The Enduring Effect of Time-Series Momentum on Stock Returns over nearly 100-Years*

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Abstract

This study documents the significant profitability of "time-series momentum" strategies in individual stocks in the US markets from 1927 to 2014 and in international markets since 1975. Unlike cross-sectional momentum, time-series stock momentum performs well following both up- and down-market states, and it does not suffer from January losses and market crashes. An easily formed dual-momentum strategy, combining time-series and cross-sectional momentum, generates striking returns of 1.88% per month. We test both risk based and behavioral models for the existence and durability of time-series momentum and suggest the latter offers unique insights into its continuing factor dominance.

JEL classification: G11; G12

Keywords: Time-series stock momentum; Return predictability; Market efficiency

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1. Introduction

Time-series momentum is perhaps the most observable form of any asset return factor as it can be visually detected by any investor - smart money or dumb money, value or growth orientated, quantitative algorithm or human stock picker. An investor can look at a price graph or table and detect directional price movement - if time-series momentum exists, then if that prior and current asset price goes up it should tend to continue to go up in future (trend) and vice versa. This trend requires “memory” beyond the traditional academic one-time period of Markov models and the normal distribution of independent identical periods.

Existing studies primarily focus on time-series momentum across asset classes (Moskowitz, Ooi, and Pedersen, 2012; Baltas and Kosowski, 2013), its relation with volatility states (Petterson, 2014), and how it could be optimally implemented by managed-futures hedge funds, commodity trading advisors and certain macro traders (Hurst, Ooi, and Pedersen, 2013, 2014; Levine and Pedersen, 2015; Baltas and Kosowski, 2015). Moskowitz, Ooi, and Pedersen (2012) were among the first to document the time-series momentum effect in the future market. They show that prior-year returns of a futures contract is a positive predictor of its future return for the next year, and that the strategy of financing the acquisition of up-trend futures by selling those down-trend futures generates substantially abnormal returns. Yet, the academic literature has devoted surprisingly little attention to the most conventional asset class. We document a strong presence of time-series momentum in individual stocks over a significant time period without any significant reduction in its factor persistence. We also uncover its unique characteristics and features, which supplement the properties of well-known cross-sectional momentum. [1]

This paper assesses the durable strength of a specific type of time-series momentum by creating a rudimentary trading strategy around stocks. We then compare the strategy returns relative to market returns to determine its effectiveness. Our paper is in contrast to other momentum literature which has more complex return factor combinations (e.g. how do collective

[1] There are a number of studies that document the robust profitability of cross-sectional momentum strategy for US individual stock returns (Jegadeesh and Titman, 1993, 2001; Grundy and Martin, 2001; Asness, Moskowitz, and Pedersen, 2013; Novy-Marx, 2012, 2015a). Cross-sectional momentum strategy has also been found to be successful outside the US equity market (Rouwenhorst, 1998; Liew and Vassalou, 2000; Griffin, Ji, and Martin, 2003; Chui, Titman, and Wei, 2010). The effects of cross-sectional momentum strategy are robust not only in the international market, but also in other asset classes, including industry level, equity index, currency, commodity, and global bond futures (Shleifer and Summers, 1990; Asness, Liew, and Stevens, 1997; Moskowitz and Grinblatt, 1999; Bhojraj and Swaminathan, 2006; Erb and Harvey, 2006; Gorton, Hayashi, and Rouwenhorst, 2008; Asness, Moskowitz and Pedersen, 2013).

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investors define value or cheapness without including biases and combine it momentum?) and utilize many moments of an asset's return distribution. We test both risk based and behavioral explanations for the existence and durability of time series momentum and suggest the latter offers unique insights into its continuing factor dominance even after the literature has grown.

Specifically, we show that time-series stock momentum strategies produced significant profits in the US markets throughout the 88-year period from 1927 to 2014 exceeding the returns from other return factors such as value and size. A strategy of going long on stocks with positive returns in the prior year and going short on stocks with negative returns during the same period yields the average monthly return of 0.55% (*t*-statistic = 5.28) for value weighting and 0.58% (*t*-statistic = 5.05) for equal weighting.[2] Further, time-series momentum also prevails in the international stock markets. We find a strong presence of time-series momentum in 10 out of the 13 major international stock markets examined, including those in Austria, Canada, Denmark, France, Germany, Italy, Netherlands, Norway, Switzerland, and the United Kingdom. For instance, the same strategy described generated the value-weighted monthly return of 1.15% per month (*t*-statistic = 5.06) in Denmark over the 1975−2014 sample period.

We find that time-series stock momentum is profitable regardless of formation and holding periods for 16 different combinations. Even when we use market-adjusted excess returns instead of raw returns and a different weighting system (e.g., inverse volatility weighting) to form long-short portfolios, time-series stock momentum profits remain statistically and economically significant. The robustness of time-series stock momentum in the global equity market is a contradiction to the conventional wisdom of the random walk theory, which predicts that a stock's past price movement or direction cannot be used to predict its future movement.

Time-series stock momentum exhibits three unique characteristics. Firstly, our regression analyses shows that time-series stock momentum can fully subsume cross-sectional stock momentum, while cross-sectional stock momentum cannot capture time-series stock momentum. Secondly, cross-sectional momentum is existent in up markets only (Cooper Gutierrez and Hameed, 2004), while time-series momentum is present following both up and down markets. Specifically, time-series momentum produces an average monthly raw return of 0.57% (*t*-statistic = 2.09) following down market states and 0.54% (*t*-statistic = 5.30) following up market

[2] The average return for size and value factors of Fama and French (1992) is 0.22% and 0.39%, with t-statistics of 2.27 and 3.64, respectively, from 1927 to 2014.

states. Thirdly, cross-sectional momentum has a seasonal component, being profitable in all months except in January but suffering considerable losses in January (Jegadeesh and Titman, 1993; Grundy and Martin, 2001; Yao, 2012), whereas time-series momentum does not experience significant losses in January.

Given these distinctive features, we further propose a dual momentum strategy by simply combining time-series and cross-sectional stock momentum characteristics. We find that such a strategy generates a striking profit of 1.88% per month (*t*-statistic = 5.60), which is considerably higher than both time-series and cross-sectional stock momentum strategies separately and which remains strong in all subperiods examined.

To understand the driving forces of time-series stock momentum, we first examine its relation to existing asset pricing factors. We find that time-series stock momentum cannot be subsumed by conventional factors. For example, the capital asset pricing model of Sharpe (1964) and Lintner (1965) exacerbates time-series momentum, producing the risk-adjusted return of 0.65% per month (*t*-statistic = 6.83). Controlling for the three factors of Fama and French (1993) further complicates the puzzle since the risk-adjusted profit is 0.70% per month (*t*-statistic = 7.39), compared with the raw profit of 0.55% per month (*t*-statistic = 5.28). The five factors of Fama and French (2015) cannot do a better job either as the risk-adjusted profit still remains strong and significant at the 1% level, being 0.55% per month (*t*-statistic = 3.82).

We find three pieces of evidence indicating that time-series stock momentum could be at least partially explained by two prominent theories of investors' underreaction, i.e., the gradual information diffusion model of Hong and Stein (1999) and frog-in-the-pan model of Da, Gurun and Warachka (2014). First, the profitability of the time-series stock momentum strategy is strongest for small caps at 0.78% per month (*t*-statistic = 5.52), whereas it is weakest for large caps at 0.47% per month (*t*-statistic = 4.33). In other words, momentum profitability and size show a negative monotonic relation, consistent with the gradual information diffusion model of Hong and Stein (1999), which suggests that information gets out gradually across the investing public and investors cannot perform the rational expectations method of extracting information from prices. As such, we would expect that the slow diffusion of information results in investors' underreaction and consequently time-series momentum. Our analysis provides confirmative evidence pointing to an underreaction explanation for time-series momentum.

Second, time-series stock momentum profits increase from 0.20% (*t*-statistic = 1.45) for stocks with discrete information to 1.17% (*t*-statistic = 5.82) for stocks with continuous information. We find a monotonic increasing relation between momentum profitability and information discreteness proxy. In other words, the more continuously the information arrives, the higher profits time-series momentum strategies generate. Our result is consistent with the frog-in-the-pan hypothesis of Da, Gurun and Warachka (2014), which suggests that investors tend to under-react more often to information that arrives continuously in small amounts than to information that arrives discretely in large amounts. As such, if time-series momentum is attributed to investors' underreaction, then there should be a negative relation between its profitability and firm size. Our empirical results are consistent with that conjecture.

Third, our finding that time-series momentum strategies are profitable regardless of market states does not support an overreaction explanation. Daniel, Hirshleifer, and Subrahmanyam (1998) propose a behavioral model based on investor overconfidence where investors tend to attribute success (failure) to their skills (external noise) more than they should. In other words, they overreact in a good market state. As such, we conjecture that if overreaction contributes to time-series momentum, we would expect that the asymmetric reaction of investors to market states results in the differences in momentum profits following up- and down markets. However, our analysis provides little evidence for this, which is directly opposed to an overreaction explanation for time-series momentum effects.

The study proceeds as follows: Section 2 describes the data and portfolio construction; Section 3 documents the profitability of time-series stock momentum strategies; Section 4 investigates the sources of those momentum profits; Section 5 proposes the enhanced momentum strategy; Section 6 performs robustness checks; and Section 7 concludes.

2. Data and Portfolio Construction

2.1. Data

The monthly and daily prices, returns, and outstanding numbers of shares of NYSE, AMEX, and NASDAQ stocks are obtained from the Center for Research in Security Prices. The sample period is from December 1925 to December 2014.

The monthly risk-free rate, Carhart four factors (i.e., market, size, value, and momentum), and Fama-French five factors (i.e., market, size, value, profitability, and investment) are downloaded from Kenneth French's website.[3] Regarding the macroeconomic variables, term spread (TERM) and default spread (DEF) are constructed using data from the Federal Reserve Bank's Interest Rate[4]. Dividend yield, defined as the total dividend payments accruing to the CRSP value-weighted index divided by the current level of the index, is calculated using data in CRSP. The yield of three-month T-bills is the same as the risk-free rate. The growth in gross domestic product (GDP) is sourced from Datastream.

The data for the international stock markets of Austria, Belgium, Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, and Switzerland are obtained from Datastream. The start period of those markets is 1975, except for Spain and Sweden with the starting years of 1988 and 1984, respectively. The data for the UK markets is retrieved from the London Share Price Database, with the sample period from 1956 to 2014. All the data are in local currency.

2.2. Portfolios Construction

Time-series stock momentum strategies. At each month, we compute cumulative returns for each stock as follows:

$$\text{Cumulative Return} = \prod_{t-j-1}^{t-2} R_{it}$$

where *j* is the formation and R_{it} is the returns of stock *i* in month *t*.

Winner and loser stocks are categorized based on the signs of the cumulative returns as below:

$$\text{Category} = \begin{cases} \text{Winner} & \text{if } cumulative\ returns > 0 \\ \text{Loser} & \text{if } cumulative\ returns < 0 \end{cases}$$

At each month *t*, the time-series stock momentum strategy takes a long position in winners and takes a short position in losers, a zero-investment strategy. There is a one-month skip between formation and holding periods (i.e., month $t-1$) to avoid the microstructural bias (Jegadeesh, 1990; Lehmann, 1990). All portfolios are rebalanced monthly and are held for the next *k* months.

[3] Please refer to the website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html
[4] Term spread (TERM) is measured by the difference between the average yield of Treasury bonds with more than 10 years to maturity and the yield of one-month T-bills. Default spread (DEF) is measured by the difference between the average yield of bonds rated Baa by Moody's and the average yield of bonds rated Aaa.

Cross-sectional momentum strategies. At each month, all stocks are ranked by their cumulative returns in the formation period (*j*) and accordingly assigned into ten deciles. The top decile consists of those stocks with the highest formation returns, i.e., winners, while the bottom decile contains those stocks with the lowest formation returns, i.e., losers. The cross-sectional stock momentum strategy buys winners and sells losers, a zero-investment strategy. All portfolios are rebalanced monthly and are held for *k* months (holding period). Note that we skip one-month between formation and holding periods (i.e., month $t-1$) to avoid the microstructural bias documented in Jegadeesh (1990) and Lehmann (1990).

We construct both equal-weighted and value-weighted strategies. With respect to value-weighted strategy, the market value of the stocks that is used to calculate the weight in the portfolio is a one month lagged market value.

3. Profitability of Momentum Strategies

3.1. Raw Profits

We first assess the predictability of prior-month-lagged returns by regressing the excess returns for each stock in month *t* on its lagged *s*-month excess returns. Returns are scaled by the logarithm function and the regression equation is as below:

$$\log(1+R_{i,t}-R_{f,t})=\alpha+\beta\log(1+R_{i,t-s}-R_{f,t-s})+\varepsilon_{i,t}, \qquad (1)$$

where $R_{i,t}$ is the returns of stock *i* in month *t*; $R_{f,t}$ is the rate of three-month treasury bill in month *t*; *s* is the lagged month, which takes the value from 1 to 36.

[Insert Figure 1 Here]

Figure 1 plots *t*-statistics from the pooled regressions, and *t*-statistics are adjusted for heteroskedasticity and clustered by time (at monthly level). The positive and significant *t*-statistics for the first 12 months suggest return continuation (with one exception of month lag 1).[5] The negative and small *t*-statistics for the longer horizon indicate reversals, though they are mostly insignificant. In addition, the positive *t*-statistics for the multiples of month lag 12 (i.e., 12, 24, 36) indicate seasonality in time-series returns (Heston and Sadka, 2008).

In Table 1, Panel A reports the value-weighted and equal-weighted returns to time-series and cross-sectional stock momentum strategies.[6] For the time-series stock momentum strategies, at

[5] The weak prediction power of one-month lag is due to the microstructural bias.
[6] All the momentum returns are value-weighted unless specified otherwise.

the beginning of each month t, we compute cumulative returns for individual equities from month t – 12 to t – 2; if positive (negative), we define them as time-series winners (losers). The time-series stock momentum strategies take a long position in those winners and a short position in those losers. For the cross-sectional stock momentum strategies, at the beginning of each month t, all the stocks in our sample are ranked into ten deciles by their cumulative returns from month t – 12 to t – 2. Cross-sectional winners are the decile portfolio of the stocks with the highest returns in the previous 11 months whereas losers are the decile portfolio of the stocks with the lowest returns during the same period. The cross-sectional stock momentum strategies go long in the winners and go short in the losers. Those portfolios are held for one-month, month t. There is a one-month gap between formation and holding periods to avoid a microstructural bias.

[Insert Table 1 Here]

Both momentum types show strength upto the 12-month momentum bound (which practitioners often view as the mark-to-market window for performance and compensation measurement) and decrease, on average, thereafter.

Both value-weighted and equal-weighted strategies produce significant profits. The value- and equal-weighted time-series stock momentum strategies generate average monthly excess returns of 0.55% (t-statistic = 5.28) and 0.58% (t-statistic = 5.05), respectively. This indicates that time-series stock momentum is present in US equities. The value- and equal-weighted cross-sectional stock momentum strategies yield average monthly returns of 1.30% (t-statistics = 4.77) and 0.69% per month (t-statistics = 2.62).

In Table 1, Panel B reports the profitability of time-series and cross-sectional stock momentum strategies in four subperiods. The time-series stock momentum strategy exhibits robust profits across all subperiods, with the average monthly returns of 0.69% (t-statistic = 2.41) in 1927–1948, 0.47% (t-statistic = 3.60) in 1949–1970, 0.62% (t-statistic = 3.84) in 1971–1992, and 0.42% (t-statistic = 1.91) in 1993–2014, respectively. By contrast, the average monthly returns of the cross-sectional stock momentum strategy are not robust across all subperiods. The returns are 1.39% per month (t-statistics = 4.66) in 1949–1970 and 2.01% per month (t-statistic = 4.99) in 1971–1992, but they are not statistically different from zero in both 1927–1948 and 1993–2014.

We further separate the January returns profile from the rest of the year. The time-series stock momentum strategy does not suffer from the January losses since the January payoffs are not statistically significant, while the cross-sectional stock momentum suffers from January losses in 3 out of 4 subperiods.[7] The January losses of cross-sectional momentum strategies are well documented in the literature (Jegadeesh and Titman, 1993; Grundy and Martin, 2001; Yao, 2012). We find little evidence of the January seasonality in time-series momentum. Nonetheless, outside the January, both time-series and cross-sectional momentum strategies generate considerable profits.

Table 2 shows that both the winner and loser portfolios are slightly negatively skewed. The full sample period has a monthly skewness of -1.74, which is smaller than the monthly skewness of cross-sectional WML momentum[8]. In other words, there are relatively small possibilities of extreme negative returns for time-series momentum strategies. In addition, the beta of the loser portfolio is higher than that of the winner portfolio, and as a result, the beta of the WML portfolio is slightly negative on the market portfolio, -0.16. The average market capitalizations of winners (1,577 million dollars) are more than twice of that of losers (766 million dollars), which suggest that time-series winners tend to be large firms, whereas time-series losers tend to be small firms. In the latter section, we investigate the role of firm size on time-series momentum effects. Our analysis shows that time-series momentum is present regardless of firm size, though it is strong in small firms compared to large firms. The average number of the winner portfolio is 1,606 while the average number of the time-series loser portfolio is 1,237.

3.2. Risk-adjusted Profits

We investigate both strategies using three models as below in order to gain an understanding of the sources of the risks of time-series stock momentum.

[7] The January losses of the cross-sectional momentum strategies are due to betting against the size effect in January (Grundy and Martin, 2001). The prior winners tend to be small firms while the prior losers tend to be extremely small firms. Buying small firms and selling extremely small firms results in betting against the size effect which is strongest in January. Consequently, it results in the substantial losses of the cross-sectional momentum strategies in January.

[8] Table 1 of Daniel and Moskowitz (2015) shows that their sample period from 1927 to 2014 has the skewness of cross-sectional (WML) momentum portfolio as of -4.7, which indicates the severe and infrequent crashes for the cross-sectional momentum strategies.

$$R_{WML,t} = \alpha_{WML} + \beta_{WML}(R_{MK,t} - R_{f,t}) + s_{WML}SMB_t + h_{HML}HML_t + \varepsilon_{WML,t} \quad (2)$$

$$R_{WML,t} = \alpha_{WML} + \beta_{WML}(R_{MK,t} - R_{f,t}) + s_{WML}SMB_t + h_{HML}HML_t + m_{WML}UMD_t + \varepsilon_{WML,t} \quad (3)$$

$$R_{WML,t} = \alpha_{WML} + \beta_{WML}(R_{MK,t} - R_{f,t}) + s_{WML}SMB_t + h_{HML}HML_t + r_{WML}RMW_t + c_{WML}CMA_t + \varepsilon_{WML,t} \quad (4)$$

where $R_{WML,t}$ is the returns of the time-series stock momentum strategy in month *t*, $R_{MK,t}$ is the returns of the market portfolio, $R_{f,t}$ is the risk-free returns, and SMB_t is the difference between the returns on a diversified portfolio of small and large stocks, HML_t is the difference between the returns on a diversified portfolio of high and low B/M stocks, UMD_t is the difference between the returns on diversified portfolios of winners and losers, RMW_t is the difference between the returns on diversified portfolios with robust and weak profitability, and CMA_t is the difference between the returns of diversified stock portfolios of low and high investment firms.

[Insert Table 3 Here]

The regression results are summarized in Table 3. Panel A reports the regression estimates for the Fama-French three-factor model and the Carhart four-factor model in the period from 1927–2014. The first specification of Panel A shows that the raw return of the time-series momentum strategy is 0.55% per month (*t*-statistic = 5.28) during the period from 1927–2014. Specifications two through four add the market, size, and value factors, one by one. Those variables have little power to explain time-series momentum profits, and the puzzle persists. For example, specification four shows an even larger abnormal return relative to the Fama and French (1993) three-factor model, 0.70% per month (*t*-statistic = 7.39).

Further, specification five adds the cross-sectional momentum factor in the regression, which seems to accounts for about half of time-series momentum profits, but the unexplained part remains both statistically and economically significant, at 0.20% per month with an associated *t*-statistic of 2.58. In other words, the UMD factor (the cross-sectional stock momentum factor) can only partly explain the time-series stock momentum.

To further understand the relation between time-series stock momentum and cross-sectional stock momentum, their different nature and interactions, we regressing them on each other (not reported in the tables for brevity). The intercept from the regression of time-series momentum returns on cross-sectional momentum returns is 0.22% per month (*t*-statistic = 2.19) compared with the raw return of 0.55% per month (*t*-statistic = 2.55) in 1927–2014. It implies that cross-sectional stock momentum can only partially explain time-series stock momentum.[9] The intercept from the regression of cross-sectional momentum returns on time-series stock momentum returns is 0.35% per month (*t*-statistic = 1.59) compared with the raw returns of 1.30% per month (*t*-statistic = 4.77) in 1927–2014. This indicates that time-series stock momentum can entirely account for cross-sectional stock momentum. All the results suggest that there are some similarities between time-series and cross-sectional stock momentum, time-series stock momentum exhibits its unique characteristic and features, which could be fundamentally different from those of cross-sectional stock momentum.

Panel B repeats the tests in Panel A, except it uses the Fama-French five-factor model and covers the sample period from 1964–2014 to match with the availability of Fama-French five factors. Specification one shows that from 1964 to 2014, the time-series momentum strategy earned the average monthly return of 0.47% (*t*-statistic = 3.85). Specifications two through six add the investment and profitability factors in addition to the market, size and value factors, one by one. The times series momentum strategy loads negatively on the market (MKT) and value (HML) factors, but the models as a whole have little explanatory power for the profits. For example, specification six suggests that adjusting for Fama-French five factors results in the average abnormal return of 0.55% per month (*t*-statistic = 3.82), which is roughly similar to the raw return of 0.47%. All the evidence suggests that time-series momentum effects are not subsumed by the Fama and French three-factor, the Carhart four-factor, or Fama-French five-factor models.

4. Sources of Momentum Profits

In the previous section, we have established the existence of time-series momentum in individual stocks and have found little evidence that cuts clearly in favor of a risk-based explanation. Turning to behavioral explanations, there are two main theories that can give rise to positive return autocorrelations, investors' underreaction and overreaction to information. One strand of the literature argues that prices underreact initially to news and information diffuses gradually—momentum is due to an initial underreaction followed by a correction (Barberis, Shleifer, and Vishny, 1998; Hong and Stein, 1999; Hong, Lim and Stein, 2000; Da, Garun, and Warachka, 2014). Another strand of the literature contends that prices initially overreact to news,

[9] The intercept estimate of 0.20% matches closely the intercept estimate of 0.22% from Table 3, which is consistent with our expectation given the near-zero loadings on the other three factors, MKT, SMB, and HML.

then continue to overreact further for a while, but eventually are corrected to fundamental levels (De Long et al., 1990; Daniel, Hirshleifer, and Subrahmanyam, 1998). Figure 1 shows no significant reversals at a longer horizon, which largely eliminates the possibility of an overreaction explanation for time-series momentum. Nevertheless, we test underreaction and overreaction with three hypotheses.

4.1. Gradual-information-diffusion Hypothesis

The gradual-information-diffusion model, proposed by Hong and Stein (1999), suggests that information spreads gradually across the investing public and investors cannot perform the rational expectations trick of extracting information from prices, resulting in investors' underreaction and return continuation. Their model implies that the market has two types of agents: newswatchers and momentum traders. Newswatchers trade based on private information, which spreads slowly among newswatchers and causes the underreaction in stock prices. Momentum traders—who trade based on the past prices—can profit from this trend. Since momentum traders cannot observe the extent of news diffusion, they keep buying and generate overreaction eventually. Following Hong, Lim and Stein (2000), we take one step in this indicated direction with this conjecture: if time-series momentum comes from gradual information flow, then there should be more time-series momentum in small stocks for which information diffuses more slowly.

At each month, we split the stocks into the small-, medium-, and large-cap groups based on 30- and 70-percentile NYSE size breakpoints. The time-series stock momentum strategies are constructed with each size group. The time-series stock momentum strategy buys stocks with positive cumulative returns in the prior 11 months and sells short stocks with negative cumulative returns during the same period, skips one-month, and holds the winner-minus-loser portfolio for the subsequent one-month. The results are reported in Table 4. Panel A reports the characteristics of the winner-minus-loser portfolios each size group. We can see that the number of firms in the small size group is largest and the number of firms in the large size group is smallest, which are 1,810 and 382 firms, respectively. However, the small size group accounts for only 4.27% while the large size group accounts for 83.27% of total market capitalization.

[Insert Table 4 Here]

Panel B presents the average monthly returns of the winner-minus-loser portfolios constructed within size-based subsamples of stocks. Panel C represents the risk-adjusted returns of those winner-minus-loser portfolios relative to the CAPM, the Fama and French (1996) three-factor model, and the Fama and French (2015) five-factor model. The sample period is from 1927 to 2014. We find that the small size group produces the highest momentum profits (0.78% per month with an associated *t*-statistic of 5.52) while the large size group generates the lowest momentum profits (0.47% per month with an associated *t*-statistic of 4.33). In other words, the profitability of time-series momentum strategies is negatively correlated to firm size. Even after the adjustments for risk, the negative relation between firm size and momentum profits still exists. For robustness, we also perform a subperiod test for each size group, and find that 3 out of 4 subperiods have seen the same relation between size and momentum profits. The tables that summarize subperiod results are available as Online Appendices. All results suggest that time-series momentum is strong for those small stocks for which information spreads slowly, whereas time-series momentum is weak for those large stocks for which information spreads fast, which supports the gradual-information-diffusion hypothesis of Hong and Stein (1999). In other words, investors' underreaction can contribute to time-series momentum effects.

4.2. Frog-in-the-pan Hypothesis

Next, motivated by the more recent development in the behavioral literature, we test the frog-in-the-pan hypothesis in our context of time-series momentum. The frog-in-the-pan hypothesis proposed by Da, Gurun and Warachka (2014) is based on the idea that investors have limited attention. The hypothesis suggests that investors are less aware of information that arrives continuously in small amounts than information that arrives in large amounts at discrete points in time. This is similar to proverbial frog behavior. Frogs jump out of a pan of boiling water following a sudden change in temperature, but they underreact to the water temperature in the pan if it is boiled slowly, and then die. According to the frog-in-the-pan hypothesis, if investors underreact to small amounts of information that arrive continuously, the underreaction to continuous information induces strong persistent return continuation. Along this line, we conjecture that if time-series stock momentum is driven by investors' underreaction to information, then there should be a monotonic increase in momentum profits for stocks with discrete information compared to stocks with continuous information.

Following Da, Gurun and Warachka (2014), we define a proxy variable, Information Discreteness, as below, to determine the extent to which information is discrete or continuous:

$$ID = \mathrm{sign}(\mathrm{PRET}) \times [\%\,neg - \%\,pos]$$

where PRET is the cumulative returns during the 11-month formation period of the time-series momentum strategies, the sign of PRET is denoted as sign(PRET), which equals +1 when PRET > 0 and -1 when PRET < 0, %neg and %pos represent the percentages of days during the formation period with negative and positive returns, respectively.

A large ID represents discrete information, while a small ID represents continuous information. For robustness, we form both sequential double-sorted portfolios and independent double-sorted portfolios by time-series momentum (the prior-11 month returns) and discreteness proxy (ID). For sequential double-sort, we first sort stocks into two momentum groups by the absolute cut-off point, and then, within each momentum group, further sort stocks into quintiles by ID. For independent double-sort, after we sort the stocks into momentum groups, we independently sort the stocks into quintiles according to ID ranking in descending order.[10]

The results based on sequential double-sorts are summarized in Panel A of Table 5. The unadjusted returns of the momentum strategies increase from 0.36% per month (*t*-statistic = 1.87) in the low ID quintile of stocks with discrete information to 0.95% per month (*t*-statistic = 4.75) in the high ID quintile of stocks with continuous information. Using CAPM, FF3FM, and FF5FM leads to similar results that momentum profits increase monotonically from those stocks with discrete information compared to those stocks with continuous information. The result based on independent sorts is presented in Panel B of Table 5, and it provides confirming evidence. For example, the unadjusted momentum spreads increase from 0.20% per month (*t*-statistic = 1.45) for the discrete-information group to 1.17% per month (*t*-statistic = 5.82) in the continuous-information group. For robustness, we also perform tests in 4 different subperiods and find that the results hold in 3 out of 4 subperiods. The tables are available as Online Appendices. All the evidence points to the possibility of an underreaction story since time-series momentum effects are strong for stocks with continuous information versus stocks with discrete information.

[10] There are some months during which the number of stocks is not enough to implement the double-sorted strategy for time-series stock momentum ranking into ID groups. Accordingly, such months are excluded from the table. This usually occurs in the period before 1949 since the number of stocks is small compared to the later periods. However, we can ensure that the missing months have a trivial impact on our double-sorted results.

[Insert Table 5 Here]

4.3. Market States

So far, we have examined two hypotheses related to investors' underreaction to information. The evidence supports an underreaction explanation for time-series momentum effects. In the following section, we will investigate the investors' overreaction hypothesis to look into the possibilities of an overreaction explanation.

Daniel, Hirshleifer, and Subrahmanyam (1998) propose a behavioral model based on investor overconfidence, bolstered by biased self-attributions, and the belief that they have access to private information. They argue that investors tend to attribute success (failure) to their skills (external noise) more than they should. As such, investors in aggregate attribute market gains to their skills and that increases overconfidence following market gains. This causes short-run positive autocorrelations and long-run negative autocorrelations. Cooper, Gutierrez, and Hameed (2004) conjecture that the asymmetric reaction of investors to market states results in the differences in momentum profits—stronger overreactions following UP markets generate greater momentum. Their evidence shows average monthly momentum profits following markets moving up are positive, while average monthly momentum profits following markets moving down are negative. If time-series momentum is driven by investors' overreaction, we would expect to see the differences in returns following different market states.

We investigate the relation between market state and time-series momentum in a manner analogous to the examination offered by Cooper, Gutierrez, and Hameed (2004). We define the market as UP if the returns of the value-weighted CRSP index are positive in the prior year and the DOWN if the returns of the value-weighted CRSP index are negative in the prior year. In our sample period, there are 782 months defined as UP market states and 274 months defined as DOWN market states. The results for the UP market state are summarized in Table 6, Panel A, and the results for the DOWN market state are summarized in Panel B. Panel A of Table 6 shows that in the UP market state, the average monthly returns of the time-series stock momentum and cross-sectional stock momentum strategies are 0.54% (*t*-statistic = 5.30) and 1.49% (*t*-statistic = 6.43) per month, respectively. The risk-adjusted monthly returns increase up to 0.66% (*t*-statistic = 4.83) and 1.97% (*t*-statistic = 6.13), respectively. The findings suggest that in the UP market state, both time-series and cross-sectional stock momentum strategies perform well.

[Insert Table 6 Here]

Panel B repeats the exercises for the DOWN market states. Following the DOWN market state, the average monthly return of the time-series stock momentum strategy is 0.57% (*t*-statistic = 2.09), whereas the average monthly return of the cross-sectional stock momentum strategy is not statistically significant. Consistent with prior studies, cross-sectional stock momentum cannot generate positive returns following the DOWN market state (Cooper, Gutierrez, and Hameed, 2004), though time-series stock momentum can. Moskowitz, Ooi, and Pedersen (2012) suggest that time-series stock momentum performs well regardless of market states, including financial crisis. The risk-adjustments lead to the time-series stock momentum profits being insignificant, which is attributed to the negative loading of the time-series momentum strategy on the market factor.[11]

In Panel C, we perform the difference tests in momentum returns following UP and DOWN market states for both strategies. With respect to time-series stock momentum, there is no significant difference in both raw returns and risk-adjusted returns between UP and DOWN market states. With respect to cross-sectional stock momentum, the risk-adjusted returns are significantly different between UP and DOWN market states at the 1% level (*t*-statistic = 2.68) for CAPM model, and the 5% level (*t*-statistics = 2.49 and 2.06) for FF3FM and FF5FM, respectively.

To summarize, time-series momentum is robust in both UP and DOWN market states. The findings demonstrate that time-series momentum is likely not driven by investors' overreaction to information.

5. Enhancing Momentum Strategy

Time-series momentum examines the trend of an asset with respect to its own past performance, while cross-sectional momentum compares an asset with respect to another asset. We propose a dual momentum strategy that combines both time-series momentum and cross-sectional momentum. We implement this dual strategy by sequential double-sorts first conditioning on absolute momentum measure, and then on relative strength momentum measure.

Specifically, we assign stocks to a time-series loser (T1) group if the prior 11-month returns are positive and to a time-series winner (T2) group if negative. Within the two time-series momentum groups, stocks are further ranked into quintiles based on the prior 11-month returns,

[11] Table 3 shows that the returns to the time-series momentum strategy load negatively on the market (MKT) factor.

where P1 is the value-weighted portfolio of stocks in the worst-performing 20% and P5 is the value-weighted portfolio of stocks in the best-performing 20%. The dual momentum strategy buys the strongest winner portfolio (T2 and P5) and short sells the weakest loser portfolio (T1 and P1), a zero-investment strategy.

Table 7 presents summary statistics of dual momentum portfolios. The average annualized return of the dual momentum strategy is 22.36%, which is nearly triple when compared with that of the time-series momentum strategy (6.58%) in Table 2. The high profit earned by the dual momentum strategy is associated with high volatility (37.53% per year). The market betas of the winner and loser portfolios are 1.65 and 1.36, respectively, which indicates that the winner and loser portfolios are highly sensitive to the market's movement. On average, the dual momentum has a negative market beta of -0.29.

[Insert Table 7 Here]

Is the profitability of the dual momentum strategies due to their exposure to common factors? We examine the risk-adjusted profitability of the dual momentum strategy and its performance compared with the time-series and cross-sectional momentum strategies. There are five specifications in Table 8. The first specification is the raw returns of the strategy. The second and third specifications are the risk-adjusted profits with respect to C4FM and FF5FM, respectively. The fourth and fifth specifications are the results from regression of dual momentum on time-series and cross-sectional stock momentum, respectively. The difference tests between dual momentum and time-series (cross-sectional) stock momentum are also reported.

[Insert Table 8 Here]

In the first specification, the raw monthly return of dual momentum strategy is 1.88% (*t*-statistic = 5.60) from 1927 to 2014. The *t*-statistics of the difference tests between dual momentum and time-series (cross-sectional) stock momentum strategies are 4.17 (1.89). Therefore, it is clear that the dual momentum strategy statistically outperforms both strategies.

In the second specification, the risk-adjusted return relative to the four-factor model of Carhart (1997) is 1.02% per month (*t*-statistic = 2.95). That the risk-adjusted return decreases from the raw return is because part of the profitability is captured by the UMD factor—the dual momentum loads positively and significantly on UMD by 1.07 (*t*-statistic = 2.53). In the third specification, using the five-factor model of Fama and French (2015) leads to the risk-adjusted return being 2.04% per month (*t*-statistic = 5.51). Dual momentum loads negatively and statistically significantly on the market and value factors while it loads positively and statistically significantly on the profitability and investment factors, which are similar to the results from the cross-sectional stock momentum regression.

In the fourth and fifth specifications, it appears that cross-sectional stock momentum has more explanatory power with respect to dual momentum than has the time-series stock momentum. Dual momentum loads positively and significantly on time-series and cross-sectional stock momentum by 1.05 (*t*-statistic = 1.72) and 0.66 (*t*-statistic = 2.75), respectively. Nonetheless, neither of them is able to explain dual momentum completely because the intercepts are still significant at the 5% and 10% levels, respectively.

For robustness, we also construct dual momentum strategies based on different combinations of formation and holding periods. The value-weighted dual momentum strategies are profitable for all different combinations, though the equal-weighted results are not as strong as the value-weighted. Nevertheless, large caps are liquid and investable assets to investors compared with small caps. We also perform the difference tests in the value-weighted returns between dual momentum and time-series/cross-sectional momentum, which provides supportive evidence of the dual momentum strategy being statistically different from time-series and cross-sectional momentum strategies. All those results are available as Online Appendices.

Figure 2 presents the cumulative monthly returns from January 1927 to December 2014 for the following five investment strategies: (1) cross sectional momentum: the top decile past winner portfolio minus the bottom decile past loser portfolio; (2) time-series momentum: the past positive return portfolio minus the past negative return portfolio; (3) dual momentum as described above; (4) size: the bottom decile small size portfolio minus the top decile large size portfolio; (5) value: the top decile Book-to-Market portfolio minus the bottom decile Book-to-Market portfolio.

[Insert Figure 2 Here]

Consistent with our above findings, the dual momentum strategy significantly outperforms other strategies. Additionally, the pattern of the dual momentum is similar to cross-sectional stock momentum, but dual momentum suffers less in the crash periods which occurs in 1932 and 2009. Note also the drawdowns cross-sectional momentum suffers relative to time-series momentum.

To sum up, the dual momentum strategy is an enhanced momentum strategy since it outperforms both time-series and cross-sectional stock momentum. Hence, it is an attractive and innovative tool for investors who would like to pursue an enhanced strategy that combines absolute momentum and relative strength momentum.

6. Robustness Check

In this section, we provide further confirmative evidence to substantiate the existence of time-series stock momentum.

6.1. Macroeconomic Risk

We investigate the possible sources driving the common variation of time-series momentum strategies in macroeconomic risks.[12] Specifically, we run the following regression:[13]

$$R_{WML,t} = \alpha_{WML} + \beta_1 DIV_{t-1} + \beta_2 YLD_{t-1} + \beta_3 TERM_{t-1} + \beta_4 DEF_{t-1} + \beta_5 GDP_{t-1} + \varepsilon_{WML,t} \quad (5)$$

where $R_{WML,t}$ is the excess returns of the momentum strategies at month *t*, DIV_{t-1} is the one month lagged dividend yield on the market, YLD_{t-1} is the one month lagged yield of three-month T-bill, $TERM_{t-1}$ is the one-month lagged term spread (measured by the difference between the average yield of Treasury bonds with more than 10 years to maturity and the yield of one-month T-bills, DEF_{t-1} is the one-month lagged default spread (measured by the difference between the average yield of bonds rated Baa by Moody's and the average yield of bonds rated Aaa), and GDP_{t-1} is the one month lagged GDP growth.

The correlation matrix between momentum strategies and macroeconomic risk variables is presented in Table 9. Time-series and cross-sectional stock momentum positively correlate with each other at approximately 66%. Time-series stock momentum negatively correlates with DEF by 8%. On the other hand, cross-sectional stock momentum positively correlates with both YLD and GDP by 8% while it negatively correlates with DEF by 12%. Furthermore, compared with the Fama-French factor variables, the macroeconomic risk variables have a lower correlation with momentum strategies.

[12] There are long-standing debates whether macroeconomic risk can account for the sources of cross-sectional momentum profits. Chordia and Shivakumar (2002) and Liu and Zhang (2008) claim that macroeconomic risk can explain momentum profits, while Griffin, Ji and Martin (2003) contend the opposite.
[13] The regression model follows Chordia and Shivakumar (2002) and Griffin, Ji, and Martin (2003). Note: we add an additional macroeconomic factor to the model, namely GDP growth motivated (Asness, Moskowitz, and Pedersen, 2013).

[Insert Table 9 Here]

Table 10 represents the result of the regression of momentum strategies on macro-economic variables. Cross-sectional stock momentum is positively related to YLD at the 1% significance level by 4.20, which is consistent with Table 4 of the Chordia and Shivakumar (2002) study. Since YLD serves as a proxy for future economic activity, it indicates that cross-sectional stock momentum returns also depend on the market states (Chordia and Shivakumar, 2002). In an economic boom period, then, we would expect high profits earned by cross-sectional stock momentum strategy. Otherwise, we would expect the returns earned by cross-sectional stock momentum strategy to be low or even negative. Cross-sectional stock momentum is negatively related to DEF at the 1% significance level, which is consistent with the results presented in Table 4 of Chordia and Shivakumar (2002) and Table 3 of Asness, Moskowitz, and Pedersen (2013). Default premiums can be used to trace the long-term business cycle, which tends to be high in the recession period and low in the expansion period. The negative loading on DEF indicates that the profitability of cross-sectional stock momentum strategies is related to economic conditions, similar to the case with the YLD.

[Insert Table 10 Here]

In a marked contrast, time-series stock momentum is not related statistically to any macroeconomic variables with one exception. Table 10 shows that time-series stock momentum is negatively related to DEF at the 10% significance level, which is a weak relationship compared with cross-sectional stock momentum. All the findings point to the fact that time-series stock momentum is related to the economic state of the market, but the relationship is not strong compared to cross-sectional stock momentum.

6.2. Central Bank Chairperson

There has been a growing belief in popular media that the Federal Reserve Bank policy, and its sitting chairperson, is exacerbating the momentum factor. Specifically, decreases in interest rates or increases in the size of Federal Reserve balance sheet will increase the role of momentum on stock returns due to “animal spirits”, “speculation” or “wealth effect” narratives. We find no evidence that time-series momentum (winners minus losers [WML] as a symmetric whole) has increased by Federal Reserve chairperson and, counter-intuitive to media perception, is in fact declining in recent years.

[Insert Table 11 Here]

More research in this area is being conducted to see the impact of margin debt and short sale constraints on winners and losers on an individual (not net momentum basis).

6.3. Alternative Portfolio Construction

We have shown so far the presence of time-series momentum using the 11/1/1 momentum construction that sorts stocks based on their prior 11-month returns, skips one-month, and holds the winner-minus-loser portfolio for the subsequent one-month. We now show that this evidence is robust to the general *J/K* construction that sorts stocks based on their prior *J*-month returns, skips one-month, and holds the winner-minus-loser portfolio for the subsequent K months, where J = 3, 6, 9, 12 and K = 3, 6, 9, 12. Thus, we examine 16 strategies in total.

[Insert Table 12 Here]

Table 12 reports the detailed evidence. Panel A presents the value-weighted results. Panel A shows the strong presence of time-series stock momentum effects because every *J/K* combination produces significant profits with one exception $J = 3/K = 3$. The most profitable time-series momentum strategy is based on the $J = 12/K = 3$ construction, generating the value-weighted monthly return of 0.44% (*t*-statistic = 4.57). Panel B presents the equal-weighted results. We find that 12 out of 16 combinations exhibit statistically significant monthly returns. The most profitable equal-weighted strategy is the one constructed on the basis of $J = 9/K = 3$. To sum up, all the evidence points to the fact that time-series stock momentum effects are robust across different formations and holding periods. Additionally, they are also robust under both value-weighted and equal-weighted portfolios.

6.4. Inverse Volatility-Weighting Scheme

Since the volatilities of stocks traded on the NYSE, AMEX, and NASDAQ vary dramatically, we use inverse volatility-weighting in addition to equal- and value-weighting to investigate time-series momentum effects. The inverse volatility-weighting gives lower weights to those stocks with higher volatility.

The volatility is estimated as follows:

$$\sigma_{i,t}^{2} = \frac{1}{N}\sum_{\tau=1}^{N}(R_{i,\tau} - \overline{R}_{i,t})^{2}$$

where $\sigma_{i,t}^{2}$ is the monthly variance for stock i in month t; N represents the number of trading days in month t; $R_{i,\tau}$ is the daily returns, and $\overline{R}_{i,t}$ is the average returns of stock i in month t.

The portfolio formation procedure here is similar to that used earlier in this paper, the only different is that it weights the position of each stock in inverse proportion to the stock's ex-ante volatility (IVOL), $1/\sigma_{i,t-1}$.

Table 13 reports the results based on 5 specifications. The first specification represents the raw returns of time-series stock momentum using the IVOL weighting scheme. The second, third, fourth, and fifth specifications represent the risk-adjusted profitability and the factor loadings using CAPM, FF3FM, C4FM, and FF5FM, respectively. The raw profit of the strategy is 0.56% per month (t-statistic = 5.77), which is similar to the matching returns of the value-weighted and equal-weighted strategy. The risk-adjustments for CAPM, FF3FM, and FF5FM lead to the increase in the profits to 0.72% per month (t-statistic = 8.47), 0.80% per month (t-statistic = 9.88) and 0.63% per month (t-statistic = 5.30), respectively, but the risk adjustment for C4FM results in the decrease in the profits down to 0.32% per month (t-statistic = 5.28). This indicates that the momentum factor has some explanatory power with the strategy. Nevertheless, the Carhart four-factor intercept remains statistically significant, which means that the momentum factor can only partially explain time-series stock momentum.

[Insert Table 13 Here]

Further, we construct the time-series stock momentum strategies using the IVOL weighting scheme for various formation and holding periods to ensure robustness. The results are presented as Online Appendices, which show the significant profitability of the time-series momentum strategies for all the combinations of formation and holding periods with one exception out of 16 strategies. Once again, using inverse volatility-weighting provides further confirmation of the evidence of time-series stock momentum in addition to equal- and value-weighed findings.

6.5. International Evidence

Although cross-sectional momentum was first documented in individual equities in the US, subsequent research has demonstrated its strong existence among common stocks in many other markets (Rouwenhorst, 1998; Griffin, Ji, and Martin, 2003; Asness, Moskowitz, and Pedersen, 2013). We investigate whether the same time-series stock momentum we observe in US equities are also present in other markets.

We construct the time-series stock momentum strategies in other markets, including Austria, Belgium, Canada, Denmark, France, Germany, Italy, Netherlands, Norway, Spain, Sweden, Switzerland, and the United Kingdom. The results are summarized in Table 14.[14] Austria, Canada, Denmark, France, Germany, Italy, Netherlands, Norway, Switzerland, and the United Kingdom show the strong existence of time-series momentum in individual equities. The time-series stock momentum earns the highest returns is Denmark, with the average monthly return of 1.15% (*t*-statistic = 5.06). Furthermore, the risk-adjusted profitability in all countries is significant, which is consistent with the longer period of US results. In summary, the international results suggest that time-series momentum effect prevails the European, UK, and North American markets. Such evidence largely eliminates the possibility that time-series stock momentum is sample specific.

[Insert Table 14 Here]

7. Conclusion

We document strong evidence of time-series momentum in individual equities that appears to dominate the value or size effect – the latter factors which are often connected to rational-based models used by fundamental, active stock pickers. Our results show that the existence of time-series stock momentum has been a persistent phenomenon in the U.S. equity markets throughout the 88-year period since 1927. Moreover, the profitability of the strategy is robust for 16 different combinations of formation and holding periods, different benchmarks, and weighting systems in up and down markets thereby nullifying the documented weaknesses of

[14] In the data for Austria, Belgium, Denmark, Italy, Norway, and Sweden, there are some months where the number of stocks is small relative to other countries. So, the stocks usually fall into one group, which is either winner or loser. Hence, those months are excluded from the table. This usually occurs in the first decade of the investigation period. However, efforts have been taken to ensure that the missing months have negligible impact on the results of the present investigation.

cross-sectional momentum strategies around the January effect and market crashes. Further, time-series stock momentum also prevails in the international markets.

We also looked at time-series momentum relative to common macro variables and found little correlation to dividends yield, bond rates as well as to GDP. To this point we note that time series momentum is weakly impacted by state of the market, including recessionary economic cycles, compared to cross-sectional markets. Counter-intuitive to media perceptions, we also find no evidence that recent Federal Reserve Bank actions, by chairperson, have exacerbated the momentum effect.

While time-series stock momentum generates strong and consistent profitability, it cannot be captured by existing rational based models. None of the classic models, such as the Fama-French three-factor model, the Carhart four-factor model, nor the Fama-French five-factor model, can explain the profits of time-series stock momentum strategies as these models appear focused on cross-sectional and risk-based reasoning rather than behavioral biases that involve non-linear feedback loops.

Moreover, we find that behavioral models tend to explain the time-series momentum factor, although they do not categorially rule out advances in risk-based model explanations. Our results demonstrate that investors' underreaction is the main source of time-series stock momentum profits, partly because there appears to be no bias in defining what is value or size as momentum is based on pure price signals.

We also find that time-series stock momentum is related to, but different from, cross-sectional stock momentum. Given this, we developed an enhanced momentum strategy of combining time-series and cross-sectional momentum to produce considerably larger profits.

All of these results, over such a large study period, pose a significant challenge to the random walk hypothesis, assumptions about the normal distribution of stock returns and elements of the efficient market hypothesis. The relevance and persistence of momentum despite the significant academic research documenting its existence for over 25 years (and practical journals or newspaper articles for over 100 years) is an ongoing puzzle. Practically, this suggests money managers will continue to develop and exploit simple and complex momentum rules until exhaustion is reached within the 12-month momentum bound (which practitioners often view as the mark-to-market window for performance and compensation measurement). Until that point is reached, we expect hedge funds, mutual funds or exchanged traded funds utilizing "smart" beta products and algorithmic trading rules to grow until a tipping point is reached to reduce momentum's enduring effect.

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Figure 1: Returns predictability of lagged-month returns

This figure reports the *t*-statistics of the estimated coefficient of lagged excess returns from 1-month lagged to 36-month lagged. The regression model is:

$$\log(1+R_{i,t}-R_{f,t})=\alpha+\beta\log(1+R_{i,t-s}-R_{f,t-s})+\varepsilon_{i,t}$$

Pooled regression is estimated across all stocks. *t*-statistics are computed using robust standard errors that are clustered by month. The sample period is from January 1926 to December 2014.

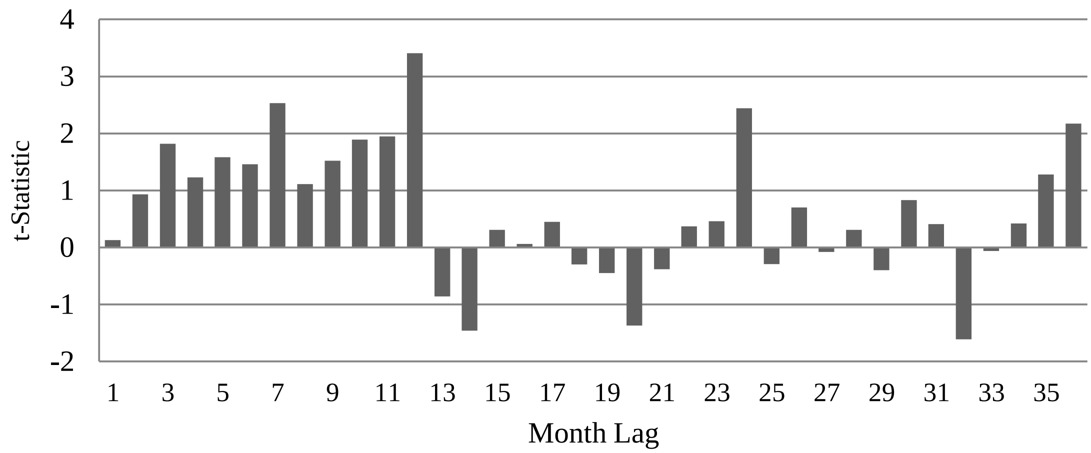
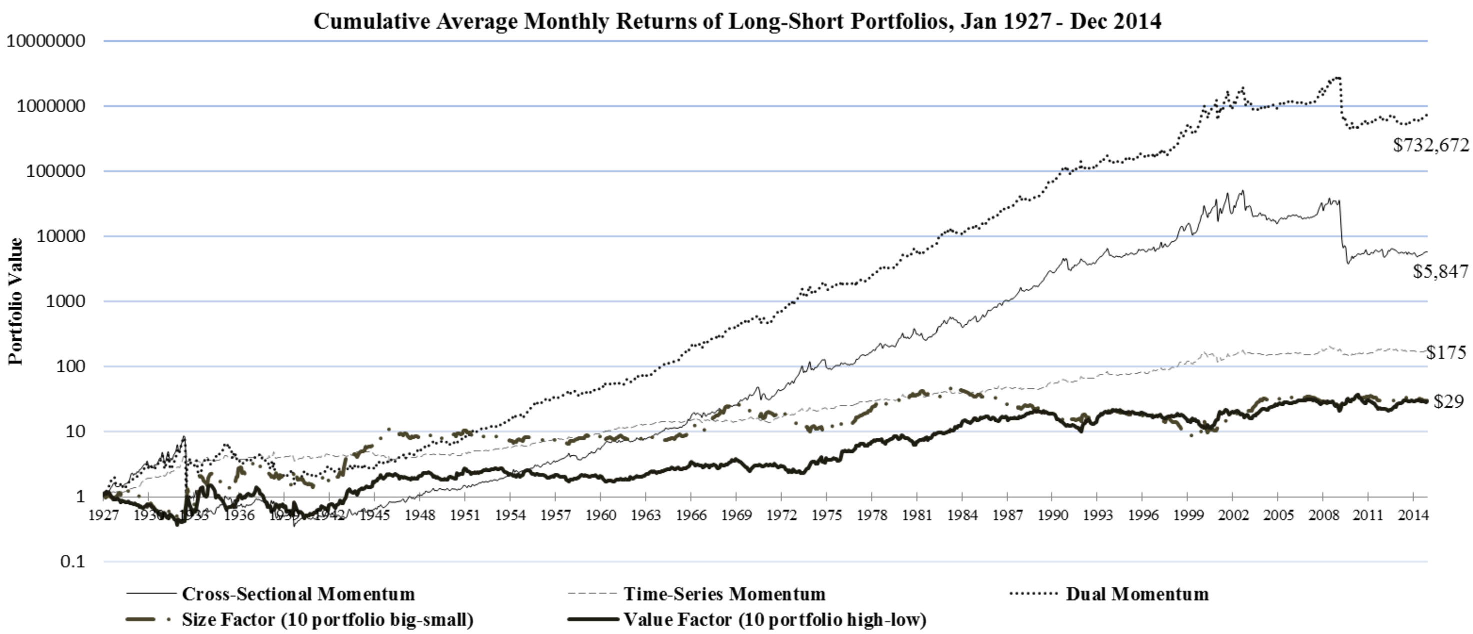


Figure 2: Cumulative Excess Returns of Momentum and Conventional Strategies

This figure shows the cumulative excess returns of time-series stock momentum (positive-negative portfolio spread), cross-sectional stock momentum (winner-loser decile portfolio spread), dual momentum (combined time-series and cross-sectional momentum), size (small-large decile portfolio spread) and value (high B/M – low B/M decile portfolio spread) strategies, assuming $ 1.00 was invested at the beginning of January 1927. The sample period is from January 1927 to December 2014.

Panel A: Cumulative Resturns



Panel B: Drawdowns relative the High-Water-Mark

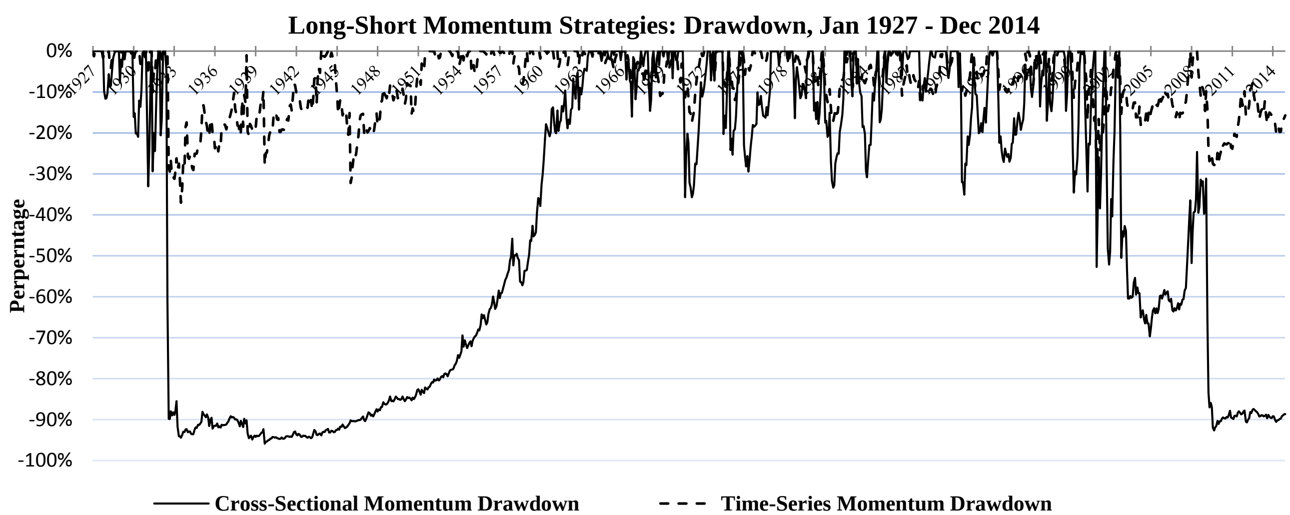


Table 1: Returns of momentum strategies

This table presents the average monthly returns to the winner, loser, and winner-minus-loser (WML) portfolios of the time-series stock momentum (TSMOM) and cross-sectional stock momentum (XSMOM) strategies. For the time-series stock momentum strategies, at each month t, we consider whether the cumulative returns for individual equities from month t – 12 to t – 2 are positive or negative. If positive, we define them as time-series winners; if negative, we define them as time-series losers. The time-series stock momentum strategies go long if positive and go short if negative. For the cross-sectional stock momentum strategies, at each month t, we rank all stocks into ten deciles by their cumulative returns from month t – 12 to t – 2. Cross-sectional winners are the decile portfolio of the best performers in the previous 11 months whereas losers are the decile portfolio of the worst performers. The cross-sectional stock momentum strategies go long in the cross-sectional winners and go short in the cross-sectional losers. Those portfolios are held for one-month, month t. There is a one-month gap between formation and holding periods to avoid a microstructural bias. The sample period is from 1927 to 2014. t-statistics are reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Panel A: 1927–2014				
	VW		EW	
	TSMOM	XSMOM	TSMOM	XSMOM
Loser	0.55***	0.31	0.97***	1.16***
	(2.95)	(0.94)	(3.84)	(3.17)
Winner	1.10***	1.62***	1.55***	1.85***
	(6.99)	(7.63)	(7.85)	(7.89)
WML	0.55***	1.30***	0.58***	0.69***
	(5.28)	(4.77)	(5.05)	(2.62)
Panel B: Sub-period analysis				
	1927–1948	1949–1970	1971–1992	1993–2014
Time-series Stock Momentum Strategy				
Overall	0.69**	0.47***	0.62***	0.42*
	(2.41)	(3.60)	(3.84)	(1.91)
January	-1.70	-0.58	-0.84	-1.20
	(-1.42)	(-1.46)	(-1.10)	(-1.21)
Feb–Dec	0.91***	0.56***	0.75***	0.56***
	(3.13)	(4.15)	(4.71)	(2.57)
Cross-Sectional Stock Momentum Strategy				
Overall	0.95	1.39***	2.01***	0.87
	(1.38)	(4.66)	(4.99)	(1.26)
January	-4.48***	-2.11*	-4.00*	-3.35
	(-2.75)	(-2.07)	(-1.87)	(-1.14)
Feb–Dec	1.44*	1.70***	2.56***	1.25*
	(1.99)	(5.61)	(6.78)	(1.79)

Table 2: Summary statistics of time-series stock momentum portfolios

The time-series stock momentum strategy sorts stocks based on their prior 11-month returns, skips one-month, and holds the winner-minus-loser portfolio for the subsequent one-month. Winners are those stocks with positive returns in the past 11 months whereas losers are those stocks with negative returns during the same portfolio formation period. This table reports annualized mean returns, excess returns of the risk-free rate, and its corresponding volatility (standard deviation), Sharpe Ratio of the loser, winner and winner-minus-loser (WML) portfolios of the time-series stock momentum strategy. Skewness denotes the realized skewness of the monthly log returns to the portfolios. The market beta is estimated from regressing time-series momentum returns on the value-weighted CRSP market index. The average numbers of stocks held in the winner and loser portfolios, and the average size of stocks in those portfolios are also presented. The sample period is from 1927 to 2014.

	Loser	Winner	WML
$\bar{r}$	6.57%	13.16%	6.58%
$\overline{r - r_f}$	3.17%	9.75%	6.58%
$\sigma_{\bar{r}}$	20.89%	17.65%	11.69%
$\sigma_{\overline{r-r_f}}$	20.93%	17.69%	11.69%
Skewness	-0.37	-0.10	-1.74
β	1.03	0.88	-0.16
Sharpe Ratio	0.15	0.58	0.58
Mean size (in millions)	766	1,577	-
No. stocks	1237	1606	-

Table 3: Performance of the time-series stock momentum strategy.

The time-series stock momentum strategy sorts stocks based on their prior 11-month returns, skips one-month, and holds the winner-minus-loser portfolio for the subsequent one-month. Winners are those stocks with positive returns in the past 11 months, whereas losers are those stocks with negative returns during the same portfolio formation period. Panel A presents the results from time-series regression of monthly returns of the time-series stock momentum strategy on the returns of the Fama and French three factors and Carhart four factors, MKT, SMB, HML and UMD, representing market, size, value and (cross-sectional) momentum premiums in the US markets over the entire sample period from 1927 to 2014. Panel B reports the results from time-series regression of monthly returns of the time-series momentum strategy on the returns of the Fama and French five factors, MKT, SMB, HML, RMW, and CMA, where RMW and CMA represent profitability and investment premiums in the US markets from 1964 to 2014. *t*-statistics, reported in the parenthesis, are adjusted for the heteroskedasticity using White's heteroskedasticity-consistent estimator. ***, **, and * denote statistical significance at the 1%, 5%, and 10% significance levels, respectively.

Independent	y = WML Portfolio					
Variable	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: The Fama-French Three-Factor and the Carhart Four-Factor Models						
Intercept	0.55***	0.65***	0.66***	0.70***	0.20***	
	(5.28)	(6.83)	(7.02)	(7.39)	(2.58)	
MKT		-0.16***	-0.13***	-0.11***	0.00	
		(-3.37)	(-2.73)	(-2.65)	(0.07)	
SMB			-0.15**	-0.14*	-0.12*	
			(-2.01)	(-1.89)	(-1.95)	
HML				-0.14	0.09	
				(-1.56)	(1.20)	
UMD					0.50***	
					(10.07)	
Adj. R^2		6%	8%	10%	48%	
Panel B: The Fama-French Five-Factor Model						
Intercept	0.47***	0.52***	0.53***	0.60***	0.57***	0.55***
	(3.85)	(4.31)	(4.44)	(4.71)	(4.19)	(3.82)
MKT		-0.10***	-0.09**	-0.12***	-0.11***	-0.10***
		(-2.90)	(-2.40)	(-3.18)	(-3.01)	(-2.68)
SMB			-0.06	-0.06	-0.05	-0.04
			(-0.85)	(-1.00)	(-0.74)	(-0.68)
HML				-0.15**	-0.15**	-0.19**
				(-2.04)	(-2.04)	(-2.29)
RMW					0.08	0.10
					(0.74)	(0.90)
CMA						0.09
						(0.74)
Adj. R^2		2%	2%	4%	4%	4%

Table 4: Time-series stock momentum: Sorting by size

At each month, we use 30th and 70th NYSE breakpoints to allocate all the stocks in our sample into three groups: the smallest firms are in size class Small, the next in Medium, and the largest are in size class Large. Within each size group, we implement the time-series momentum strategy. The time-series stock momentum strategy sorts stocks based on their prior 11-month returns, skips one-month, and holds the winner-minus-loser portfolio for the subsequent one-month. Time-series winners are those stocks with positive returns in the past 11 months whereas time-series losers are those stocks with negative returns during the same portfolio formation period. Panel A reports the summary statistics of the winner-minus-loser portfolios constructed within each size group. Panel B presents the average monthly returns of the winner-minus-loser portfolios constructed within size-based subsamples of stocks. Panel C represents the risk-adjusted returns of those winner-minus-loser portfolios relative to the CAPM, the Fama and French (1996) three-factor model, and the Fama and French (2015) five-factor model. The sample period is from 1927 to 2014.

	Size Class (NYSE Breakpoints)		
	Small	Medium	Large
Panel A: Summary statistics			
No. stocks	1,810	650	382
% of stocks	64%	23%	13%
Total market cap, $\$10^9$	149	433	2,898
% of market cap	4%	13%	83%
Firm size, $\$10^6$	82	667	7,579
Panel B: Raw returns			
Loser	0.86	0.70	0.57
	(2.94)	(2.98)	(3.17)
Winner	1.65	1.44	1.04
	(6.60)	(6.84)	(6.74)
WML	0.78	0.73	0.47
	(5.52)	(6.04)	(4.33)
Panel C: Risk-adjusted returns			
CAPM	0.96	0.84	0.56
	(7.60)	(7.79)	(5.50)
FF3FM	1.06	0.86	0.61
	(8.37)	(7.82)	(5.98)
FF5FM	0.98	0.63	0.40
	(6.52)	(4.04)	(2.56)

Table 5: Time-series stock momentum: Sorting by information discreteness

This table reports average returns of double-sorted portfolio involving formation-period returns (PRET) and the proxy for information discreteness (ID). ID is defined as $\text{sign}(CRET) \times [\%neg - \%pos]$ where $\%neg$ and $\%pos$ denote the respective percentages of negative and positive daily returns during the 11-month formation period from month t - 2 to t - 12. PRET denotes the prior 11-month returns, with the most recent month t - 1 being skipped. ID captures the distribution of daily returns during the portfolio formation period. Continuous information goes out frequently in small amounts, while discrete information goes out infrequently in large amounts. Both the raw returns and risk-adjusted returns relative to CAPM, the three-factor model of Fama-French (1993), the five-factor model of Fama and French (2015) are presented over one-month holding period. The results in Panel A are based on sequential double-sorts involving PRET quintiles, and then ID quintiles. The results in Panel B are based on independent sorts. The sample period is from 1927 to 2014 except for FF5FM, which is from 1964 to 2014.

					Raw		CAPM		FF3FM		FF5FM	
ID	winner	*t*-value	loser	*t*-value	returns	*t*-value	alpha	*t*-value	alpha	*t*-value	alpha	*t*-value
Panel A: Sequential double-sorts involving PRET and ID												
discrete	1.04	(4.14)	0.69	(3.85)	0.36	(1.87)	0.22	(1.92)	0.08	(0.58)	0.00	(-0.01)
2	1.08	(5.73)	0.57	(3.03)	0.51	(4.26)	0.50	(4.53)	0.45	(4.05)	0.31	(2.28)
3	1.03	(6.65)	0.63	(3.09)	0.39	(2.97)	0.56	(4.72)	0.65	(5.50)	0.50	(3.04)
4	1.08	(7.03)	0.34	(1.55)	0.74	(4.52)	0.95	(6.10)	1.09	(7.28)	0.90	(4.51)
continuous	1.20	(7.72)	0.24	(1.01)	0.95	(4.75)	1.22	(6.63)	1.35	(7.29)	1.21	(4.38)
Panel B: Independent double-sorts involving PRET and ID												
discrete	0.95	(5.54)	0.76	(3.74)	0.20	(1.45)	0.21	(1.49)	0.19	(1.33)	0.05	(0.31)
2	1.03	(6.74)	0.73	(3.79)	0.28	(2.26)	0.38	(3.07)	0.42	(3.46)	0.38	(2.65)
3	1.14	(7.02)	0.61	(3.18)	0.55	(4.40)	0.61	(4.88)	0.67	(5.33)	0.53	(3.15)
4	1.02	(6.10)	0.58	(2.67)	0.40	(2.57)	0.54	(3.52)	0.60	(3.56)	0.66	(2.94)
continuous	1.41	(8.65)	0.23	(1.00)	1.17	(5.82)	1.43	(7.47)	1.56	(8.05)	1.39	(4.74)

Table 6: Market states and momentum profits

This table reports the profits of time-series stock momentum (TSMOM) and cross-sectional stock momentum (XSMOM) following UP and DOWN market states. Panel A reports the profits in UP market states. Panel B reports the DOWN market states. Panel C reports robust *t*-statistics of difference tests between market conditions. The UP market state is defined when the returns of the value-weighted CRSP index are positive in the past 12 months while the DOWN market state is defined when the returns of the value-weighted CRSP index are negative during the same period. The raw returns and risk-adjusted returns relative to CAPM of Sharpe (1964) and Lintner (1965), the three-factor model of Fama and French (1993), and the five-factor model of Fama and French (2015) are reported. *t*-statistics, reported in the parenthesis, are adjusted for the heteroscedasticity using White's heteroscedasticity-consistent estimator. ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

	TSMOM	XSMOM
Panel A: UP Market States		
N	782	782
Raw	0.54***	1.49***
(*t*-statistic)	(5.30)	(6.43)
CAPM alpha	0.57***	1.62***
(*t*-statistic)	(5.71)	(7.06)
FF3FM alpha	0.64***	1.80***
(*t*-statistic)	(6.34)	(7.68)
FF5FM alpha	0.66***	1.97***
(*t*-statistic)	(4.83)	(6.13)
Panel B: DOWN Market States		
N	274	274
Raw	0.57**	0.76
(*t*-statistic)	(2.09)	(0.93)
CAPM alpha	0.22	-0.60
(*t*-statistic)	(0.73)	(-0.86)
FF3FM alpha	0.20	-0.21
(*t*-statistic)	(0.80)	(-0.33)
FF5FM alpha	-0.28	-1.95*
(*t*-statistic)	(-0.77)	(-1.76)
Panel C: Difference Tests		
Raw	(-0.12)	(0.86)
CAPM alpha	(1.08)	(2.68)***
FF3FM alpha	(0.88)	(2.49)**
FF5FM alpha	(1.39)	(2.06)**

Table 7: Summary statistics of dual momentum portfolios

The dual momentum strategy uses sequential double-sorts first conditioning on absolute momentum measure and then on relative strength momentum measure. Specifically, at each month, we assign stocks to the time-series loser (T1) group if the prior 11-month returns are negative and to the time-series winner (T2) group if the prior 11-month returns are positive. Within two time-series momentum groups, stocks are further ranked into quintiles based on the prior 11-month returns, where P1 is the value-weighted portfolio of stocks in the worst-performing 20 percent and P5 is the value-weighted portfolio of stocks in the best-performing 20 percent. The dual momentum strategy buys the strongest winner portfolio (T2 and P5) and sells the weakest loser portfolio (T1 and P1), a zero-investment strategy. This table reports annualized mean returns, excess returns of the risk-free rate, and its corresponding volatility (standard deviation), Sharpe Ratio of the loser, and winner and winner-minus-loser (WML) portfolios of the dual momentum strategy. Skewness denotes the realized skewness of the monthly log returns to the portfolios. The market beta is estimated from regressing dual momentum returns on the value-weighted CRSP market index. The average number of stocks held in the winner and loser portfolios, and the average size of stocks in those portfolios are also presented. The sample period is from 1927 to 2014.

	Loser	Winner	WML
$\bar{r}$	-0.06%	22.30%	22.36%
$\overline{r - r_f}$	-3.47%	18.89%	22.36%
$\sigma_{\bar{r}}$	37.88%	39.66%	37.53%
$\sigma_{\overline{r-r_f}}$	37.96%	39.69%	37.53%
Skewness	-0.08	3.78	-5.59
Β	1.65	1.36	-0.29
Sharpe Ratio	-0.09	0.52	0.66
No. stocks	245	319	-
Mean size (in millions)	116	826	-

Table 8: Performance of dual momentum strategy

The dual momentum strategy uses sequential double-sorts first conditioning on absolute momentum measure, and then relative strength momentum measure. Specifically, at each month, we assign stocks into the time-series loser (T1) group if the prior 11-month returns are negative and the time-series winner (T2) group if the prior 11-month returns are positive. Within two time-series momentum groups, stocks are further ranked into quintiles based on the prior 11-month returns, where P1 is the value-weighted portfolio of stocks in the worst-performing 20 percent and P5 is the value-weighted portfolio of stocks in the best-performing 20 percent. The dual momentum strategy buys the strongest winner portfolio (T2 and P5) and short sells the weakest loser portfolio (T1 and P1), a zero-investment strategy. The table presents the results from time-series regression of monthly returns of the dual stock momentum strategy on the returns of the four factors of Carhart (1997), MKT, SMB, HML and UMD, representing market, size, value and (cross-sectional) momentum premiums in the US markets over the entire sample period from 1927 to 2014. It also reports the results from time-series regression of monthly returns of the time-series momentum strategy on the returns of the Fama and French five factors, MKT, SMB, HML, RMW, and CMA, where RMW and CMA represent profitability and investment premiums in the US markets from 1964 to 2014. *t*-statistics of the difference tests in the raw returns between dual momentum and time-series/cross-sectional momentum are reported. Diff Test (1) is the difference test between dual momentum and time-series stock momentum and Diff Test (2) is the difference test between dual momentum and cross-sectional stock momentum. ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Independent	y = WML Portfolio				
Variable	(1)	(2)	(3)	(4)	(5)
Intercept	1.88***	1.02***	2.04***	1.29**	1.01*
	(5.60)	(2.95)	(5.51)	(2.18)	(1.74)
R_{MKT}		-0.01	-0.37***		
		(-0.11)	(-3.29)		
SMB		-0.12	-0.17		
		(-0.59)	(-0.92)		
HML		0.39	-0.72***		
		(1.02)	(-2.62)		
RMW			0.55*		
			(1.87)		
CMA			0.61*		
			(1.68)		
UMD		1.07***			
		(2.53)			
TSMOM				1.05*	
				(1.72)	
XSMOM					0.66***
					(2.75)
Adj R^2		18.98%	9.30%	10.77%	28.95%
Diff Test (1)	(4.17)***				
Diff Test (2)	(1.89)*				

Table 9: Correlation matrix between momentum strategies and macroeconomic variables

This table presents the correlations matrix between momentum strategies, which are time-series stock momentum (TSMOM) and cross-sectional stock momentum (XSMOM), and macroeconomic risks variables. The first two columns represent momentum strategies. The macroeconomic risks variables are as followed: the dividend yield (DIV) on the market is defined as the total dividend payments accruing to the CRSP value-weighted index divided by the current level of the index; YLD is the yield on the three-month T-bills; the term spread (TERM) is measured by the difference between the average yield of Treasury bonds with more than 10 years to maturity and the yield of one-month T-bills; the default spread (DEF) is measured by the difference between the average yield of bonds rated BAA by Moodys and the average yield of bonds rated AAA; GDP is the growth of gross domestic product. The sample period of all variables is from 1951 to 2014. ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

	TSMOM	XSMOM	DIV	YLD	TERM	DEF
XSMOM	0.66***					
DIV	0.03	0.00				
YLD	0.00	0.08**	0.17***			
TERM	-0.05	-0.05	0.00	0.09**		
DEF	-0.08**	-0.12***	0.09***	0.38***	0.10***	
GDP	0.06	0.08**	-0.03	-0.09**	-0.14***	-0.31***

Table 10: Factor loadings of momentum strategies on macroeconomic variables

This table presents the results from time-series regression of momentum returns on macroeconomic variables. The independent variables includes the following: dividend yield (DIV) is measured as the total dividend payments accruing to the CRSP value-weighted index divided by the current level of the index; YLD is the yield on the three-month T-bills; term spread(TERM) is measured by the difference between the average yield of Treasury bonds with more than 10 years to maturity and the yield of one-month T-bills; default spread (DEF) is measured by the difference between the average yield of bonds rated BAA by Moodys and the average yield of bonds rated AAA by Moodys; GDP is the growth of gross domestic product. The sample period is from 1951 to 2014. The *t*-statistics, reported in the parenthesis, are adjusted for the heteroscedasticity using White's heteroscedasticity-consistent estimator. ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

		Dependent Variable	
		XSMOM	TSMOM
Independent Variables	Intercept	2.44	0.70
		(2.45)	(2.07)
	DIV	-0.22	0.45
		(-0.16)	(0.82)
	YLD	4.20***	0.39
		(2.79)	(0.94)
	TERM	-0.13	-0.04
		(-1.19)	(-1.13)
	DEF	-2.97***	-0.56*
		(-2.30)	(-1.74)
	GDP	0.34	0.09
		(1.20)	(0.84)
	Adj. R^2	3.78%	1.24%

Table 11: Time-series Momentum by Federal Reserve Chairperson Term

This table presents the average monthly returns of previous winner, loser and winner minus loser portfolios by U.S Federal Reserve Chairperson term. At each month *t*, we consider whether the cumulative returns for individual equities from month $t-12$ to $t-2$ are positive (winner) or negative (loser).

Chairperson	Start	End	Winners	t-stat	Losers	t-stat	WML	t-stat	Winners			Losers		
									High	Low	Median	High	Low	Median
Daniel Crissinger	Jan-27	Sep-27	3.00	(2.71)	1.00	(0.84)	1.99	(3.06)	8.52	-2.00	2.36	5.42	-3.51	1.47
Roy A. Young	Oct-27	Aug-30	1.10	(0.98)	-0.43	(-0.37)	1.53	(3.46)	12.40	-18.12	1.76	8.32	-25.05	0.28
Eugene Meyer	Sep-30	May-33	1.37	(0.55)	-0.72	(-0.26)	2.09	(1.47)	54.92	-25.00	-0.97	40.14	-29.27	-2.63
Eugene Black	Jun-33	Aug-34	0.70	(0.32)	0.30	(0.11)	0.39	(0.24)	12.32	-9.77	0.11	22.01	-19.60	-0.66
Marriner Eccles	Sep-34	Feb-48	0.97	(2.39)	0.82	(1.49)	0.15	(0.49)	12.77	-21.57	1.32	30.26	-26.89	0.61
Thomas McCabe	Mar-48	Apr-51	1.93	(2.98)	1.46	(2.24)	0.47	(1.16)	9.42	-9.57	2.96	8.98	-8.63	1.66
William Martin	May-51	Feb-70	1.13	(2.29)	0.57	(4.87)	0.56	(4.27)	10.56	-8.44	1.42	11.96	-10.90	0.69
Arthur F. Burns	Mar-70	Jan-78	0.53	(1.09)	-0.14	(-0.23)	0.67	(2.39)	20.56	-10.84	0.32	16.86	-14.22	-1.29
G. William Miller	Feb-78	Aug-79	1.97	(1.99)	1.88	(1.77)	0.09	(0.24)	6.83	-11.11	2.73	9.81	-10.42	2.27
Paul Volcker	Sep-79	Aug-87	1.77	(3.92)	1.27	(2.58)	0.50	(1.68)	13.17	-12.35	1.79	13.31	-10.53	1.28
Alan Greenspan	Sep-87	Jan-06	1.03	(3.57)	0.40	(1.10)	0.63	(2.62)	11.98	-22.41	1.45	14.97	-22.22	0.71
Ben Bernanke	Feb-06	Jan-14	0.54	(0.76)	0.43	(1.16)	0.11	(0.37)	11.44	-15.95	1.44	14.58	-18.50	0.97
Janet Yellen	Feb-14	Dec-14	1.37	(2.01)	1.34	(1.65)	0.03	(0.05)	4.57	-2.03	2.32	5.19	-4.67	1.90

Table 12: Returns of time-series stock momentum: Various formation and holding periods

This table presents the average monthly returns of the 16 time-series stock momentum strategies. For each formation period (J = 3, 6, 9, and 12), all NYSE, AMEX, and NASDAQ stocks are assigned into two groups by the signs of their cumulative returns from t - 2 to t – J - 1. The loser portfolio consists of stocks with negative cumulative returns while the winner portfolio consists of stocks with positive cumulative returns. The time-series stock momentum strategy takes a long position in winners and takes a short position in losers. The winner-minus-loser portfolios held for K months, where K equals to 3, 6, 9, and 12. There is one-month gap between formation and holding. The sample period is from 1927 to 2014. t-statistic is also reported in the parenthesis. ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

J	*K*=	3	6	9	12
Panel A: Value Weighted					
3		0.09	0.16**	0.20***	0.18***
		(1.23)	(2.51)	(3.44)	(3.58)
6		0.26***	0.34***	0.34***	0.27***
		(2.84)	(4.11)	(4.65)	(4.04)
9		0.43***	0.42***	0.36***	0.26***
		(4.52)	(4.82)	(4.41)	(3.50)
12		0.44***	0.39***	0.31***	0.23***
		(4.57)	(4.34)	(3.63)	(2.80)
Panel B: Equal Weighted					
3		0.10	0.16**	0.18**	0.14**
		(1.10)	(2.00)	(2.45)	(2.23)
6		0.31***	0.34***	0.29***	0.19**
		(2.80)	(3.35)	(3.14)	(2.20)
9		0.42***	0.35***	0.23**	0.12
		(3.59)	(3.24)	(2.24)	(1.22)
12		0.39***	0.25**	0.13	0.03
		(3.38)	(2.27)	(1.20)	(0.31)

Table 13: Performance of time-series stock momentum: Using inverse volatility weighting

The time-series stock momentum strategy is constructed in a similar way as Table 2, except instead of weighting the position of each stock inverse proportion to the stock's ex-ante volatility (IVOL), $1/\sigma_{i,t-1}$. The volatility is estimated as follows:

$$\sigma_{i,t}^2 = \frac{1}{N}\sum_{\tau=1}^{N}(R_{i,\tau} - \overline{R}_{i,t})^2$$

Where $\sigma_{i,t}^2$ is the monthly variance for stock *i* in month *t*; *N* represents the number of trading days in month *t*; $R_{i,\tau}$ is the daily returns, and $\overline{R}_{i,t}$ is the average returns of stock *i* in month *t*. The table reports the results from time-series regression of monthly returns of the time-series stock momentum strategy on the returns of the CAPM, the Fama and French three factors and Carhart four factors, MKT, SMB, HML and UMD, representing market, size, value and (cross-sectional) momentum premiums in the US markets over the entire sample period from 1927 to 2014. It also reports the results from time-series regression of monthly returns of the time-series momentum strategy on the returns of the Fama and French five factors, MKT, SMB, HML, RMW, and CMA, where RMW and CMA represent profitability and investment premiums in the US markets from 1964 to 2014. *t*-statistics, reported in the parenthesis, are adjusted for the heteroscedasticity using White's heteroscedasticity-consistent estimator. ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Independent Variable	y = Momentum Portfolio				
	(1)	(2)	(3)	(4)	(5)
Intercept	0.56***	0.72***	0.80***	0.32***	0.63***
	(5.77)	(8.47)	(9.88)	(5.28)	(5.30)
R_{MKT}		-0.24***	-0.17***	-0.06***	-0.11***
		(-7.52)	(-5.83)	(-3.71)	(-3.26)
SMB			-0.21***	-0.19***	-0.16***
			(-3.94)	(-6.97)	(-2.69)
HML			-0.22***	0.00	-0.25***
			(-4.18)	(0.01)	(-3.00)
RMW					0.20**
					(2.16)
CMA					0.21**
					(1.96)
UMD				0.48***	
				(11.21)	
Adj. R^2		17%	27%	67%	15%

Table 14: Time-series stock momentum in international equity markets

This table reports raw returns and risk-adjusted returns (in percent) of time-series stock momentum strategy in 13 international equity markets. The time-series stock momentum strategy sorts stocks based on their prior 11-month returns, skips one-month, and holds the winner-minus-loser portfolio for the subsequent one-month. Winners are those stocks with positive returns in the past 11 months whereas losers are those stocks with negative returns during the same portfolio formation period. Average number of stocks is monthly average and rounded up to the unit. The risk-adjusted monthly returns are adjusted using CAPM and FF3FM. The risk factors, used as CAPM and FF3FM, are European risks factors for all European countries and North America risks factors for the Canadian market. *t*-statistics, reported in the parenthesis, are adjusted for the heteroscedasticity using White's heteroscedasticity-consistent estimator. The symbol ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

	Data		Raw		CAPM		FF3FM	
Countries	start year	No. stocks	Returns	*t*-statistics	Alpha	*t*-statistics	Alpha	*t*-statistics
Austria	1975	102	0.88***	(3.24)	0.73**	(2.32)	0.76**	(2.45)
Belgium	1975	139	0.08	(0.25)	0.32	(0.90)	0.32	(0.86)
Canada	1975	1842	0.72***	(3.64)	1.03***	(3.59)	1.09***	(4.00)
Denmark	1975	222	1.15***	(5.06)	0.90***	(3.23)	0.97***	(3.66)
France	1975	768	0.35*	(1.92)	0.35	(1.62)	0.38*	(1.75)
Germany	1975	718	0.47**	(2.33)	0.62**	(2.24)	0.69**	(2.48)
Italy	1975	266	0.71**	(2.23)	1.12***	(3.62)	1.20***	(3.86)
Netherlands	1975	239	0.62***	(2.90)	0.48*	(1.82)	0.57**	(2.27)
Norway	1975	187	0.77***	(2.62)	0.58*	(1.91)	0.57*	(1.90)
Spain	1988	144	0.43	(1.06)	0.46	(1.19)	0.53	(1.33)
Sweden	1984	372	0.09	(0.25)	0.14	(0.36)	0.21	(0.53)
Switzerland	1975	242	0.43**	(2.35)	0.59**	(2.57)	0.65***	(2.85)
UK	1956	1991	0.44***	(2.76)	0.78***	(3.83)	0.89***	(4.56)

Online Appendices

Appendix A: Robustness Check for Source of Momentum Profits

Table A1: Time-series stock momentum: Sorting by size, sub-period analysis

The time-series stock momentum strategy sorts stocks based on their prior 11-month returns, skips one-month, and holds the winner-minus-loser portfolio for the subsequent one-month. Time-series winners are those stocks with positive returns in the past 11 months whereas time-series losers are those stocks with negative returns during the same portfolio formation period. This table presents the raw returns and risk-adjusted monthly returns of the time-series stock momentum strategy constructed within size-based subsamples of stocks. Using 30th and 70th NYSE breakpoints, the smallest firms are in size class Small, the next in Medium, and the largest are in size class Large. The sample period is from 1927 to 2014.

	1927–1948			1949–1970		
	Small	Medium	Large	Small	Medium	Large
Panel A: Summary characteristics						
No. firms	207	272	216	556	441	327
Percent of firms	29.85%	39.10%	31.05%	41.99%	33.35%	24.67%
Total Mkt. Cap. (Billions of Dollars)	1	4	35	10	35	256
Percent of Capitalization	1.61%	9.73%	88.67%	3.19%	11.52%	85.29%
Avg. Mkt. Cap. (Millions of Dollars)	3	14	163	17	78	784
Panel B: Raw returns						
Loser	1.53	0.74	0.33	0.77	0.69	0.75
	(1.61)	(1.04)	(0.64)	(2.41)	(2.45)	(3.18)
Winner	2.02	1.81	1.06	1.55	1.35	1.13
	(2.49)	(2.75)	(2.40)	(5.31)	(5.34)	(5.31)
WML	0.47	1.07	0.74	0.78	0.66	0.39
	(1.00)	(3.02)	(2.49)	(5.91)	(4.90)	(2.68)
Panel C: Risk-adjusted returns						
CAPM	0.74	1.19	0.88	0.83	0.72	0.38
	(1.81)	(3.99)	(3.48)	(6.16)	(5.35)	(2.64)
FF3FM	0.84	1.19	0.93	0.87	0.80	0.50
	(2.16)	(4.34)	(3.88)	(6.72)	(6.04)	(3.62)

Table A1 (Continued)

	1971–1992			1993–2014		
	Small	Medium	Large	Small	Medium	Large
Panel A: Summary characteristics						
No. firms	3,104	872	444	3,373	1,016	545
Percent of firms	70.22%	19.74%	10.04%	68.39%	20.59%	11.02%
Total Mkt. Cap. (Billions of Dollars)	92	261	1,234	493	1434	10,068
Percent of Capitalization	5.77%	16.46%	77.76%	4.11%	11.95%	83.94%
Avg. Mkt. Cap. (Millions of Dollars)	30	300	2,782	146	1412	18,518
Panel B: Raw returns						
Loser	0.52	0.73	0.69	0.62	0.66	0.51
	(1.25)	(2.01)	(2.20)	(1.40)	(1.60)	(1.58)
Winner	1.65	1.54	1.11	1.37	1.05	0.86
	(4.55)	(4.62)	(3.99)	(3.91)	(3.37)	(3.42)
WML	1.14	0.81	0.43	0.74	0.39	0.35
	(7.82)	(5.25)	(2.30)	(2.92)	(1.50)	(1.55)
Panel C: Risk-adjusted returns						
CAPM	1.16	0.82	0.43	0.92	0.58	0.45
	(8.49)	(5.37)	(2.25)	(3.98)	(2.38)	(2.02)
FF3FM	1.29	0.92	0.51	0.98	0.61	0.48
	(10.24)	(5.84)	(2.56)	(4.06)	(2.43)	(2.11)
FF5FM	1.15	0.79	0.46	0.79	0.50	0.44
	(7.45)	(4.15)	(2.08)	(2.97)	(1.86)	(1.76)

Table A2: Time-series stock momentum: Sorting by information discreteness, sub-period analysis

This table reports average returns of double-sorted portfolio involving formation-period returns (PRET) and the proxy for information discreteness (ID). ID is defined as $\mathrm{sign}(\mathrm{CRET}) \times [\%\,neg - \%\,pos]$ where $\%\,neg$ and $\%\,pos$ denote the respective percentages of negative and positive daily returns during the 11-month formation period from month t - 2 to t - 12. PRET denotes the prior 11-month returns, with the most recent month t - 1 being skipped. ID captures the distribution of daily returns during the portfolio formation period. Continuous information goes out frequently in small amounts, while discrete information goes out infrequently in large amounts. Both the raw returns and risk-adjusted returns relative to CAPM, the three-factor model of Fama-French (1993), the five-factor model of Fama and French (2015) are presented over one-month holding period. The results in Panel A are based on sequential double-sorts involving PRET quintiles, and then ID quintiles. The results in Panel B are based on independent sorts. The sample period is from 1927 to 2014 except for FF5FM, which is from 1964 to 2014.

					Raw		CAPM		FF3FM		FF5FM	
ID	winner	(*t*-statistic)	loser	(*t*-statistic)	returns	(*t*-statistic)	alpha	(*t*-statistic)	alpha	(*t*-statistic)	alpha	(*t*-statistic)
Panel A: Sequential double-sorts involving PRET and ID												
1927–1948												
discrete	1.76	(2.00)	0.74	(1.42)	1.02	(1.44)	0.79	(1.56)	0.56	(1.50)		
2	1.31	(2.20)	0.26	(0.47)	1.07	(2.81)	1.02	(2.97)	0.95	(2.92)		
3	0.99	(2.35)	0.61	(1.04)	0.35	(0.96)	0.59	(1.99)	0.69	(2.35)		
4	0.99	(2.39)	0.32	(0.51)	0.69	(1.45)	0.99	(2.30)	1.14	(2.87)		
continuous	0.84	(2.02)	0.28	(0.44)	0.50	(0.96)	0.83	(1.87)	0.99	(2.26)		
1949–1970												
discrete	0.87	(3.41)	0.72	(3.12)	0.15	(0.89)	0.01	(0.03)	0.02	(0.10)		
2	1.11	(4.76)	0.92	(3.88)	0.19	(1.31)	0.17	(1.17)	0.22	(1.45)		
3	1.12	(4.88)	0.82	(3.10)	0.29	(1.73)	0.35	(2.11)	0.47	(2.94)		
4	1.19	(5.30)	0.48	(1.64)	0.71	(3.64)	0.83	(4.30)	0.95	(5.05)		
continuous	1.36	(6.07)	0.29	(0.95)	1.07	(4.51)	1.20	(5.10)	1.37	(6.19)		
1971–1992												
discrete	0.96	(3.11)	0.76	(2.47)	0.20	(1.34)	0.18	(1.22)	0.06	(0.41)	-0.06	(-0.35)
2	1.18	(3.98)	0.68	(2.09)	0.50	(2.97)	0.51	(2.97)	0.56	(3.10)	0.47	(2.27)
3	1.10	(3.62)	0.57	(1.60)	0.53	(2.40)	0.55	(2.52)	0.72	(3.27)	0.62	(2.36)
4	1.22	(4.14)	0.17	(0.45)	1.05	(4.15)	1.11	(4.46)	1.24	(5.30)	1.10	(4.14)
continuous	1.52	(5.23)	0.07	(0.18)	1.45	(4.74)	1.55	(5.21)	1.80	(6.62)	1.52	(4.90)

Table A2 (Continued)

ID	winner	(*t*-statistic)	loser	(*t*-statistic)	raw returns	raw (*t*-statistic)	CAPM alpha	CAPM (*t*-statistics)	FF3FM alpha	FF3FM (*t*-statistic)	FF5FM alpha	FF5FM (*t*-statistic)
Panel A: Sequential double-sorts involving PRET and ID												
						1993–2014						
discrete	0.59	(2.03)	0.52	(1.70)	0.07	(0.36)	0.08	(0.38)	0.04	(0.16)	0.18	(0.77)
2	0.72	(2.66)	0.43	(1.30)	0.29	(1.51)	0.36	(1.82)	0.34	(1.71)	0.30	(1.33)
3	0.90	(3.66)	0.52	(1.46)	0.38	(1.50)	0.56	(2.28)	0.57	(2.26)	0.42	(1.57)
4	0.91	(3.46)	0.40	(1.00)	0.51	(1.58)	0.72	(2.33)	0.83	(2.70)	0.64	(1.88)
continuous	1.08	(3.88)	0.33	(0.64)	0.76	(1.61)	1.10	(2.42)	1.15	(2.47)	0.74	(1.49)
Panel B: Independent double-sorts involving PRET and ID												
						1927–1948						
discrete	1.08	(2.19)	0.74	(1.18)	0.44	(0.94)	0.47	(1.02)	0.37	(0.82)		
2	1.05	(2.44)	0.84	(1.44)	0.15	(0.37)	0.29	(0.77)	0.31	(0.82)		
3	1.26	(2.72)	0.38	(0.68)	1.01	(2.97)	1.10	(3.36)	1.14	(3.48)		
4	0.77	(1.59)	0.50	(0.78)	0.01	(0.03)	0.22	(0.53)	0.21	(0.48)		
continuous	1.32	(3.21)	0.28	(0.44)	1.00	(1.87)	1.29	(2.71)	1.40	(2.97)		
						1949–1970						
discrete	0.97	(4.07)	0.86	(3.26)	0.11	(0.52)	-0.03	(-0.17)	0.02	(0.08)		
2	1.11	(4.94)	0.90	(3.74)	0.21	(1.40)	0.18	(1.20)	0.22	(1.47)		
3	1.25	(5.45)	0.90	(3.53)	0.32	(1.93)	0.32	(1.85)	0.45	(2.83)		
4	1.23%	(4.92)	0.85%	(3.03)	0.43%	(2.07)	0.51%	(2.42)	0.66%	(3.23)		
continuous	1.57%	(6.73)	0.29%	(0.97)	1.25%	(5.38)	1.39%	(6.26)	1.52%	(6.93)		

Table A2 (Continued)

ID	winner	(*t*-statistics)	loser	(*t*-statistic)	raw returns	(*t*-statistic)	CAPM alpha	(*t*-statistic)	FF3FM alpha	(*t*-statistic)	FF5FM alpha	(*t*-statistic)
Panel B: independent double-sorts involving PRET and ID												
1971–1992												
discrete	1.06	(3.48)	0.92	(2.72)	0.14	(0.75)	0.13	(0.68)	0.06	(0.32)	-0.05	(-0.27)
2	1.12	(3.89)	0.68	(2.11)	0.44	(2.31)	0.45	(2.40)	0.45	(2.31)	0.34	(1.53)
3	1.24	(4.10)	0.64	(1.97)	0.60	(2.88)	0.59	(2.84)	0.67	(3.07)	0.64	(2.64)
4	1.13	(3.85)	0.51	(1.43)	0.62	(2.29)	0.70	(2.61)	0.90	(3.35)	0.64	(2.11)
continuous	1.58	(5.41)	0.10	(0.26)	1.48	(4.92)	1.62	(5.69)	1.82	(6.32)	1.59	(4.71)
1993–2014												
discrete	0.68	(2.47)	0.54	(1.63)	0.14	(0.73)	0.19	(0.98)	0.17	(0.83)	0.19	(0.88)
2	0.84	(3.41)	0.51	(1.56)	0.33	(1.65)	0.43	(2.16)	0.44	(2.15)	0.47	(2.06)
3	0.81	(3.03)	0.52	(1.54)	0.29	(1.12)	0.39	(1.48)	0.46	(1.76)	0.43	(1.58)
4	0.94	(3.16)	0.45	(1.15)	0.49	(1.45)	0.66	(1.95)	0.72	(2.09)	0.55	(1.48)
continuous	1.16	(3.36)	0.25	(0.54)	0.92	(1.89)	1.19	(2.50)	1.32	(2.75)	0.93	(1.73)

Appendix B: Robustness Check for Dual Momentum

Table B1: Returns of dual momentum strategy: Sub-period analysis

This table presents the average monthly returns (in percent) of the value-weighted dual momentum strategy in different sub-period. The full period starts in 1927 and ends in 2014. There are 4 subperiods, which are split evenly. The first row (All) is the returns for the whole year while the second row is the returns in January. The last row is the returns from February to December. The symbol ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Months	1927–1948	1949–1970	1971–1992	1993–2014
All	2.09*	1.76***	2.26***	1.34**
	(1.97)	(6.09)	(5.83)	(2.05)
January	-4.55***	-1.80*	-3.14	-3.40
	(-3.90)	(-1.90)	(-1.36)	(-1.21)
Feb-Dec	2.69**	2.08***	2.75***	1.78***
	(2.36)	(7.06)	(7.77)	(2.68)

Table B2: Returns of dual momentum strategies: Various formation and holding periods

This table presents the average monthly returns (in percent) of loser, winner and momentum portfolios (WML) using time-series stock momentum strategy. For each formation period (J) that equals to 3, 6, 9, and 12, all NYSE, AMEX, and NASDAQ stocks are defined into two groups using an absolute value (0) according to their cumulative returns from *t*-2 to *t*-*k*-1. Then all stocks are ranked into quintiles in each group based on their cumulative returns. The portfolios are formed one-month after the formation period (skipped *t*-1) and held for K months, equal to 3, 6, 9, and 12. Loser portfolio is the first quintiles portfolio in the group that contains stocks with negative cumulative returns. Winner portfolio is the last quintile portfolio in the group that contains stocks with positive cumulative returns. WML is the Winner portfolio minus Loser portfolio. Panel A represents value-weighted portfolios and Panel B represents equal-weighted portfolios. *t*-statistic is also reported in the parenthesis. The symbol ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

J	*K*=	3	6	9	12
Panel A: Value Weighted					
3		0.86***	0.90***	0.78***	0.66***
		(4.50)	(5.37)	(4.39)	(4.64)
6		1.23***	1.15***	0.99***	0.74***
		(4.83)	(4.51)	(4.48)	(3.75)
9		1.42***	1.20***	0.88***	0.59***
		(5.63)	(5.02)	(3.82)	(2.79)
12		1.27***	1.00***	0.70***	0.48**
		(4.90)	(4.12)	(3.00)	(2.17)
Panel B: Equal Weighted					
3		0.22	0.30*	0.31**	0.22
		(1.12)	(1.75)	(1.98)	(1.60)
6		0.54**	0.53**	0.43**	0.19
		(2.26)	(2.39)	(2.18)	(1.05)
9		0.74***	0.55***	0.27	0.02
		(3.07)	(2.42)	(1.21)	(0.12)
12		0.54***	0.25	-0.01	-0.21
		(2.12)	(1.03)	(-0.03)	(-0.91)

Table B3: Difference test

This table presents the differences of the average monthly returns between dual momentum strategy and other strategies based on 3, 6, 9, and 12 months formation and holding periods. The differences (in percent) are shown in the first line of each formation period and the *t*-statistic is reported in parenthesis. Both value-weighted and equal-weighted are reported in each Panel. Panel A is the difference test between dual momentum and cross-sectional stock momentum strategy. Panel B is the difference test between dual momentum and time-series stock momentum strategy. The symbol ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

Panel A: Dual momentum strategy vs. Cross-sectional momentum strategy											
			Value Weighted					Equal Weighted			
J		*K*=	3	6	9	12	*K*=	3	6	9	12
3	Diff		0.20**	0.21***	0.05	0.08		0.02	0.03	0.00	0.02
			(2.10)	(2.89)	(0.56)	(1.20)		(0.37)	(0.51)	(0.02)	(0.62)
6	Diff		0.31***	0.16	0.10	0.14*		0.13	0.04	0.05	0.06
			(2.85)	(1.20)	(0.98)	(1.68)		(1.43)	(0.60)	(0.82)	(1.23)
9	Diff		0.33**	0.22*	0.14	0.18*		0.18	0.11	0.08	0.10
			(2.47)	(1.85)	(1.31)	(1.84)		(1.51)	(1.06)	(0.92)	(1.39)
12	Diff		0.33**	0.27***	0.24***	0.29***		0.15	0.10	0.08	0.11*
			(2.53)	(2.80)	(2.78)	(3.44)		(1.24)	(1.25)	(1.15)	(1.69)
Panel B: Dual momentum strategy vs. Time-series momentum strategy											
			Value Weighted					Equal Weighted			
J		*K*=	3	6	9	12	*K*=	3	6	9	12
3	Diff		0.77***	0.75***	0.59***	0.48***		0.12	0.13	0.13	0.08
			(5.46)	(6.11)	(4.28)	(4.39)		(1.05)	(1.39)	(1.47)	(0.97)
6	Diff		0.97***	0.81***	0.65***	0.47***		0.23	0.19	0.15	0.01
			(5.15)	(4.15)	(3.93)	(3.20)		(1.64)	(1.48)	(1.27)	(0.06)
9	Diff		0.99***	0.78***	0.53***	0.33**		0.33**	0.20	0.04	-0.09
			(5.10)	(4.31)	(3.04)	(2.09)		(2.19)	(1.48)	(0.32)	(-0.78)
12	Diff		0.84***	0.61***	0.39**	0.25		0.15	0.00	-0.13	-0.24*
			(4.24)	(3.42)	(2.30)	(1.57)		(0.97)	(-0.02)	(-0.95)	(-1.79)

Appendix C: Robustness Check for Market Returns as Benchmark

Table C: Returns of time-series stock momentum: Using market returns as benchmark, various formation and holding periods

This table presents the average monthly returns (in percent) of time-series stock momentum portfolio using market returns as benchmark. For each formation period (*j*) that equals to 3, 6, 9, and 12, all NYSE, AMEX, and NASDAQ stocks are defined into two groups using a sign according to their cumulative excess returns from *t*-2 to *t*-*k*-1. The portfolios are formed one-month after the formation period (skipped *t*-1) and held for (*k*) months, equal to 3, 6, 9, and 12. Loser portfolio is the portfolio that contains stocks with negative cumulative excess returns using market returns as benchmark. Winner portfolio is the portfolio that contains stocks with positive cumulative excess returns using market returns as benchmark. Time-series stock momentum portfolio is winner-minus-loser portfolio. The sample period is from 1927 to 2014. Panel A represents value-weighted portfolios and Panel B represents equal-weighted portfolios. *t*-statistic is also reported in the parenthesis. The symbol ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

J *K*=	3	6	9	12
Panel A: Value Weighted				
3	0.00	0.10	0.15***	0.12**
	(-0.02)	(1.55)	(2.63)	(2.32)
6	0.14	0.24***	0.23***	0.16**
	(1.52)	(2.87)	(2.98)	(2.28)
9	0.29***	0.29***	0.23***	0.13*
	(3.01)	(3.19)	(2.67)	(1.66)
12	0.26***	0.22**	0.13	0.05
	(2.67)	(2.31)	(1.51)	(0.63)
Panel B: Equal Weighted				
3	0.06	0.13	0.16**	0.11*
	(0.65)	(1.63)	(2.31)	(1.79)
6	0.23**	0.27***	0.23***	0.12
	(2.08)	(2.81)	(2.67)	(1.50)
9	0.36***	0.30***	0.18*	0.06
	(3.17)	(2.91)	(1.96)	(0.63)
12	0.27**	0.17	0.05	-0.06
	(2.39)	(1.59)	(0.53)	(-0.60)

Appendix D: Robustness Check for using inverse volatility weighting scheme

Table D: Returns of time-series stock momentum: Using inverse volatility weighting scheme, various formation and holding periods

This table presents the average monthly returns (in percent) of time-series stock momentum portfolio using inverse volatility weighting. For each formation period (*j*) that equals to 3, 6, 9, and 12, all NYSE, AMEX, and NASDAQ stocks are defined into two groups using a sign according to their cumulative excess returns from *t*-2 to *t*-*k*-1. The portfolios are formed one-month after the formation period (skipped *t*-1) and held for (*k*) months, equal to 3, 6, 9, and 12. Loser portfolio is the portfolio that contains stocks with negative cumulative excess returns using market returns as benchmark. Winner portfolio is the portfolio that contains stocks with positive cumulative excess returns using market returns as benchmark. Time-series stock momentum portfolio is winner-minus-loser portfolio. The sample period is from 1927 to 2014. *t*-statistic is also reported in the parenthesis. The symbol ***, **, and * denote statistical significance at the 1%, 5% and 10% significance levels, respectively.

J	*K*=	3	6	9	12
3		0.13*	0.16**	0.18***	0.15**
		(1.66)	(2.10)	(2.82)	(2.53)
6		0.34***	0.33***	0.30***	0.22***
		(3.52)	(3.72)	(3.85)	(3.03)
9		0.45***	0.39***	0.29***	0.19**
		(4.51)	(4.17)	(3.32)	(2.31)
12		0.44***	0.32***	0.21**	0.14
		(4.55)	(3.40)	(2.35)	(1.60)