248***	1.122***	1.035***	0.981***	0.964***	0.940***	0.943***	0.937***	0.984***	1.027***
	(35.35)	(38.95)	(33.53)	(31.17)	(30.95)	(29.28)	(29.30)	(29.24)	(25.53)	(26.05)
r_{trd}	0.200***	0.160***	0.157***	0.128***	0.160***	0.149***	0.154***	0.176***	0.207***	0.257***
	(3.30)	(3.47)	(3.20)	(2.66)	(3.09)	(2.88)	(2.88)	(3.39)	(3.31)	(3.62)
α(%)	-0.086	0.129	0.293***	0.350***	0.438***	0.509***	0.611***	0.626***	0.794***	0.905***
	(-0.59)	(1.12)	(2.67)	(3.37)	(4.08)	(4.88)	(5.77)	(5.87)	(6.39)	(6.09)
r_{mkt}	1.266***	1.135***	1.046***	0.988***	0.976***	0.950***	0.953***	0.952***	0.995***	1.048***
	(38.38)	(38.01)	(31.71)	(29.72)	(29.12)	(27.50)	(27.06)	(27.29)	(25.13)	(25.39)
r_{umd}	-0.125*	-0.124***	-0.132***	-0.127***	-0.122***	-0.128***	-0.138***	-0.131***	-0.206***	-0.194***
	(-1.87)	(-2.92)	(-3.42)	(-3.49)	(-3.29)	(-3.31)	(-3.41)	(-3.53)	(-3.70)	(-3.48)

Panel C: D/P Decile Portfolios										
$\alpha(\%)$	-0.087	0.131	0.038	0.093	0.080	-0.032	0.000	-0.101	-0.161	-0.545**
	(-0.62)	(1.23)	(0.46)	(1.05)	(0.80)	(-0.26)	(0.00)	(-0.61)	(-0.97)	(-2.24)
r_{mkt}	1.175***	1.059***	1.021***	1.008***	0.972***	0.979***	0.917***	0.940***	0.927***	0.977***
	(39.71)	(32.60)	(53.23)	(49.49)	(48.45)	(36.93)	(42.02)	(31.99)	(21.68)	(14.31)
r_{trd}	0.069*	0.041	0.059***	0.074***	0.066**	0.117***	0.129***	0.151***	0.171***	0.277***
	(1.65)	(1.42)	(3.17)	(3.29)	(2.37)	(3.24)	(2.77)	(2.77)	(3.22)	(3.32)
$\alpha(\%)$	0.114	0.249***	0.245***	0.391***	0.378***	0.460***	0.495***	0.523***	0.564***	0.609***
	(1.24)	(2.76)	(3.15)	(5.16)	(4.82)	(6.01)	(6.08)	(6.33)	(6.26)	(4.77)
r_{mkt}	1.193***	1.071***	1.025***	0.999***	0.954***	0.959***	0.911***	0.918***	0.895***	0.934***
	(43.00)	(42.15)	(50.68)	(42.51)	(46.67)	(34.42)	(30.04)	(28.11)	(21.71)	(16.42)
r_{umd}	-0.001	0.001	-0.040	-0.093***	-0.120***	-0.170***	-0.134***	-0.206***	-0.257***	-0.391***
	(-0.02)	(0.02)	(-1.38)	(-3.41)	(-4.27)	(-7.12)	(-4.56)	(-7.71)	(-7.25)	(-5.59)
Panel D: Industry Portfolios										
$\alpha(\%)$	-0.401*	-0.782**	-0.354	0.048	-0.354**	0.132	-0.516**	-0.021	-0.133	-0.501*
	(-1.94)	(-2.45)	(-1.52)	(0.13)	(-1.97)	(0.70)	(-2.25)	(-0.11)	(-0.70)	(-1.72)
r_{mkt}	1.009***	1.356***	1.254***	1.140***	1.370***	1.027***	1.092***	1.015***	0.899***	1.169***
	(26.23)	(30.23)	(28.96)	(17.73)	(39.52)	(27.38)	(31.69)	(27.58)	(16.58)	(17.53)
r_{trd}	0.208***	0.282***	0.206***	0.136	0.221***	0.061	0.248***	0.147**	0.132**	0.249***
	(3.29)	(2.70)	(2.76)	(1.25)	(4.46)	(1.26)	(3.31)	(2.43)	(2.36)	(2.70)
$\alpha(\%)$	0.416***	0.282*	0.463***	0.580***	0.389**	0.419**	0.401***	0.413***	0.408***	0.528***
	(3.70)	(1.88)	(4.25)	(2.93)	(2.35)	(2.41)	(2.83)	(2.76)	(2.77)	(3.69)
r_{mkt}	0.993***	1.350***	1.236***	1.131***	1.396***	1.007***	1.093***	1.053***	0.882***	1.134***
	(24.94)	(23.25)	(30.15)	(24.12)	(36.75)	(26.03)	(25.81)	(29.10)	(20.65)	(29.20)
r_{umd}	-0.238***	-0.271***	-0.241***	-0.150*	-0.109	-0.123	-0.217***	-0.004	-0.174**	-0.338***
	(-6.43)	(-5.54)	(-6.71)	(-1.79)	(-1.41)	(-1.49)	(-4.01)	(-0.07)	(-2.56)	(-5.50)