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

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First Version: June, 2012
Current Version: October, 2013

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We are grateful to Michael Cooper, Darrell Duffie, Wayne Ferson, Campbell Harvey, Fuwei Jiang, Wei Jiang, Raymond Kan, Robert Kieschnick, Steve LeCompte, George Tauchen, Jun Tu, Yuhang Xing, Xiaoyan Zhang, seminar participants at London Imperial College, Tsinghua University, University of Houston, University of Texas–Dallas, University of Warwick, and Washington University in St. Louis, and conference participants at the 2013 Society for Financial Studies Cavalcade, 2013 China International Conference in Finance, and 2013 China Finance Review International Conference for very helpful comments.

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Abstract

We propose a trend factor capturing cross-section short-term, intermediate-term and long-term stock price trends. In contrast, the popular momentum factor relies only on one long-term momentum signal. The trend factor has an average return of 1.61% per month, which is more than twice that of the momentum factor and more than doubles the Sharpe ratio. In addition, during the recent financial crisis, it earns 1.65% per month while the momentum factor loses 1.33% per month. Moreover, its performance is robust to a variety of control variables and it explains well the cross-section returns better than the momentum factor.

JEL Classification: G11, G14

Keywords: Trends, Moving Averages, Predictability, Momentum, Factor Models.

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) 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 set of firm and market characteristics. More recently, Cooper, Gulen, and Schill (2008) find that a firm's annual asset growth rate is an economically and statistically significant predictor. Jagannathan, Skoulakis, and Wang (2009), Subrahmanyam (2010), and Goyal (2012) provide surveys on more variables that predict cross-section stock returns. The second line of research is to construct factors that explain the cross-section stock returns contemporaneously for understanding 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), the 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 numerous studies in 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 stock prices have strong trends that can be either rational or behavioral (to be discussed). To capture these trends, we, following the practice of traders and investors in practice, use simple moving average indictors to measure them instead of complex econometric models. At the end of each month, we run a cross section regression of stock returns on the trend indictors to forecast next month returns, and then form a spread portfolio, similar to the popular size or book-market or momentum factor, by buying stocks with the highest forecasted expected returns and shorting those with the lowest ones. From a cross-section predictability point of view, we find that the trend factor earns an average return of 1.61% per month, and a risk-adjusted abnormal return about 1.50% per month (out-of-sample), more than quadrupling those of the size and book-to-market factors, and more than twice that of the momentum factor.

From an asset pricing perspective, the trend factor explains better than the momentum factor (Jegadeesh and Titman, 1993) the cross-section portfolio returns sorted by the short-term reversal, the long-term reversal, 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 reduce neither the magnitude nor the significance of the abnormal returns. For example, the CAPM alpha of the lowest ranked portfolio in the long-term reversal sorted portfolios is 0.881% per month and highly significant (t statistic is 3.87). Adding the trend factor, however, reduces the alpha to 0.276% and insignificant (t statistic is 0.69). In comparison, adding the momentum factor fails to explain any of the abnormal returns and even increases the magnitudes of the alphas. For example, the aforementioned lowest ranked long-term reversal decile portfolio now has a significant alpha of 1.320% (versus 0.881% in CAPM) per month in the presence of the momentum factor. Moreover, the trend factor also does a better job explaining the abnormal returns of the decile portfolios sorted by various price ratios. The pricing error is sometimes reduced by more than half once the momentum factor is replaced by the trend factor.

Our factor is related to the momentum factor conceptually, but differs from it substantially. Intuitively, the momentum factor also attempts to capture trends because it ranks stock returns in terms of their past performances over, say, past twelve months. If a firm's price rises persistently, the momentum factor is likely to pick it up. Indeed, due to attempting to capture the same overall price trends, the long portfolios of both the momentum and trend factors have a correlation about 90%. The same is true for their short portfolios.

However, an uptrend of a stock could have reversed by now, though its year-to-date return could still be high and so the stock could remain in the long portfolio of the momentum factor. On the other hand, instead of using information measured from only two points, the trend factor utilizes trend indicators of varying horizons, daily, weekly, monthly and yearly, and hence the trend reversed stock might be eliminated from the long portfolio of the trend factor due to its poor recent performance. Therefore, the trend factor is likely to be more successful in capturing genuine price trends in the stock market. Indeed, the trend factor has an average return of 1.61% from September 1927 to December 2012, instead of 0.68% of the momentum factor. In terms of the risk and return tradeoff, our factor yields a Sharpe ratio that is more than twice greater than those of both the market and the momentum factors. Moreover, during the recent financial crisis, our factor earns 1.65% per month while the momentum factor loses 1.33% per month. Finally, the trend factor has much smaller and fewer negative return outliers than the momentum factor, of which Daniel, Jagannathan, and Kim (2012) provide an interesting and more detailed study on the tail risk.

Interestingly, the trend factor has a very small correlation with the momentum factor. Why is it the case as both factors are trend capturing? Although there are over 90% correlations between their long (short) portfolios, the factors themselves, as the spreads of the longs and shorts, can have theoretically, any possible level of correlations. Since the trend factor does a much better job in capturing the trend, its long portfolio has a much higher average return than that of the momentum factor, and its short portfolio has a much lower average return than that of the momentum factor. This means that both the long and short portfolios of the trend factor outperform those of the momentum factor, and so the trend factor, as the spread portfolio, is likely to have little correlation with the momentum factor. Indeed, the trend factor earns positive returns during recessions while the momentum factor loses money, but both earn positive returns during expansions which last longer. This explains why the two factors have only a very small positive correlation (0.02 and insignificant) empirically.

The abnormal return on the trend factor is very robust. It is robust to various ways of constructing the trend signals using the moving average prices (we in fact use only a naive procedure of incorporating all the common trend indicators without any optimal selection or design). 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 the market size, last month return, B/M, trading turnover rate, idiosyncratic volatility, liquidity, and momentum.

What economic forces contribute to the trends in the stock market? Theoretically, Brunnermeier (2001) reviews quite a few models in which asymmetric information among investors justifies predictable trends even in rational equilibriums. Recently, Cespa and Vives (2012) show further that the presence of liquidity traders and asset payoff uncertainty will also generate rational trends in the market. Intuitively, the hedging demand by hedgers takes time to fulfill in the market due to limited liquidity. The greater the risk to be hedged, the greater the liquidity demand, and so the greater the persistence of the price trend. In addition, stocks may rise steadily in reaction to future good news, and the price reaction can have not only self-fulfilling effects but also positive feedback effects.[1] Moreover, from the perspective of behavior finance, 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 trends. Daniel, Hirshleifer, and Subrahmanyam (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. Finally, any theory that explains momentum can be potentially useful for explaining the trend factor as well since the momentum is a particular trend.

In practice, large fundamental changes tend to generate long and persistent trends, of which recent internet bubble and financial crisis are the extreme examples.[2] For an example of price trends of a real stock, consider Apple Inc. (stock symbol AAPL). It is famous and was once the largest stock in capitalization in the world. Figure 1 plots its weekly prices along with its 20-week moving averages (to indicate a possible trend) from October 2006 to date.[3] Since the release of the first generation of iPhone on June 29, 2007, the stock price rose steadily from about \$70 to roughly \$200 before the end of 2008, and then went down briefly with the market as the financial crisis worsened. Then it went back up unstoppably. Later on April 3, 2010, its second major new product, the iPad, was released. The stock went up sharply and steadily from about \$230 to a high of \$700 in September 2012, a return of more than 200% in two years. Since then, concerns about competitions of similar products

[1] An uptrend in stock prices can positively affect firm fundamentals that in turn lead to even higher prices, which underlies the trading strategies of hedge fund guru Soros (2003) and is validated in a theoretical model by Edmans, Goldstein, and Jiang (2012).

[2] Hedge funds that exploit global macroeconomic trends are called global macro, which is one of the most profitable and best performing styles of all the hedge funds.

[3] Daily prices show the same pattern, which is omitted due to space limitation.

from Google, Amazon and Samsung put the stock on a spiral down trend till April 2013 when the company announced the largest stock buyback by using its huge cash reserves and by issuing debt. It is worthwhile noting that, even for a stock as liquid as AAPL and as widely followed as any other stock in the world, the price trend is apparent, and may well predictable by any trend capturing algorithms. For example, a predictive regression of its return on its past scaled 20-day moving average price will yield a significant and positive slope (0.12 with a t-stat 12.32).

On the relation between trends and uncertainty, Zhang (2006) argues that price trends are 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 this argument. For example, when we use the idiosyncratic volatility to proxy for information uncertainty and sort stocks first by idiosyncratic volatility and then by trend signals, the abnormal return of the trend spread portfolio increases monotonically from 0.543% to 2.452% per month as the idiosyncratic volatility (information uncertainty) increases from low to high. We obtain similar results using other information uncertainty proxies such as share turnover rates, analyst coverage, and firm ages.

The rest of the paper is organized as follows. Section 2 discusses the data and methodology for constructing the trend factor. Section 3 provides the summary statistics of the trend factor and the associated quintile portfolios. Section 4 examines the robustness of the trend factor in various dimensions. Section 5 explores the link of the trend factor to information uncertainty. Section 6 investigates its cross-section pricing power to various portfolios and compares it to the momentum factor. Section 7 concludes.

2. Data and methodology

To calculate the trend signals, we use CRSP daily stock prices from January 1926 to December 2012, though our portfolios or factors are formed and traded at the monthly frequency. 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 portfolios, we first calculate the moving average prices on the second to the last trading day of each month.[4] The moving average (MA) price at the second to the last trading day of month t of lag L is defined as

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

where P^t_{jd} is the closing price for stock j on the second to the last trading day d of month t, and L is the lag length. Then, we normalize the moving average prices by the closing price on the second to the last trading day of the month to make the signals as stationary processes.[5]

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

The moving averages are some of the most popular technical indicators widely used by practitioners (see, e.g., Schwager, 1989; Covel, 2009; Lo and Hasanhodzic, 2010) to identify price trends believed to persist into the future. Brock, Lakonishok, and LeBaron (1992), and Lo, Mamaysky, and Wang (2000), among others, find the value of the moving averages

[4]The results are even stronger if we use the last trading day of each month. We use the second to the last trading day to avoid any concerns on real-time implementation. (The main results of this paper have been replicated by many practitioners, PhDs and other researchers.)

[5]Keim and Stambaugh (1986) use a similar strategy to make the S&P 500 index stationary.

in forecasting returns. However, their studies and almost all others use the moving averages only to indicate either an up or a down trend. In contrast, we make a full use of the moving averages here by scaling them with the price to measure the strength of the trend. Hence, our trend indicators reflect not only the direction of the trend, but also its degree of persistence. Interestingly, we have motivated the functional form in Eq. (2) intuitively and found it valuable empirically; Zhou and Zhu (2013) derive the same functional form theoretically. In an equilibrium model with both informed and technical traders, they justify the use of moving averages scaled by the price as predictors of the stock price trends.

To predict the monthly expected stock returns cross-sectionally, we follow the procedure outlined in Haugen and Baker (1996). We first run a cross-section regression each month t by regressing monthly stock returns on the prior month trend signals to obtain a time-series of the coefficients on the trend signals.[6]

$$r_{j,t} = \beta_{0,t} + \sum_i \beta_{i,t} \tilde{A}_{jt-1,L_i} + \epsilon_{j,t}, \quad j = 1, \cdots, n \tag{3}$$

where

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

It should be mentioned that only information in month t or prior are used above.

Then we estimate the expected return for month $t+1$ from

$$E_t[r_{j,t+1}] = \sum_i E_t[\beta_{i,t+1}] \tilde{A}_{jt,L_i}, \tag{4}$$

[6] Jegadeesh (1990) also uses a similar cross-sectional regressions to predict individual stock returns, but he uses past returns instead of trend indicators.

where $E_t[r_{j,t+1}]$ is our estimated expected return on stock j for month $t+1$, and $E_t[\beta_{i,t+1}]$ is the estimated expected coefficient of the trend signal with lag L_i, and is give by

$$E_t[\beta_{i,t+1}] = \frac{1}{12}\sum_{m=1}^{12}\beta_{i,t+1-m},$$

which is the average of the estimated coefficients of the trend signals over the past 12 months (the same estimator as Haugen and Baker, 1996). Note that we do not include an intercept above because it is the same for all stocks in the same cross-section and thus it plays no role in ranking the stocks below. Again, it is worth noting that only information in month t or prior is used to estimate the expected returns.

Now, following the standard procedure on cross-section studies, 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 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 an equal-weighted portfolio is constructed from stocks in the quintile. The sort procedure thus produces five quintile portfolios that are re-balanced every month. The High-Low spread portfolio is our trend factor, constructed as a zero-cost arbitrage portfolio that takes a long position in the highest ranked quintile portfolio (High) and takes a short position in the lowest ranked quintile portfolio (Low). Note that the trend factor is a portfolio formed out of sample, as many other factors used in finance.

The popular momentum factor (Jegadeesh and Titman, 1993) can be interpreted as a special case of the above procedure. If there is only one trend signal, past year price, and if the beta is one, the trend factor coincides with the momentum factor. Of course, we use multiple signals to capture trends in various time horizons, daily, weekly, monthly and up to yearly. Following, for example, Brock, Lakonishok, and LeBaron (1992), we consider all the common trend indicators, the moving averages of lag lengths 1-, 3-, 5- 10-, 20-, 50-, 100-, and 200-days. Intuitively, they indicate the daily, weekly, monthly, quarterly and yearly trends of the underlying asset. Note that we simply use all of these popular indicators without any alterations or removals to optimize the estimation efficiency or improve the abnormal return. We do not use any other complicated trend signals either. Our reasoning is that the naive procedure might be more powerful to show the existence of genuine trends in the market than complicated procedures because the latter, though could perform much better, are difficult to overcome the concern of data-mining. Nevertheless, we do examine for robustness reasons some alternative specifications that include various number of trend signals and lag-lengths up to 500 days. The results are largely unchanged or better, supporting the main conclusion of the paper that the trend factor matters.

We include a variety of firm characteristics as controls in the analysis. 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 daily returns over the total number of daily 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 $t-6$. We define the 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 the 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 the sales-to-price ratio (S/P), we divide 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.

In addition to the market size, we also use a number of other variables to proxy for information uncertainty. We estimate the idiosyncratic volatility (Idio Vol) as the standard error of the residuals from regressing the monthly excess returns in the past 60 months on the Fama-French three factors. We estimate the trading turnover rate (Turnover) as the monthly trading volume normalized by the total shares outstanding. The third proxy we use is the analyst coverage defined as the number of analysts following a stock in IBES. We eliminate stocks with no analyst following. The last proxy is the firm age in years. These proxies are lagged by one month in the analysis.

3. Summary statistics

In this section, we provide first the summary statistics of the trend factor and compare them with other common factors. Then we provide such summary statistics for the associated trend quintile portfolios and discuss some of their general characteristics.

3.1. Trend and other factors

In order to compute the trend signals and estimate their expected coefficients, we have to skip the first 200 days and subsequent 12 months. So the effective sample period for our study is from September, 1927, a total of 1024 observations, during which the trend factor is well defined. Table 1 reports the summary statistics of the trend factor as well as the Fama-French three factors (Market, SMB, and HML) and the momentum factor (UMD).[7]

[7]Data on the trend factor will be posted, and the latter four factors are available from Ken French's online data library.

The average monthly return of the trend factor from September 1927 to December 2012 (in Panel A) is 1.61%, or 19.32% per annum, more than doubling the average return of any of the other four factors, whose average returns are much less than 1% per month. The standard deviation of the trend factor is about 5.59%, which is comparable to the other factors. As a result, the Sharpe ratio of the trend factor is much higher than those of the other factors. For example, the trend factor has a Sharpe ratio of 0.29, whereas the next highest Sharpe ratio is only 0.14 generated by the momentum factor. Daniel and Moskowitz (2012) and Barroso and Santa-Clara (2012) show that returns generated from the momentum strategies are negatively skewed with large kurtosis, which implies a very fat left tail. Consistent with these results, Table 1 shows that the momentum factor has a large negative skewness (−3.02) and large kurtosis (26.7). In contrast, the trend factor has a large positive skewness (1.80) and large kurtosis (46.2), indicating a fat right tail, great chances for large positive returns.

It is of interest to see how the factors perform in bad times. Panel B of Table 1 shows that both the average returns and Sharpe ratio of the trend factor are higher in the recession periods than for the whole sample period, while the volatility is virtually the same. In sharp contrast, all the other factors experience lower returns and lower Sharpe ratios, but higher volatilities. For example, both the market and SMB factors have negative average returns during the recession periods, and the momentum factor experiences the highest increase, more than 60%, in volatility.

Panel C of Table 1 reports the summary statistics for the most recent financial crisis period. The average return of the trend factor is about 1.65% per month, and the Sharp ratio is about 0.21. In contrast, all the other factors except the SMB factor experience large losses: the market yields −2.03% per month, the HML factor yields −0.44% per month, and the UMD factor yields −1.33% per month. In addition, the volatility of the UMD factor increases to 10.6%, an increase of more than 120% compared to the whole sample period. The skewness and kurtosis are mostly smaller in recessions and in the most recent financial crisis. For example, the trend factor has a reduced skewness (kurtosis) of 0.91 (4.39) during the recessions and 1.52 (2.17) during the most recent financial crisis.

Daniel, Jagannathan, and Kim (2012) show that the momentum strategy suffers loss exceeding 20% per month in 13 months out of the 978 months from 1929 to 2010. Barroso and Santa-Clara (2012) show that the momentum strategy delivers a −91.59% return in just two months in 1932 and a −73.42% over three months in 2009. This evidence motivates us to examine the worst case scenarios for the trend factor. Table 2 compares the maximum drawdown, Calmar ratio, and frequency of big losses of the trend factor with the other four factors (Panel A). The maximum drawdown is defined as the largest percentage drop in price from a peak to a bottom, which measures the maximum loss of an investor who invest in the asset at the worst time. From 1927 to 2012, the maximum drawdown is 58.8% for the trend factor, 84.6% for the market, and 76.1% for the momentum factor. The size and value factors deliver better results, 52.6% and 46.1%, respectively. The Calmar ratio, widely used in the investment industry, is defined as the annualized rate of return divided by the maximum drawdown, which measures return versus downside risk. The higher the ratio, the better the risk-return tradeoff. From 1927 to 2012, the trend factor has a Calmar ratio of 32.9%, whereas the other four factors have much lower Calmar ratios. For example, the momentum factor yields a Calmar ratio of only 10.7%.

Out of the 1024 months, the trend factor suffers a loss in 327 month, i.e., about 32% chance of negative returns from September 1927 to December 2012. In contrast, the other four factors all suffer more losses. The least one among them is the momentum factor, which suffers 375 monthly losses or has 37% chance of negative returns. For the extreme losses, out of the 1024 months, only in ten months did the trend factor experience a negative return exceeding -10% and only in two months exceeding -20%. In contrast, the momentum factor experiences a negative return exceeding -10% in 17 months and exceeding -20% in six months. The worst is the market, which has 31 monthly losses more than -10% and has six months more than -20%. However, the SMB and HML factors do not seem to have extreme downside risks, with only one and five, respectively, monthly return exceeding -10% and have no returns exceeding -20%.

Panel B of Table 2 reports the correlation matrix of the trend factor with the four factors. The trend factor is correlated with the Fama-French three factors - the correlation is 0.17 with the market portfolio, 0.25 with the SMB factor, and 0.25 with the HML factor, all of which are comparable to the correlations among the three factors themselves. But the correlation is only 0.02 (insignificant) with the momentum factor.

Why does the trend factor have an almost zero correlation with the momentum factor? Indeed, this seems at first glance somewhat puzzling since both factors are trend capturing. However, this becomes easy to understand once we separate the long and short sides of both factors. Table 3 reports the summary statistics for their long and short portfolios.[8] Due to capturing overall the same trend, the long (short) portfolios of both factors are indeed positively correlated as expected, and the correlation is in fact as high as 87% (92%) (Panel A). However, the trend factor does a much better job in capturing the trend, and so it has a much greater average return, 2.223% versus 1.820% of the momentum factor for the long leg, and has a much smaller average return, 0.604% versus 1.015% for the short leg.[9]

[8]The long and short portfolios of the momentum used are the 10^{th} and first equal-weighted decile portfolios taken from Ken French's online data library. Results are similar if we use the size and momentum double sorted portfolios that constitute the UMD factor.

[9]Note that we are somewhat biased against the trend factor as the quintile portfolios in contrast to the decile portfolios of the momentum are used. If trend deciles are used, the long and short portfolios will have average returns of 2.397% and 0.118% per month, respectively, thus yielding an average return of 2.279%

The differences are statistically significant at the 1% level. This means that both long and short portfolios of the trend factor outperform those of the momentum factor, and so the trend factor, as the spread portfolio, must outperform the momentum factor.[10] Moreover, we find that the trend factor earns a much higher average return during recessions while the momentum factor earns a small positive average return only because the short leg is a bit more negative than the long leg (Panel B). This is why returns on the two factors are not correlated over the entire sample period. In expansion periods as shown in Panel C, the trend factor still earns a higher average return than does the momentum factor because both long and short legs of the trend factor outperform those of the momentum factor.

3.2. The quintile portfolios

Table 4 reports the average returns and characteristics of the equal-weighted quintile portfolios sorted by the expected returns forecasted using the trend signals (trend quintile portfolios). 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 forecasted to have the highest expected returns (strongest trend forecasts) yield the highest returns on average in the subsequent month, about 2.221% per month, whereas stocks forecasted to have the lowest expected returns (weakest trend forecasts) yield the lowest returns on average in the subsequent month, only about 0.609% per month.

Also worth noting are the large gaps in average returns between the lowest and the second quintiles and the highest and the fourth quintiles - the average return increases by

per month for the decile trend factor.

[10]The spread portfolio between the 10^{th} momentum decile and the first momentum decile has an average return of 0.8% per month, close to 0.7% of the UMD factor.

74% (0.451% per month) and 55% (0.784% per month), respectively.

The market size displays a hump shape across the quintiles - both quintile Low and High have smaller market size than the other quintiles, while the book-to-market (B/M) 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 ($R_{-2,-6}$) increase monotonically across the quintiles. Clearly the abnormal returns are potentially related to the 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 (Idio Vol) displays a U-shaped pattern across the quintiles - the two extreme quintiles have much 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, Ogden, and Trzcinka, 1999). While the percentage of zero returns stays roughly constant across quintiles, the turnover rate displays a U-shape - the turnover rate is higher for both extreme quintiles. The last two columns in Table 4 report price ratios. While the cash-flow-to-price ratio (C/P) displays a hump shape pattern, the sales-to-price ratio (S/P) increases monotonically across the quintiles.

3.3. Risk adjusted returns

Can common risk factors explain the return on the trend factor? Table 5 reports Jensen's alpha and risk loadings for the trend quintile portfolios, the trend and momentum factors, with respect to the CAPM and Fama-French three-factor model, respectively. The quintile alphas increase monotonically from the lowest quintile to the highest quintile, from -0.444% to 1.059% with respect to the CAPM, and from -0.592% to 0.767% with respect to the Fama-French three-factor model, respectively. As a result, the trend factor, which is the

High-Low spread portfolio, has a CAPM alpha of 1.503% per month, and a Fama-French alpha of 1.359% per month, only slightly lower than the unadjusted abnormal return (1.612% per month in Table 4). While the market beta and SMB beta are asymmetrically U-shaped, the HML beta increases monotonically across the quintiles. Hance the trend factor has small and insignificant loading on the market and small and marginally significant SMB beta in the Fama-French three-factor model.

Schwert (2003) finds that, out of all the existing major anomalies, the momentum is the only one that is alive after its publication. Impressively, it survives the high hurdle proposed by Harvey, Liu, and Zhu (2013) to detect false discoveries. In comparison with the momentum, the alpha of the trend factor is almost twice as large, and has a t-statistic of 9.15 vs 7.09. Hence, the trend factor is more reliable and anomalous than the momentum factor. This is expected since the trend factor utilizes also short-term trend indicators. The short-term indicators are important not only in the US, but also in the world's second largest economy, the Chinese stock market. While there are no momentum effects in China (see, e.g, Griffin, Ji, and Martin, 2003), there are strong short-term trends (Han, Wang, Zhou, and Zou, 2013). Intuitively speaking, our trend factor is a combination of short- and long-term trends. Our results are also consistent with recent studies of Moskowitz, Ooi, and Pedersen (2012) and Asness, Moskowitz, and Pedersen (2013) who find pervasive price trends exist across commonly traded equity index, currency, commodity, and bond futures.

Markets or asset prices can trend strongly from time to time (e.g., the recent financial crisis and the Apple price) perhaps due to business cycles or fads in consumer products and services. Moreover, any new investment idea may take time to fruit (e.g., Warren Buffet may take time to build a large position due to practical liquidity problem, and take yet another long time to realize the gain). Hence, asset price trends are likely there to stay. While there are many theories (reviewed in the introduction) providing economic reasons for their presence, new theories are needed to fully account for the risks and to precisely quantify the risk premiums of following trends. Since much remains to be done for the less complicated momentum factor in that regard, it will likely take a long time to resolve the issue for the trend factor.

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 the trend signals and estimates of the true coefficients, controlling for a variety of firm attributes, including in particular, the momentum. Robustness can also be demonstrated with the alternative Fama-MacBeth regressions.

4.1. Robustness to trend signals

Figure 2 plots the time-series of the eight coefficients in the cross-sectional predictive regression. All the coefficients vary considerably over the sample period. Greater variations are observed for the Great Depression and pre-World War II era. Some coefficients have more variations than others. Of the eight coefficients, four are statistically significant, $\tilde{A}_{jt,1}, \tilde{A}_{jt,20}, \tilde{A}_{jt,50}$, and $\tilde{A}_{jt,200}$.

In Table 6 we report the performance of using various specifications of the trend signals to forecast future returns in Panel A and various ways to estimate the true coefficients in Panel B. In Panel A, the first specification is to use only the trend signals having statistically significant coefficients. To adjust for risk compensation, the performance in this table and the subsequent tables is always measured by the Fama-French alpha unless otherwise specified.

Clearly, the performance is the same if not slightly better than what is reported in Table 5 which uses all the moving averages up to 200 days (1.366% versus 1.359% in Table 5). Note that this strategy is not achievable ex ante as the significance of the coefficients is determined ex post. Adding more long lagged trend signals further improves the performance - the Fama-French alpha is 1.493% per month. Eliminating the 1-day moving average has virtually no impact on the performance - the Fama-French alpha is 1.328% per month. Finally, using only the short-term trend signals up to 20 days slightly reduces the performance, although the outperformance is still economically and statistically significant (the Fama-French alpha is 1.251% per month).

We follow Haugen and Baker (1996) to estimate the true coefficients of the trend signals using the trailing 12-month moving averages. In Panel B, we test the robustness of the estimated true coefficients and use 1-month, 3-month, 24-month, and 60-month trailing moving averages to estimate the true coefficients. When the coefficients are estimated using just last month coefficients, the performance is reduced - the Fama-French alpha of the High-Low spread portfolio is about 0.756% per month. Using the 6-month trailing averages improves the Fama-French alpha to 1.042% per month. Finally, estimating the coefficients with the 24-month or 60-month trailing averages does not further improve the performance - the Fama-French alphas is 1.354% and 1.387% per month, respectively.

4.2. Robustness to control variables

To understand better about the trend factor, we also sort the stocks by controlling for a variety of firm characteristics that are known to predict cross-section returns.

Table 7 provides the results of controlling for these characteristics. Panel A reports the results of controlling for the market size. Following the literature, we use a two-step sort procedure to control for the market size. Stocks are first sorted by the market size into five quintile groups, and within each quintile of the market size, stocks are further sorted by the trend forecasts to construct five trend quintile portfolios. As a result, 5×5 trend quintile portfolios are constructed; each market size quintile has five trend quintile portfolios, and each trend forecasts quintile has five trend quintile portfolios as well. We then average the resulting 5×5 trend quintile portfolios across the five quintiles of the market size to form five new trend quintile portfolios, all of which should have similar market size to achieve the effect of controlling for the market size. This procedure has been widely used in the literature to check the robustness of the cross-section pricing power of predictors; examples are Ang, Hodrick, Xing, and Zhang (2006, 2009), Avramov, Chordia, Jostova, and Philipov (2009), Yu (2011), and Wahal and Yavuz (2013), to name a few. The performance, as measured by the Fama-French alpha, of the 5×5 quintile portfolios and the five new trend quintile portfolios after controlling for the market size is reported in Panel A.

Clearly, Panel A shows that the performance is much stronger for the small stocks. For the smallest stocks, the High-Low spread portfolio yields a Fama-French alpha of 2.753% per month. A close examination of the individual quintiles shows that the superior performance is mainly driven from the quintile with the strongest trend forecasts (the alpha is 2.190% per month for quintile High). Performance decreases as the market size increases, and not surprisingly, the decrease in performance is mainly due to the decreased alpha of quintile High. For example, quintile High of the largest stocks has a Fama-French alpha of only 0.269% per month, although still statistically significant. However, it should be noted that the abnormal performance of the High-Low spread portfolio of the largest stocks is still significant both statistically and economically (0.483% per month). Controlling for the market size by averaging across the different market size quintiles, still yields a Fama-French alpha of 1.235% per month for the High-Low spread portfolio, similar to the performance reported in Table 5.

Panel B reports the performance of the trend quintile portfolios after controlling for other firm characteristics. We similarly control for the book-to-market ratio (B/M), last month return, and percentage of zero returns. The superior performance remains largely unchanged. For example, controlling for B/M yields a Fama-French alpha of 1.116% per month for the High-Low spread portfolio. Controlling for the last month return does reduce the performance to some extent - the High-Low spread portfolio now yields a Fama-French alpha of 0.843% per month. We also control for liquidity as measured by the percentage of zeros and the performance remains unchanged.

4.3. Robustness to the momentum

In this subsection, we examine whether the momentum can explain the abnormal returns of the trend signals. We first subject the trend quintile portfolios to the four-factor model that also includes the UMD factor in addition to the Fama-French three factors. We then control for the past six-month cumulative returns from $t-2$ to $t-6$ in sort as described above. Results are reported in Table 8.

In Panel A, the alpha after controlling for the exposure to the momentum factor still displays a monotonic relation with the trend forecasts. Weak trend forecasts are associated with low alphas and strong trend forecasts are associated with high alphas. The High-Low spread portfolio yields an alpha of 1.118% per month, which is comparable to the alphas under both the CAPM and Fama-French models. All quintile portfolios except for the fourth quintile have significant yet negative exposures to the momentum factor, but the High-Low spread portfolio has significantly positive risk exposure to the UMD factor.

Panel B reports the 5×5 trend quintile portfolios double sorted by the past six-month returns from $t-2$ to $t-6$ and the trend forecasts. At each level of the past returns (momentum), the Fama-French alpha increases monotonically from quintile Low to quintile High and thus the High-Low spread portfolio yields a positive and significant abnormal return. Furthermore, 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 2.280% per month. The High-Low alphas generally decrease moving from Losers to Winners, but all remain highly statistically and economically significant. For example, the smallest alpha (in fourth group of the past returns) is still about 0.903% per month. If the quintile portfolios are averaged across the five levels of the past returns, the High-Low alpha is 1.311%, which is very closed to that of the single sort reported in Table 5, suggesting that momentum can not explain the abnormal returns generated from using the trend signals.

4.4. Fama-MacBeth regressions

Portfolio sorting, although powerful and capable of capturing nonlinear predictive relation, is often difficult to 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 (linear) effect. Therefore we run the 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 9 reports the results of regressing the monthly returns on the trend forecasts (ER_{trd}) and various control variables using the weighted Fama-MacBeth cross-sectional regression framework. In the first regression, we examine the predictability of ER_{trd} while controlling for the market beta, market size and book-to-market ratio. As expected, ER_{trd} has a significant and positive coefficient indicating the trend signals can predict future cross-section returns independent of the market beta, size, and book-to-market. These results are consistent with the double sort results in Table 7. In the second regression, we add last-month return (short-term reversal) and six-month cumulative return from $t-2$ to $t-6$ (momentum) as additional controls. ER_{trd} remains highly significant and the coefficient is only slightly reduced despite the significant presence of the last-month return, which is also consistent with the sort results in Table 7 and Table 8. The last regression results are very similar to the second regression results despite the additional control variables added - ER_{trd} remains significant and positive.

5. Trends and information uncertainty

In this section, we examine the performance of the trend forecasts for different groups of stocks that are characterized by different degrees of 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 are likely more profitable for the high information uncertain stocks than for the low information uncertain stocks.

We use a number of variables to proxy for information uncertainty, including the market size, idiosyncratic volatility, trading turnover rate, analyst coverage (number of analysts following), and firm age. All the proxies are used in the previous literature. For example, Zhang (2006) uses the market size, firm age, analyst coverage, analyst forecast dispersion, stock volatility, and cash flow volatility as proxies for information uncertainty. Berkman, Dimitrov, Jain, Koch, and Tice (2009) use income volatility, stock volatility, analyst forecast dispersion and firm age to proxy for information uncertainty.[11]

We use double sort procedure described previously to examine the impact of information uncertainty on the performance of the trend forecasts. Briefly, we sort stocks first by the proxy of information uncertainty into five quintiles, and then sort further each quintile into five trend quintile portfolios for each level of information uncertainty, thus producing 5×5 trend quintile portfolios. We also examine the performance of the trend forecasts after controlling for the information uncertainty proxy by averaging across all levels of the information uncertainty proxy as described previously.

The results for using the market size as the proxy for information uncertainty is reported earlier in Panel A of Table 7. The Fama-French alpha of the High-Low spread portfolio monotonically increases from 0.483% to 2.753% as the market size (information uncertainty) decreases (increases) from the largest to the smallest.

Table 10 reports the performance of the trend forecasts under different levels of information uncertainty as measured by other proxies. In Panel A the Fama-French alpha of the High-Low spread portfolio monotonically increases as the idiosyncratic volatility (information uncertainty) increases. The abnormal returns of both the weakest and the strongest trend forecasts quintiles change drastically as idiosyncratic volatility (information uncertainty) increases, but in the opposite directions. The abnormal return of the weakest trend forecasts quintile (Low) decreases as the information uncertainty increases, while the per-

[11]We also examine dispersions in analyst earnings forecasts and quarterly operating income volatility and obtain similar results, which are available upon request.

formance of the strongest trend forecasts quintile (High) increases at the same time. As a result, the Fama-French alpha of the High-Low spread portfolio increases from 0.543% when the information uncertainty is the lowest to as high as 2.452% per month when the information uncertainty is the highest. The remaining quintiles are somewhat insensitive to the changes in the information uncertainty. In addition, controlling for the information uncertainty (idiosyncratic volatility) by averaging over the five quintiles of idiosyncratic volatility yields similar performance to the single sort in Table 5.

In Panel B a similar pattern is observed when trading turnover rate is used to proxy for information uncertainty - low turnover stocks have high degree of information uncertainty. The performance of the High-Low spread portfolio increases monotonically as the turnover rate (information uncertainty) decreases (increases); the Fama-French alpha increases from 0.740% per month to 1.554% per month. Similarly, controlling for the trading turnover rate does not materially reduce the performance.

In Panel C, we use analyst coverage 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 increases as the number of analysts following (information uncertainty) decreases (increases) across the quintiles – the Fama-French alpha increases from 0.346% per month to 1.560% per month. Again, the weakest and strongest trend forecasts quintiles move in the opposite directions, while other quintiles are somewhat insensitive to the changes in information uncertainty. The Fama-French alpha of the weakest trend forecasts quintile (Low) decreases from -0.256% to -0.674% per month, while the Fama-French alpha of the strongest trend forecasts quintile increases from 0.091% to 0.887% per month. Controlling for the number of analysts following by averaging across the quintiles still yields similar abnormal returns.

Finally, We use the age of the firm to proxy for information uncertainty or noise-signal ratio in Panel D. Younger firms[12] are subject to higher information uncertainty. We observe a similar pattern – from the oldest age quintile (Old) to the youngest age quintile (Young), the abnormal returns (Fama-French alphas) increase monotonically from 0.690% per month to 1.531% per month. Again, controlling for firm age still yields significant abnormal returns and the magnitude is similar to what is achieved in the single sort shown in Table 5.

6. Cross-section pricing

In this section, we examine how well the trend factor can explain some common anomalies as compared with the momentum factor.

Consider first the well-known short-term reversal anomaly. Ten short-term reversal decile portfolios[13] are regressed under either the CAPM or the CAPM with either the trend factor or the momentum factor. Panel A of Table 11 reports the CAPM results. All but two short-term reversal portfolios have highly significant alphas. The first portfolio (*STRev1*), which contains the lowest last month returns, yields the highest abnormal returns (1.620% per month), whereas the 10^{th} portfolio (*STRev10*), which contains the highest last-month returns, yields the lowest abnormal returns (-1.020% per month). When the trend factor is added to the regression as shown in Panel B, all but four decile portfolios have insignificant pricing errors. The loadings on the trend factors across all ten deciles are highly significant and positive (except for the 10^{th} decile), and decrease more or less monotonically from the first decile to the 10^{th} decile. That is, the decile portfolio that has the lowest last-month returns has the highest exposure to the trend factor, whereas the decile portfolio that has

[12] We exclude firms younger than two years old.

[13] All portfolios in this section other than the trend factor are obtained from Ken French's online data library.

the highest last-month returns has no exposure to the trend factor. In contrast, all but two decile portfolios have highly significant pricing errors when the momentum factor is added to the regression. In addition, the magnitudes of the pricing errors are about twice of what are in the CAPM. Evidence on the alphas is clearly in favor of the trend factor in explaining the short-term reversal anomaly.

To assess further the cross-section pricing errors, we report in the last column Δ, with

$$\Delta = \alpha' \Sigma^{-1} \alpha, \tag{5}$$

where Σ is the variance-covariance matrix of the residuals across the ten decile portfolios. Shanken (1992) seems the first to introduce this measure (different from his paper by a scalar), which is a summary of the cross-section pricing errors and is related to the optimal portfolio that exploits the pricing errors. The larger the Δ, the greater the difference between investing in the factor portfolios and all the decile portfolios used in the regression. Consistent with the performance in terms of the alphas, the CAPM plus the momentum factor has a pricing error of 0.345, whereas adding the trend factor reduces it to 0.266.

Consider now the long-term reversal decile portfolios. Table 12 reports stronger results. The CAPM is able to explain only the last two decile portfolios. Adding the trend factor, however, explains all the decile portfolios, whereas adding the momentum factor instead makes the pricing error of every decile portfolio (except for the last one) more significant and greater. The pricing error is 0.042, 0.030, and 0.062, respectively, for the CAPM, CAPM plus the trend factor, and CAPM plus the momentum factor.

Finally, Table 13 reports the results using decile portfolios sorted by earnings-to-price ratio (E/P) in Panel A, cash-flow-to-price ratio (C/P) in Panel B, and dividend-to-price ratio (D/P) in Panel C. For each set of decile portfolios, we report the regression results of the trend factor or the momentum factor in the context of the CAPM. In each case, the trend factor can explain the majority of the abnormal returns and thus the alphas are largely insignificant. By contrast, the alphas of most of the decile portfolios remain significant after including the momentum factor. The pricing errors with the trend factor are about half of those with the momentum factor.

7. Conclusion

We form a trend factor with a cross-section regression approach that makes use of multiple trend indicators containing daily, weekly, monthly and yearly information. Stocks that have high forecasted expected returns from the cross-section regression 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 is the trend factor, which has a return around 1.61% per month. The return is more than quadrupling those of the size and book-to-market factors, and more than twice that of the momentum factor.

The cross-section predictability and profitability of the trend factor is robust to various firm and market characteristics, such as size, book-to-market ratio, past return, trading volume, business cycles, etc. The strategy of using trend indicators 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 provide evidence that our new trend factor is capable of explaining cross-section stock returns. It 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 interest to see whether the trend factor is of economic significance across countries.[14] Moreover, following Moskowitz, Ooi, and Pedersen (2012) and Asness, Moskowitz, and Pedersen (2013), it is of interest to apply the trending detecting strategy of this paper to other asset classes, such as foreign exchanges and bonds.

[14]Our preliminary analysis using data from France, Germany and Singapore show their country trend factors have a comparable monthly return of 2–3%, and one internal report at an investment bank finds the global robustness of the US findings.

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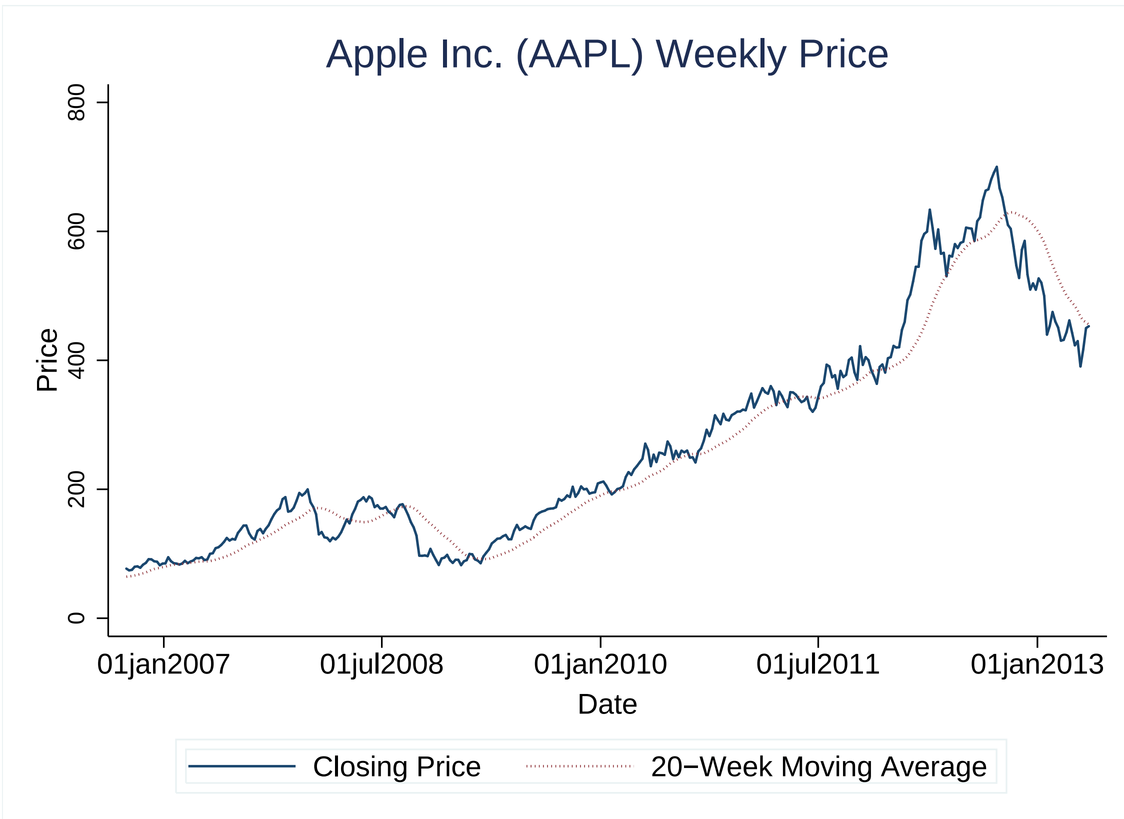
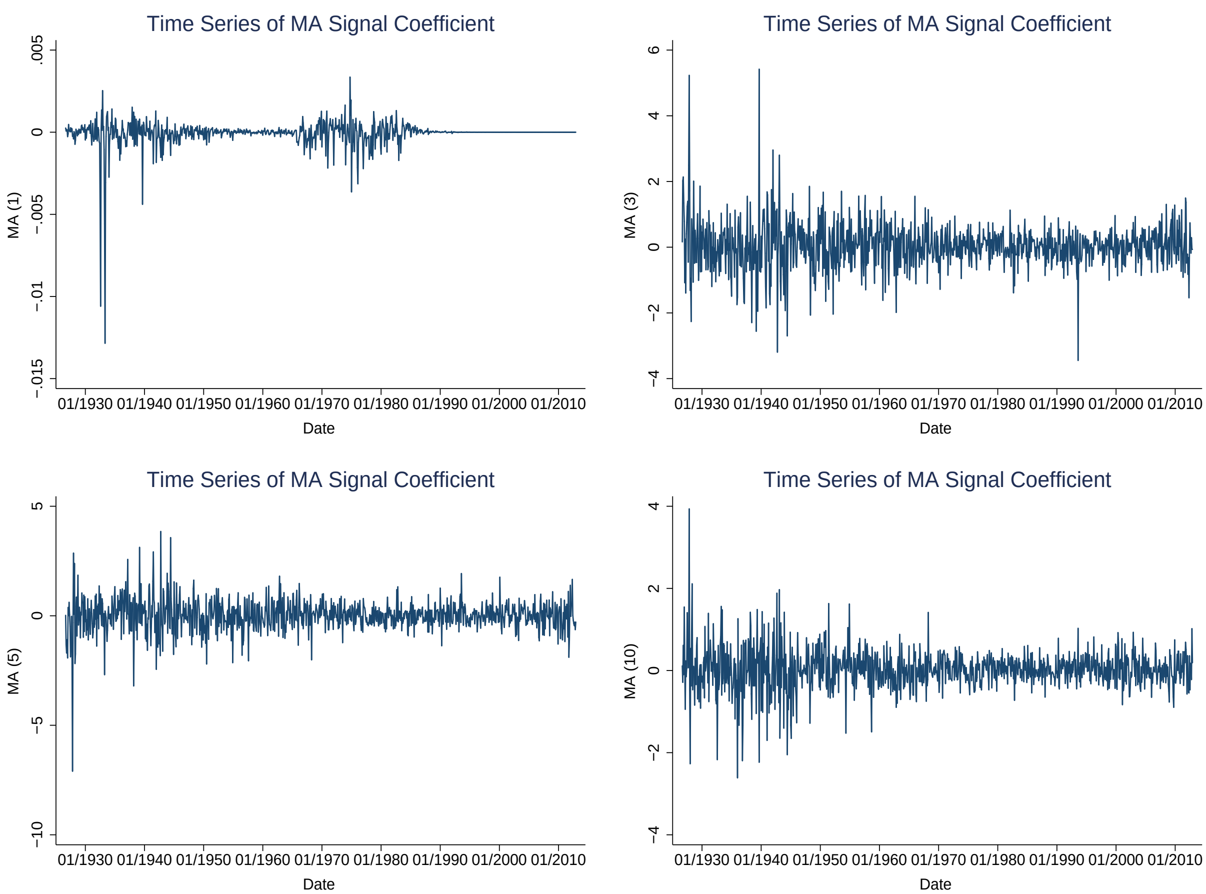


Figure 1: Weekly Prices of Apple Inc. from Year 2007 to 2013

Panel A: First Four Coefficients



Panel B: Last Four Coefficients

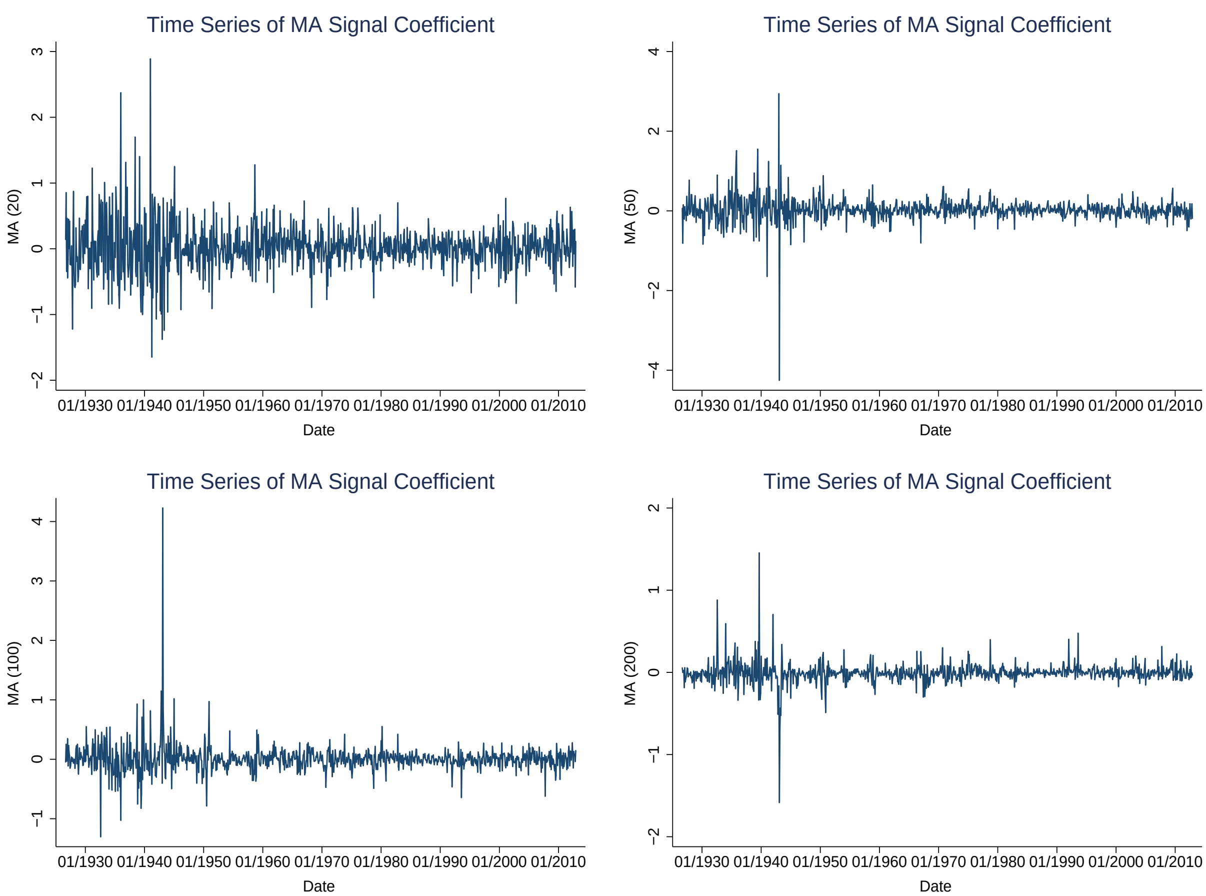


Figure 2: Time Series of Coefficients of the Trend Signals

Table 1: The Trend Factor and Other Factors: Summary Statistics

This table reports the summary statistics of the trend factor and four other factors including the market portfolio, Fama-French factors (SMB and HML) and the momentum factor (UMD). We report the summary statistics such as sample mean in percentage, sample standard deviation in percentage, Sharpe ratio, skewness, and kurtosis for the whole sample period (Panel A), the recession periods (Panel B) and the most recent financial crisis period (Panel C). The sample period is from September 1927 to December 2012.

Variable	Mean (%)	Std Dev (%)	Sharpe Ratio	Skewness	Kurtosis
	Panel A: Whole Sample Period				
Trend	1.61	5.59	0.29	1.80	46.2
Market	0.61	5.45	0.11	0.17	7.31
SMB	0.25	3.32	0.07	2.18	22.2
HML	0.39	3.56	0.11	1.85	15.9
UMD	0.68	4.79	0.14	-3.02	26.7
	Panel B: Recession Periods				
Trend	2.49	5.70	0.44	0.91	4.39
Market	-0.69	8.18	-0.08	0.39	3.60
SMB	-0.01	3.51	-0.00	0.83	4.46
HML	0.14	4.87	0.03	2.71	17.7
UMD	0.43	7.86	0.05	-2.90	15.1
	Panel C: Financial Criss (12/2007 - 06/2009)				
Trend	1.65	7.83	0.21	1.52	2.17
Market	-2.03	7.06	-0.29	-0.21	-0.24
SMB	0.63	2.49	0.25	0.26	-0.77
HML	-0.44	3.80	-0.12	-0.83	0.87
UMD	-1.33	10.6	-0.13	-1.81	4.70

Table 2: The Trend Factor and Other Factors: Extreme Values and Correlation Matrix

This table reports the maximum drawdown, Calmar ratio, and frequency of big losses of the trend factor, the market portfolio, Fama-French factors and the momentum factor in Panel A and the correlation matrix of the factors in Panel B, respectively. The sample period is from September 1927 to December 2012.

Panel A: Extreme Values

Variable	Obs	MaxDrawDown (%)	Calmar Ratio (%)	$R < 0\%$	$R < -10\%$	$R < -20\%$
Trend	1,024	58.8	32.9	327	10	2
Market	1,024	84.6	8.66	413	31	6
SMB	1,024	52.6	5.66	498	1	0
HML	1,024	46.1	10.0	467	5	0
UMD	1,024	76.1	10.7	375	17	6

Panel B: Correlation Matrix

	Trend	Market	SMB	HML	UMD
Trend	1	0.17	0.25	0.25	0.02
Market		1	0.33	0.22	-0.34
SMB			1	0.10	-0.16
HML				1	-0.39
UMD					1

Table 3: Comparison of Trend and Momentum

This table compares the long and short portfolios of the trend factor and momentum factor. The summary statistics are reported for each of the long and short portfolios over the whole sample period (Panel A), the recession periods (Panel B) and the expansion periods (Panel C) identified by the NBER. A one-sided test of equal mean between the long (short) portfolios of the trend factor and momentum factor is reported in the table labeled as *Differ. For the long portfolio, the test is* $H_0 : \mu^l_{trd} = \mu^l_{mom}$; $H_1 : \mu^l_{trd} > \mu^l_{mom}$; *for the short portfolio, the test is* $H_0 : \mu^s_{trd} = \mu^s_{mom}$; $H_1 : \mu^s_{trd} < \mu^s_{mom}$, *where the subscript* trd *and* mom *denote the trend and momentum, respectively; superscript* l *and* s *denote long and short portfolios, respectively. The last column (Corr) reports the correlation between the long (short) portfolios of the trend factor and momentum factor. Significance at the 1%, 5%, and 10% levels is given by an ***, and **, and an *, respectively. The sample period is from September 1927 to December 2012.*

Variable	*Mean (%)*	*Std Dev (%)*	*Skewness*	*Kurtosis*	*N*	*Differ*	*Corr*
			Panel A: Whole Sample Period				
Trend Long	*2.223*	*9.442*	*2.394*	*22.64*	*1,019*	*0.403****	*0.870*
Momentum Long	*1.820*	*7.484*	*0.112*	*8.609*	*1,019*		
Trend Short	*0.604*	*8.130*	*1.801*	*21.03*	*1,019*	*-0.411****	*0.919*
Momentum Short	*1.015*	*11.33*	*2.838*	*24.81*	*1,019*		
			Panel B: Recession Periods				
Trend Long	*1.011*	*12.27*	*1.690*	*10.90*	*222*	*1.092****	*0.842*
Momentum Long	*-0.082*	*8.449*	*-0.441*	*4.111*	*222*		
Trend Short	*-1.271*	*11.35*	*1.565*	*13.22*	*222*	*-0.970***	*0.952*
Momentum Short	*-0.300*	*15.97*	*2.278*	*15.50*	*222*		
			Panel C: Expansion Periods				
Trend Long	*2.561*	*8.468*	*2.953*	*31.75*	*797*	*0.212**	*0.891*
Momentum Long	*2.350*	*7.108*	*0.469*	*10.70*	*797*		
Trend Short	*1.127*	*6.894*	*2.237*	*26.24*	*797*	*-0.255**	*0.895*
Momentum Short	*1.381*	*9.637*	*3.231*	*29.36*	*797*		

Table 4: Average Returns and Other Characteristics of the Trend Quintile Portfolios

This table reports the average return and other characteristics of the five trend quintile portfolios. Market size 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 September 1927 to December 2012.

Rank	Return(%)	Market Size	*log*B/M	R_{-1}(%)	$R_{-6,-2}$(%)	Idio Vol(%)	%Zero	Turnover(%)	C/P(%)	S/P
Low	0.609**	491.2***	1.623***	8.194***	0.042**	2.133***	22.43***	7.798***	-0.903	61.96***
	(2.310)	(9.430)	(19.74)	(13.60)	(2.560)	(16.33)	(24.26)	(14.11)	(-0.980)	(7.770)
2	1.060***	820.9***	1.801***	2.947***	0.055***	1.367***	22.58***	5.567***	2.703***	62.00***
	(4.530)	(7.730)	(22.07)	(9.630)	(4.810)	(19.36)	(24.27)	(14.11)	(9.200)	(11.40)
3	1.207***	932.3***	1.870***	0.945***	0.063***	1.253***	23.09***	4.999***	3.018***	64.18***
	(5.150)	(7.380)	(24.14)	(3.970)	(6.110)	(20.14)	(24.07)	(13.95)	(10.86)	(11.95)
4	1.437***	830.3***	1.837***	-0.911***	0.072***	1.441***	23.03***	5.299***	2.656***	66.23***
	(5.560)	(7.620)	(23.35)	(-3.730)	(6.890)	(18.35)	(23.46)	(14.09)	(8.550)	(11.60)
High	2.221***	503.9***	1.706***	-4.654***	0.090***	2.320***	24.08***	7.000***	-2.761**	79.42***
	(6.540)	(8.820)	(19.51)	(-11.33)	(6.400)	(17.36)	(22.45)	(13.70)	(-2.360)	(7.590)

Table 5: CAPM and Fama-French Alphas

This table reports Jensen's alpha and risk loadings with respect to the CAPM and Fama-French three-factor model, respectively, for the five trend quintile portfolios, the trend factor, and the UMD factor. 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 September 1927 to December 2012.

	Panel A: CAPM		**Panel B: Fama-French**			
Rank	α	β_{mkt}	α	β_{mkt}	β_{smb}	β_{hml}
Low	-0.444***	1.248***	-0.592***	1.057***	0.844***	0.143
	(-3.660)	(22.81)	(-6.270)	(30.07)	(6.480)	(1.310)
2	0.058	1.166***	-0.110**	0.989***	0.677***	0.278***
	(0.670)	(28.72)	(-2.340)	(61.41)	(12.53)	(6.750)
3	0.210**	1.157***	0.017	0.965***	0.693***	0.358***
	(2.390)	(26.65)	(0.420)	(68.69)	(14.66)	(11.33)
4	0.394***	1.232***	0.180***	1.016***	0.793***	0.385***
	(3.780)	(21.04)	(3.770)	(49.54)	(11.39)	(7.830)
High	1.059***	1.426***	0.767***	1.113***	1.207***	0.476***
	(5.900)	(19.42)	(6.660)	(41.40)	(12.17)	(7.530)
High-Low	1.503***	0.178*	1.359***	0.056	0.363*	0.333**
(Trend)	(9.150)	(1.920)	(8.940)	(1.290)	(1.670)	(2.330)
UMD	0.862***	-0.300**	1.000***	-0.221**	-0.065	-0.448***
	(7.090)	(-2.977)	(8.089)	(-3.274)	(-0.752)	(-3.425)

Table 6: Performance of Alternative Trend Forecasts Specifications

This table reports the performance of various specifications of trend signals in Panel A and various estimates of the true coefficients in Panel B. The performance is measured by the Fama-French alpha 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 September 1927 to December 2012.

	Fama-French Alpha					
	Low	2	3	4	High	High-Low
	Panel A: Different Specifications of Trend Signals					
1-,20-,50-,200-day	-0.587***	-0.157***	0.030	0.196***	0.779***	1.366***
	(-5.536)	(-3.179)	(0.798)	(3.730)	(6.710)	(8.143)
1-,3-,5-,10-,20-,50-,100-,200-,300-,500-day	-0.648***	-0.122***	0.083**	0.261***	0.845***	1.493***
	(-6.934)	(-2.738)	(2.211)	(5.497)	(7.320)	(9.772)
3-,5-,10-,20-,50-,100-,200-day	-0.630***	-0.026	0.091**	0.137***	0.698***	1.328***
	(-7.210)	(-0.550)	(2.157)	(2.682)	(6.255)	(9.134)
1-,3-,5-,10-,20-day	-0.587***	-0.096**	0.052	0.114**	0.664***	1.251***
	(-6.780)	(-1.963)	(1.230)	(2.376)	(6.048)	(8.709)
	Panel B: Different Estimates of Expected Coefficients					
Traling 1 Month Average	-0.299***	-0.105**	0.043	0.152***	0.456***	0.756***
	(-3.212)	(-2.280)	(1.078)	(3.164)	(4.579)	(5.625)
Trailing 6 months Average	-0.441***	-0.123***	0.029	0.188***	0.601***	1.042***
	(-4.672)	(-2.603)	(0.781)	(3.771)	(5.336)	(7.122)
Trailing 24 months Average	-0.600***	-0.136***	0.064	0.155***	0.754***	1.354***
	(-6.448)	(-2.895)	(1.625)	(3.016)	(6.622)	(9.107)
Trailing 60 months Average	-0.609***	-0.145***	0.013	0.188***	0.778***	1.387***
	(-5.991)	(-2.832)	(0.323)	(3.565)	(7.575)	(9.612)

Table 7: Performance after Controlling for Firm Characteristics

This table reports the sort results of controlling for various firm characteristics. Stocks are first sorted by one of the control variables into five quintile groups, and then in each quintile stocks are further sorted to construct five trend quintile portfolios. We then average the resulting 5×5 trend quintile portfolios across the five quintiles of the control variable to form five new trend quintile portfolios, all of which should have similar levels of the control variable. In Panel A, we report the performance of the 5×5 quintile portfolios and the five new trend quintile portfolios after controlling for the market size. In Panel B, We report the performance of only the new trend quintile portfolios after controlling for the firm characteristics. The performance is measured by the Fama-French alpha 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 September 1927 to December 2012.

	Trend Forecasts					
	Low	2	3	4	High	High-Low
Market Size	**Panel A: Market Size**					
Small	-0.563***	0.166	0.364***	0.726***	2.190***	2.753***
	(-3.035)	(1.291)	(3.159)	(4.649)	(8.660)	(9.872)
2	-1.088***	-0.196***	-0.108	0.132	0.244*	1.332***
	(-8.832)	(-2.611)	(-1.450)	(1.573)	(1.947)	(7.648)
3	-0.714***	-0.128**	0.047	0.075	0.160*	0.875***
	(-7.680)	(-2.203)	(0.775)	(1.277)	(1.685)	(6.034)
4	-0.449***	-0.053	0.040	0.139**	0.285***	0.734***
	(-5.770)	(-0.938)	(0.832)	(2.441)	(3.404)	(5.639)
Large	-0.214***	-0.101**	0.040	0.100**	0.269***	0.483***
	(-3.268)	(-2.231)	(1.029)	(2.161)	(4.204)	(4.617)
Average over Market Size	-0.606***	-0.062	0.076*	0.234***	0.630***	1.235***
	(-7.376)	(-1.270)	(1.765)	(4.414)	(6.685)	(9.538)
	Panel B: Controlling for Firm Characteristics					
Average over B/M	-0.463***	-0.020	0.082	0.108	0.653***	1.116***
	(-3.485)	(-0.224)	(1.116)	(1.589)	(4.657)	(6.051)
Average over Last Month Return	-0.392***	-0.045	0.076**	0.156***	0.450***	0.843***
	(-4.858)	(-0.983)	(2.015)	(3.473)	(5.050)	(7.708)
Average over %Zeros	-0.550***	-0.068	0.037	0.230***	0.783***	1.333***
	(-5.482)	(-1.296)	(0.795)	(4.047)	(6.839)	(9.140)

Table 8: Performance after Controlling for Momentum

This table reports the performance of the trend quintile portfolios after controlling for the momentum. Panel A provides 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 $t-6$ using the sort procedure described in Table 7. We also report the 5×5 trend quintile portfolios. 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 September 1927 to December 2012.

Panel A: Measure Performance with Momentum Factor

Rank	α	β_{mkt}	β_{smb}	β_{hml}	β_{umd}
Low	-0.250*	0.981***	0.822***	-0.010	-0.341***
	(-1.680)	(33.16)	(7.120)	(-0.100)	(-3.630)
2	0.036	0.957***	0.667***	0.213***	-0.145***
	(0.590)	(65.15)	(14.70)	(5.800)	(-4.210)
3	0.097**	0.947***	0.688***	0.322***	-0.080***
	(2.270)	(66.01)	(15.16)	(10.74)	(-3.470)
4	0.219***	1.008***	0.791***	0.368***	-0.038
	(3.780)	(47.76)	(11.26)	(7.450)	(-1.100)
High	0.868***	1.091***	1.201***	0.431***	-0.101*
	(6.610)	(42.13)	(11.73)	(6.220)	(-1.890)
High-Low	1.118***	0.109**	0.379*	0.441***	0.240**
	(5.240)	(2.510)	(1.820)	(3.050)	(1.970)

Panel B: Control with Past 2 to 6-Month Return

Momentum	Trend Forecasts					
	Low	2	3	4	High	High-Low
Loser	-1.138***	-0.653***	-0.265**	-0.118	1.142***	2.280***
	(-6.531)	(-5.281)	(-2.184)	(-0.949)	(5.401)	(9.770)
2	-0.668***	-0.178**	-0.014	0.123*	0.519***	1.187***
	(-6.180)	(-2.575)	(-0.185)	(1.700)	(4.291)	(7.740)
3	-0.421***	-0.037	0.112**	0.172***	0.534***	0.954***
	(-4.958)	(-0.633)	(2.027)	(3.029)	(6.023)	(6.972)
4	-0.299***	0.119*	0.182***	0.188***	0.604***	0.903***
	(-3.598)	(1.869)	(3.038)	(3.038)	(6.675)	(6.752)
Winner	-0.334***	0.099	0.278***	0.444***	0.899***	1.233***
	(-2.626)	(0.913)	(2.736)	(4.611)	(6.172)	(6.982)
Average over $R_{-6,-2}$	-0.572***	-0.130***	0.059	0.162***	0.739***	1.311***
	(-7.277)	(-2.937)	(1.377)	(3.453)	(7.139)	(9.871)

Table 9: Fama-MacBeth Regression

This table reports the results of regressing monthly returns on the expected returns forecasted by the trend signals (ER_{trd}) 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 September 1927 to December 2012.

	(1)	(2)	(3)
Intercept	-0.024**	-0.013	-0.012
	(-2.55)	(-1.09)	(-0.80)
ER_{trd}	0.338***	0.212**	0.226**
	(5.37)	(2.27)	(2.02)
β_m	-0.222	0.251	0.511
	(-0.09)	(0.12)	(0.26)
Log(Size)	-0.864	-0.455	-0.001
	(-0.66)	(-0.43)	(-0.00)
log(B/M)	0.412	0.357	-0.772
	(0.24)	(0.30)	(-0.38)
R_{-1}		-0.059***	-0.071***
		(-8.91)	(-6.62)
$R_{-6,-2}$		-0.002	-0.005
		(-0.43)	(-0.56)
Idio Vol			-0.198***
			(-2.80)
%Zero			0.001
			(0.14)
Turnover			0.324*
			(1.93)

Table 10: Performance under Information Uncertainty

This table reports the performance of the trend quintile portfolios under information uncertainty proxied by idiosyncratic volatility (Panel A), share turnover rate (Panel B), number of analyst following (Panel C), and firm age (Panel D). Stocks are first sorted by one of the information uncertainty proxies into five quintile groups, and then in each quintile stocks are further sorted to construct five trend quintile portfolios. We report the Fama-French alphas for the resulting 5×5 trend quintile portfolios and the average across the five quintiles of the information uncertainty proxy. 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 September 1927 to December 2012.

	Trend Forecasts					
	Low	2	3	4	High	High-Low
Idio Vol	**Panel A: Idiosyncratic Volatility**					
Low	-0.103	0.105	0.215***	0.291***	0.441***	0.543***
	(-1.325)	(1.534)	(3.297)	(4.548)	(5.857)	(6.100)
2	-0.344***	-0.040	0.185***	0.233***	0.446***	0.790***
	(-4.859)	(-0.601)	(2.796)	(3.489)	(5.952)	(7.425)
3	-0.497***	-0.116*	0.020	0.220***	0.470***	0.967***
	(-5.933)	(-1.715)	(0.342)	(3.226)	(5.639)	(8.371)
4	-0.693***	-0.143*	0.089	0.199**	0.603***	1.296***
	(-6.076)	(-1.955)	(1.197)	(2.566)	(4.485)	(7.007)
High	-1.192***	-0.369***	-0.170	0.284**	1.259***	2.452***
	(-7.065)	(-3.113)	(-1.388)	(1.987)	(5.458)	(9.447)
Average over Idio Vol	-0.566***	-0.113**	0.068*	0.245***	0.644***	1.210***
	(-7.990)	(-2.430)	(1.765)	(5.020)	(7.648)	(10.44)
Turnover	**Panel B: Turnover Rate**					
High	-0.723***	-0.224***	-0.049	-0.031	0.016	0.740***
	(-5.516)	(-2.784)	(-0.565)	(-0.344)	(0.123)	(4.548)
4	-0.555***	-0.153**	0.055	0.199***	0.675***	1.230***
	(-5.324)	(-2.372)	(0.916)	(3.027)	(5.540)	(8.131)
3	-0.529***	-0.057	0.137**	0.278***	0.949***	1.478***
	(-5.288)	(-0.965)	(2.445)	(4.148)	(7.298)	(9.315)
2	-0.509***	-0.076	0.073	0.239***	0.973***	1.482***
	(-4.826)	(-1.041)	(1.146)	(3.458)	(7.631)	(9.656)
Low	-0.594***	-0.151	0.001	0.188**	0.960***	1.554***
	(-4.519)	(-1.587)	(0.008)	(1.995)	(5.980)	(7.737)
Average over Turnover	-0.582***	-0.132***	0.043	0.175***	0.715***	1.297***
	(-6.751)	(-2.999)	(1.169)	(3.564)	(6.704)	(9.461)

	Trend Forecasts					
	Low	2	3	4	High	High-Low
Analyst Coverage	**Panel C: Analyst Coverage**					
High	-0.256**	-0.005	0.072	0.115	0.091	0.346*
	(-1.996)	(-0.052)	(1.081)	(1.407)	(0.720)	(1.909)
4	-0.379***	-0.070	0.037	0.064	0.164	0.544***
	(-2.958)	(-0.816)	(0.510)	(0.813)	(1.248)	(2.972)
3	-0.333**	-0.071	-0.059	0.030	0.076	0.409*
	(-2.039)	(-0.715)	(-0.636)	(0.327)	(0.480)	(1.898)
2	0.208	0.386**	0.294**	0.128	0.862**	0.654**
	(0.712)	(2.562)	(2.137)	(0.923)	(2.478)	(2.218)
Low	-0.674***	-0.104	-0.039	0.114	0.887***	1.560***
	(-5.904)	(-1.568)	(-0.622)	(1.617)	(6.356)	(9.652)
Average over Analyst Coverage	-0.591***	-0.111**	0.016	0.173***	0.699***	1.290***
	(-6.733)	(-2.452)	(0.428)	(3.890)	(6.278)	(8.693)
Firm Age	**Panel D: Firm Age**					
Old	-0.353***	-0.107	0.083	0.106	0.337***	0.690***
	(-3.536)	(-1.561)	(1.316)	(1.516)	(3.313)	(4.730)
4	-0.350***	0.033	0.146***	0.207***	0.527***	0.877***
	(-3.716)	(0.583)	(2.698)	(3.455)	(5.251)	(6.562)
3	-0.451***	-0.031	0.131**	0.267***	0.783***	1.234***
	(-4.049)	(-0.499)	(2.152)	(3.830)	(6.536)	(7.572)
2	-0.549***	-0.026	0.049	0.172**	0.735***	1.284***
	(-4.483)	(-0.348)	(0.768)	(2.525)	(5.045)	(7.003)
Young	-0.656***	-0.082	0.038	0.169**	0.875***	1.531***
	(-5.223)	(-1.042)	(0.530)	(2.347)	(6.341)	(8.705)
Average over Age	-0.473***	-0.043	0.087**	0.198***	0.665***	1.138***
	(-5.528)	(-0.951)	(2.323)	(4.244)	(6.320)	(8.181)

Table 11: The Short-Term Reversal

This table reports the pricing ability of the trend factor and the momentum factor using the 10 short-term reversal decile portfolios (*STRev*). The last column is the average pricing error defined as $\Delta = \alpha' \Sigma^{-1} \alpha$, where α is a vector of the pricing errors across the ten deciles, and Σ is the variance-covariance matrix of the residuals across the ten decile portfolios. Panel A is the CAPM results, the benchmark; Panel B and C include the trend factor and the momentum factor, respectively. The intercept (α) is in percentage. β_{mkt}, β_{trd}, and β_{umd} are the risk loadings on the market portfolio, the trend factor, and the momentum factor, respectively. 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 September 1927 to December 2012.

	STRev1	STRev2	STRev3	STRev4	STRev5	STRev6	STRev7	STRev8	STRev9	STRev10	Δ
Panel A: CAPM Model											
$\alpha(\%)$	1.620***	0.457***	0.269***	0.258***	0.224**	0.222***	0.108	0.000	-0.243**	-1.020***	0.301
	(7.55)	(3.80)	(2.62)	(2.71)	(2.57)	(2.69)	(1.24)	(0.00)	(-2.52)	(-7.74)	
β_{mkt}	1.591***	1.347***	1.261***	1.149***	1.163***	1.107***	1.124***	1.163***	1.193***	1.253***	
	(17.98)	(31.36)	(31.00)	(36.51)	(29.92)	(28.76)	(20.67)	(20.27)	(17.96)	(24.33)	
Panel B: CAPM Model plus Trend Factor											
$\alpha(\%)$	1.110***	0.166	-0.055	0.047	0.017	0.025	-0.135	-0.233*	-0.428***	-1.110***	0.266
	(3.03)	(0.83)	(-0.34)	(0.34)	(0.14)	(0.22)	(-1.04)	(-1.74)	(-3.75)	(-6.46)	
β_{mkt}	1.530***	1.313***	1.223***	1.124***	1.138***	1.083***	1.095***	1.136***	1.171***	1.243***	
	(16.67)	(28.87)	(33.68)	(31.87)	(29.72)	(33.31)	(26.47)	(25.26)	(18.20)	(23.04)	
β_{trd}	0.339*	0.193**	0.215***	0.140**	0.137**	0.131**	0.161**	0.154**	0.123**	0.055	
	(1.76)	(2.00)	(2.61)	(2.09)	(2.37)	(2.26)	(2.17)	(2.00)	(2.06)	(0.62)	
Panel C: CAPM Model plus Momentum Factor											
$\alpha(\%)$	2.090***	0.721***	0.471***	0.404***	0.401***	0.358***	0.245***	0.143	-0.098	-0.885***	0.345
	(8.57)	(5.47)	(4.28)	(3.95)	(4.32)	(4.23)	(2.70)	(1.49)	(-0.84)	(-6.25)	
β_{mkt}	1.428***	1.257***	1.191***	1.099***	1.110***	1.060***	1.076***	1.114***	1.143***	1.205***	
	(20.48)	(34.38)	(32.03)	(37.88)	(37.15)	(31.48)	(22.54)	(23.07)	(25.95)	(29.83)	
β_{umd}	-0.542***	-0.303***	-0.232***	-0.168***	-0.201***	-0.156***	-0.157***	-0.164***	-0.166**	-0.159**	
	(-6.39)	(-7.01)	(-6.61)	(-4.18)	(-5.43)	(-5.71)	(-4.77)	(-4.31)	(-2.20)	(-2.13)	

Table 12: The Long-Term Reversal

This table reports the pricing ability of the trend factor and the momentum factor using the 10 long-term reversal decile portfolios (*LTRev*). The last column is the average pricing error defined as $\Delta = \alpha'\Sigma^{-1}\alpha$, where α is a vector of the pricing errors across the ten deciles, and Σ is the variance-covariance matrix of the residuals across the ten decile portfolios. Panel A is the CAPM results, the benchmark; Panel B and C include the trend factor and the momentum factor, respectively. The intercept (α) is in percentage. β_{mkt}, β_{trd}, and β_{umd} are the risk loadings on the market portfolio, the trend factor, and the momentum factor, respectively. 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 September 1927 to December 2012.

	LTRev1	LTRev2	LTRev3	LTRev4	LTRev5	LTRev6	LTRev7	LTRev8	LTRev9	LTRev10	Δ
Panel A: CAPM Model											
α(%)	0.881***	0.419***	0.339***	0.302***	0.330***	0.246***	0.249***	0.209***	0.113	-0.148	0.042
	(3.87)	(2.96)	(2.78)	(3.11)	(3.73)	(3.10)	(3.30)	(2.87)	(1.56)	(-1.61)	
β_{mkt}	1.538***	1.378***	1.293***	1.225***	1.206***	1.128***	1.143***	1.151***	1.136***	1.197***	
	(12.44)	(13.82)	(15.45)	(17.07)	(17.82)	(32.23)	(26.73)	(30.00)	(45.55)	(26.16)	
Panel B: CAPM Model plus Trend Factor											
α(%)	0.276	0.011	-0.087	0.019	0.031	0.048	0.056	0.099	0.135	-0.024	0.030
	(0.69)	(0.04)	(-0.43)	(0.12)	(0.22)	(0.45)	(0.56)	(1.05)	(1.38)	(-0.21)	
β_{mkt}	1.458***	1.324***	1.237***	1.188***	1.166***	1.102***	1.117***	1.137***	1.139***	1.214***	
	(11.18)	(14.33)	(16.86)	(18.23)	(20.83)	(36.06)	(28.95)	(28.73)	(42.42)	(30.76)	
β_{trd}	0.399*	0.269*	0.281**	0.187**	0.198***	0.131***	0.127***	0.072*	-0.014	-0.082*	
	(1.84)	(1.74)	(2.45)	(2.34)	(2.73)	(2.87)	(2.80)	(1.93)	(-0.40)	(-1.87)	
Panel C: CAPM Model plus Momentum Factor											
α(%)	1.320***	0.721***	0.571***	0.520***	0.525***	0.377***	0.388***	0.358***	0.219***	-0.054	0.062
	(4.99)	(4.55)	(4.33)	(4.78)	(5.47)	(4.71)	(4.96)	(4.64)	(2.64)	(-0.52)	
β_{mkt}	1.376***	1.266***	1.208***	1.145***	1.134***	1.080***	1.091***	1.096***	1.098***	1.163***	
	(14.86)	(16.23)	(17.92)	(21.94)	(20.86)	(36.37)	(32.79)	(44.09)	(46.85)	(26.26)	
β_{umd}	-0.526***	-0.363***	-0.279***	-0.261***	-0.233***	-0.157***	-0.167***	-0.179***	-0.127***	-0.112**	
	(-4.13)	(-4.69)	(-4.36)	(-4.82)	(-5.81)	(-7.18)	(-5.53)	(-5.94)	(-3.16)	(-2.37)	

Table 13: Price Ratio Decile Portfolios

This table reports the pricing ability of the trend factor and the momentum factor using the 10 decile portfolios sorted by various price ratios. In each panel we include either the trend factor or the momentum factor, respectively. The last column is the average pricing error defined as $\Delta = \alpha'\Sigma^{-1}\alpha$, where α is a vector of the pricing errors across the ten deciles, and Σ is the variance-covariance matrix of the residuals across the ten decile portfolios. The intercept (α) is in percentage. β_{mkt}, β_{trd} and β_{umd} are the risk loadings on the market portfolio, the trend factor and the momentum factor, respectively. 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 September 1927 to December 2012.

Panel A: E/P Decile Portfolios

	EP1	EP2	EP3	EP4	EP5	EP6	EP7	EP8	EP9	EP10	Δ
$\alpha(\%)$	-0.168	-0.000	0.070	0.128	0.167	0.256**	0.328**	0.371***	0.473***	0.497**	0.076
	(-0.84)	(-0.00)	(0.52)	(1.06)	(1.46)	(2.11)	(2.54)	(2.73)	(3.03)	(2.48)	
β_{mkt}	1.275***	1.147***	1.077***	1.015***	0.990***	0.951***	0.925***	0.931***	0.956***	1.052***	
	(37.33)	(42.06)	(37.60)	(33.63)	(31.45)	(30.93)	(29.65)	(27.80)	(26.81)	(26.44)	
β_{trd}	0.010	0.044	0.039	0.065	0.090*	0.073	0.084	0.100	0.085	0.128	
	(0.08)	(0.61)	(0.62)	(1.20)	(1.90)	(1.34)	(1.44)	(1.57)	(1.13)	(1.24)	
$\alpha(\%)$	-0.053	0.153	0.230**	0.324***	0.394***	0.456***	0.557***	0.625***	0.716***	0.823***	0.130
	(-0.37)	(1.39)	(2.22)	(3.33)	(3.99)	(4.78)	(5.67)	(5.97)	(6.28)	(5.83)	
β_{mkt}	1.262***	1.137***	1.065***	1.003***	0.980***	0.941***	0.913***	0.919***	0.943***	1.037***	
	(38.65)	(40.65)	(36.13)	(31.97)	(29.41)	(28.92)	(27.60)	(27.11)	(26.04)	(25.28)	
β_{umd}	-0.124*	-0.118***	-0.133***	-0.137***	-0.136***	-0.130***	-0.148***	-0.153***	-0.162***	-0.196***	
	(-1.82)	(-2.90)	(-3.62)	(-3.87)	(-3.67)	(-3.72)	(-3.81)	(-3.53)	(-3.47)	(-3.84)	

Panel B: C/P Decile Portfolios

	CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8	CP9	CP10	Δ
$\alpha(\%)$	-0.193	-0.021	0.062	0.151	0.226*	0.271**	0.365***	0.386***	0.450***	0.545**	0.081
	(-0.96)	(-0.14)	(0.48)	(1.22)	(1.71)	(2.17)	(2.74)	(2.69)	(2.66)	(2.57)	
β_{mkt}	1.276***	1.148***	1.059***	0.999***	0.987***	0.959***	0.964***	0.960***	1.008***	1.060***	
	(37.39)	(39.73)	(34.56)	(31.75)	(32.16)	(30.12)	(29.25)	(29.15)	(25.34)	(25.78)	
β_{trd}	-0.004	0.026	0.086	0.063	0.077	0.092*	0.091	0.092	0.117	0.128	
	(-0.03)	(0.36)	(1.58)	(1.18)	(1.30)	(1.72)	(1.55)	(1.37)	(1.33)	(1.13)	
$\alpha(\%)$	-0.091	0.118	0.283***	0.338***	0.425***	0.496***	0.599***	0.614***	0.772***	0.872***	0.143
	(-0.64)	(1.04)	(2.64)	(3.33)	(4.05)	(4.83)	(5.75)	(5.83)	(6.16)	(5.85)	
β_{mkt}	1.262***	1.136***	1.049***	0.989***	0.978***	0.950***	0.953***	0.951***	0.992***	1.045***	
	(38.96)	(38.74)	(32.52)	(30.26)	(29.78)	(28.01)	(27.36)	(27.44)	(25.16)	(25.20)	
β_{umd}	-0.130*	-0.128***	-0.135***	-0.129***	-0.122***	-0.131***	-0.142***	-0.133***	-0.208***	-0.198***	
	(-1.92)	(-3.01)	(-3.50)	(-3.51)	(-3.30)	(-3.34)	(-3.46)	(-3.52)	(-3.58)	(-3.43)	

Panel C: D/P Decile Portfolios

	DP1	DP2	DP3	DP4	DP5	DP6	DP7	DP8	DP9	DP10	Δ
$\alpha(\%)$	0.006	0.164**	0.117	0.202***	0.160**	0.162*	0.208**	0.157	0.131	-0.054	0.028
	(0.06)	(2.03)	(1.52)	(2.59)	(2.03)	(1.74)	(2.09)	(1.40)	(1.18)	(-0.36)	
β_{mkt}	1.185***	1.067***	1.030***	1.017***	0.979***	0.998***	0.933***	0.959***	0.946***	1.008***	
	(39.46)	(31.18)	(55.04)	(47.68)	(49.61)	(33.73)	(40.06)	(29.71)	(19.55)	(12.48)	
β_{trd}	0.067*	0.050**	0.057***	0.068***	0.072***	0.092***	0.110***	0.122**	0.136***	0.214***	
	(1.81)	(2.31)	(3.14)	(3.31)	(3.31)	(2.78)	(2.60)	(2.38)	(2.87)	(2.72)	
$\alpha(\%)$	0.110	0.240***	0.237***	0.386***	0.374***	0.450***	0.492***	0.520***	0.560***	0.610***	0.056
	(1.19)	(2.69)	(3.08)	(5.14)	(4.83)	(5.96)	(6.13)	(6.40)	(6.28)	(4.82)	
β_{mkt}	1.196***	1.077***	1.028***	1.001***	0.956***	0.963***	0.913***	0.919***	0.893***	0.929***	
	(42.99)	(42.55)	(50.44)	(42.42)	(46.61)	(34.51)	(29.99)	(28.10)	(21.63)	(16.26)	
β_{umd}	-0.003	0.000	-0.040	-0.094***	-0.120***	-0.170***	-0.135***	-0.205***	-0.257***	-0.391***	
	(-0.07)	(0.00)	(-1.40)	(-3.37)	(-4.22)	(-7.14)	(-4.55)	(-7.68)	(-7.17)	(-5.58)	