Impact of Market State on Momentum Portfolio Risk and Performance:

A Risk-based Explanation

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Abstract

The Momentum Puzzle has been a constant challenge to classic finance theory. Stocks that have performed better in the past tend to perform better in the future. Prior researches have failed to provide valid risk-based explanations because winner portfolios do not exhibit higher risk characteristics. Without a convincing risk explanation, the persistence of momentum profit is a violation of the Efficient Market Hypothesis. We find prior empirical efforts to measure momentum profits and its sources are contaminated by the state of the market during both formation and holding periods. By looking into different market states, classified by both traditional and non-traditional bull and bear market definition, we find the key to at least partially solve the momentum mystery. We find momentum stocks are risker when formed in bull market, and momentum profit is much higher in continuation of market than reverses of market condition, lending empirical support to a risk-based explanation. Our definition of market states is essentially based on the risk premium of major risk factors. When market risk is considered a risk factor, if realized market risk premium is positive, it is a bull market; when size is considered a proxy for risk factor, if SMB (small minus big risk premium) is positive, it is a bull market; likewise when valuation (book-to-market) ratio is a proxy for risk factor, if HML (High-minus-Low risk premium) is positive, it is a bull market. By looking into the different states of market, this paper shows risk partially explains the momentum profits previously unexplained by rational asset pricing models. This paper also explores simulations using models based on the positive relationship between risk and return. The simulation result confirms that at least part of the momentum profit can be explained by risk, but the magnitude of momemtum from simulation is weaker than empirical results

1. Introduction

Momentum effect was first ever documented by Jegadeesh and Titman (1993). Since then, various researchers have found that the momentum effect does exist across different stock markets and time periods (e.g., Jegadeesh and Titman, 2001; Rouwenhorst, 1998, 1999; Chui et al., 2000). Fama (1998) is critical of most anomalies, attributing them to methodological and other biases. However, Fama (1996) admitted that the well-documented momentum profit is difficult to be attributed to risk. Although the literature agrees that the momentum effect does exist, there is still an ongoing debate on what drives this effect. The major debate has focused on whether the momentum effect is rational or irrational, or whether it can be explained from a risk-based point of view or a behavioral perspective.

Many prior works try to explore the momentum puzzle from a risk-based point of view. Jegadeesh and Titman (1993) adjust for risk using the capital asset pricing model (CAPM) benchmark, and many others adjust for risk based on the Fama-French three-factor model benchmark (e.g., Fama and French, 1996; Jegadeesh and Titman, 2001; Grundy and Martin, 2001). In each of these cases, the risk-adjusted returns, or alphas, of the momentum strategy are significantly positive, suggesting that cross-sectional differences in risk do not explain momentum profits. It is still an open question with regard to the source of the risk-adjusted momentum profits. Conrad and Kaul (1998) argue that stocks with relatively high (low) realized returns tend to be stocks with relatively high (low) mean returns. Momentum trading strategy actually buys winner stocks with high mean returns and sells loser stocks with low mean returns. As a result, momentum strategy makes a profit as long as there is some cross-sectional variability in expected returns of the stocks. Jegadeesh and Titman (2002) argue that Conrad and Kaul (1998) reach their conclusion because they do not take into account the small sample biases in their tests and bootstrap experiments. Jegadeesh and Titman (2002) present a variation of the Conrad and Kaul bootstrap which is unbiased. In this unbiased bootstrap experiment, they find that the momentum profits are virtually zero.

Extant literature also explores the relationship between momentum effect and market states and investigates whether momentum effect depends on market states. Chordia and Shivakumar (2002) show that profits to momentum strategies can be explained by a set of lagged time-varying macroeconomic variables such as dividend yield, default spread, term spread and the yield on three-month T-bill and argue that payoffs to momentum strategies disappear once stock returns are adjusted for their predictability based on these macroeconomic variables. Stivers and Sun (2010) investigate how return dispersion affects momentum and value returns and show that time variation in the value and momentum premiums can be tied to variation in the market's cross-sectional return dispersion. Wang and Xu (2010) investigate the time-series predictability of momentum with the focus on the predictive power of market volatility and find that there exists a significant and robust link between the time-varying market volatility and momentum profits. Antoniou et al. (2013) test whether investor sentiment which is proxied by the Consumer Sentiment Index in the U.S. affects the profitability of momentum strategies and find that there is strong momentum in optimistic periods and virtually no momentum in pessimistic periods. Most recent researches focus on the momentum strategy performance during bad market states, especially when market crashes during the recent great depression. Barroso and Santa-Clara (2015) state that compared with the market, value, or size factors, momentum has offered investors the highest Sharpe ratio. However, momentum has also had the worst crashes, making the strategy unappealing to investors who dislike negative skewness and kurtosis. They find that the risk of momentum is highly variable over time and predictable and argue that risk-managed momentum is a much greater puzzle than the original version. Daniel and Moskowitz (2016) argue that despite the strong positive average returns across numerous asset classes, momentum strategies can experience infrequent and persistent strings of negative returns. These momentum crashes occur in panic states, following market declines and when market volatility is high, and are contemporaneous with market rebounds.

In addition, there are three more works that are most related to our work regarding market states and momentum. Grundy and Martin (2001) investigate the dynamics of the changing factor exposure of a momentum strategy in both the single-factor capital asset pricing model (CAPM) and Fama-French three-factor model. They argue that, in the one-factor CAPM like setting, "if the market outperforms Treasury bills, winners will tend to be stocks with betas greater than one. Thus, following up markets, a momentum strategy will tend to place a positive beta bet on the market; that is, the strategy will go long in stocks with betas greater than one and short in stocks with betas less than one. Conversely, following down markets, a momentum strategy will tend to involve a negative beta bet on the market." Similar results are found for the dynamic exposures to the three factors of the Fama-French model. Cooper et al. (2004) find that momentum profits depend on the state of the market and explain the results from a behavioral perspective based on the overreaction theory. They report that the momentum profits are in fact confined to periods following UP markets. The mean monthly momentum profit following positive market returns is 0.93% whereas the mean profit following negative market returns is -0.37%. Asem and Tian (2010) extend Cooper et al. (2004) argument and empirically investigate the effects of market reversals on momentum profits considering the asymmetric momentum profits following UP versus DOWN markets. They find that the momentum profits are higher when the markets continue in the same state than when they transition to a different state. They argue that their results are consistent and can be explain based on the behavioral theory proposed by Daniel et al. (1998).

However, none of the abovementioned literature provides explanations for the momentum effect from a rational risk-based point of view under different market state combinations in both formation and holding periods. We believe that the empirical efforts to measure momentum profits and its sources are contaminated by the state of the market during both formation and holding periods.

First, we define the formation period market state of a month as UP (DOWN) if the past six-month compound market return is higher (lower) than the contemporaneous risk-free return. We also define the formation period market state of a month as SMB positive (negative) if the past six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative) and define the formation period market state of a month as HML positive (negative) if the past six-month compound High-Minus-Low (HML) portfolio return is positive (negative). Similarly, the holding period is defined as UP market if the next six-month holding period compound market return is greater than the contemporaneous six-month compound risk-free return and is defined as DOWN market if it is less than the six-month risk-free return. The holding period is defined as SMB positive (negative) market if the next six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative) and is defined as HML positive (negative) market if the next six-month compound High-Minus-Low (HML) portfolio return is positive (negative).

Using beta, size, and book-to-market ratio as proxies for risk, we find that winner portfolio picks up stocks with high beta, high SMB factor loadings, and high HML factor loadings whereas loser portfolio picks up stocks with low beta, low SMB factor loadings, and low HML factor loadings when the momentum portfolio is formed during UP/positive market states. At the same time, winner portfolio picks up stocks with low beta, low SMB factor loadings, and low HML factor loadings whereas loser portfolio picks up stocks with high beta, high SMB factor loadings, and high HML factor loadings when the momentum portfolio is formed during DOWN/negative market states. We also find that momentum portfolio formed in UP/positive and continues to UP/positive market states outperforms momentum portfolio formed in UP/positive and reveres to DOWN/negative market states. Similarly, momentum portfolio formed in DOWN/negative and continues to DOWN/negative market states outperforms momentum portfolio formed in DOWN/negative and reveres to UP/positive market states. Overall, momentum strategy performs better in market continuation than in market reversal.

What is more, if market formed in UP/positive state continues its UP/positive state in the holding period, the high factor loading stocks in the winner portfolio should generate high returns since they co-move up higher with the market. Meanwhile, loser portfolio should generate a relatively lower return since the loser portfolio includes low factor loading stocks. In this case, the long winner short loser momentum portfolio should generate a positive return. Our findings support our hypothesis that there is a 1.20% (0.89% and 0.84%) average monthly returns when market moves from UP (SMB and HML positive) to UP (SMB and HML positive) state. Similarly, if formed during DOWN/negative market state, winner portfolio has low factor loading stocks and loser portfolio has high factor loading stocks. When market continues DOWN/negative state in the holding period during which the overall market has a negative return, the low factor loading stocks in the winner portfolio should lose less while the high factor loading stocks in the loser portfolio should perform worse since they would move down together with the market. In this case, the long winner short loser momentum portfolio should also generate a positive return. Our findings support our hypothesis that there is a 0.91% (1.60% and 1.24%) average monthly returns when market moves from DOWN (SMB and HML negative) to DOWN (SMB and HML negative) state.

However, if market reverses from UP/positive to a DOWN/negative state holding period, those high factor loading stocks in the winner portfolio should suffer the most whereas those low factor loading stocks in the loser portfolio would lose less. In this case, we expect that the momentum strategy tends to generate a negative return. This is the only exception that our findings do not support the hypothesis. The momentum strategy generates positive and statistically significant 0.90% (0.48% and 0.77%) average monthly return when market moves from UP (SMB and HML positive) to DOWN (SMB and HML negative) state. Lastly, if market reverses from DOWN/negative to a UP/positive state holding period, those low factor loading stocks in the winner portfolio may not generate high enough returns whereas those high factor loading stocks in the loser portfolio would perform much better when market bounces back. In this case, we expect that the momentum strategy would generate a negative return. Our finding supports the hypothesis that there is a -1.15% (-0.50% and -0.47%) average monthly return when market bounces back from DOWN/negative to an UP/positive state.

Overall, beta, size, and book-to-market ratio as proxies for risks can partially explain the momentum effect under different market state combinations. However, they cannot fully explain the actual momentum profits as well as the positive momentum profit exception during UP-to-DOWN/positive-to-negative market states. Potential reasons might be the following. CAPM, or beta alone, does not fully describe stock returns. There are missing risk factors in explaining stock returns. Or at least half of momentum return does not come from risk. This leads to further study of behavioral explanations, but beyond the scope of this paper.

Our findings contribute to the vast momentum literature along several dimensions. First, our results suggest that the momentum puzzle can at least partially be solved by the classic risk-based rational explanation of the cross-sectional variation of stock returns. Second, we innovatively enrich the way market states are defined by adding SMB/HML positive and negative market states. This allows me to investigate the classic risk-return relationship more clearly in explaining the momentum effect in different market transitions. Lastly, the simulation of momentum strategy to provides a better understanding of the hypotheses and presents preliminary results in a highly controlled environment before diving deep into the real-world empirical results.

The remaining sections are organized as follows. Section 2 summarizes the testable hypotheses. Section 3 presents the data and sample selection process. Section 4 presents simulation and empirical results of the single-factor situation. Section 5 discusses the multi-factor scenario. Section 6 concludes the paper.

2. Testable Hypotheses

During an UP market state formation period when the overall market has a high return, the stocks with high returns should be the stocks with high betas since beta measures the co-movement between individual stock return and the overall market return. This explains why momentum strategy tends to pick winners (who have the highest returns during the formation period) from high beta stocks during an UP formation period. Similarly, during a DOWN market formation period when the overall market has a negative return, stocks with high returns (winners) should be the stocks with low betas since individual stocks lose less with low betas. This explains why momentum strategy tends to pick winners from low beta stocks during DOWN formation period. Therefore, we hypothesize that momentum strategy will pick up winners from riskier firms during

UP market formation period. This winner portfolio will outperform loser portfolio in a continuation of UP market during the holding period but will not outperform loser portfolio if market reverses to DOWN state. On the other hand, winner portfolio formed during DOWN market will pick up firms with less risk. As a result, the winner will continue to outperform if DOWN market continues during holding period but might not outperform if market reverses.

Now it is clear that winner portfolio has high beta stocks and loser portfolio has low beta stocks when the formation period is in an UP state. If market continues its UP state in the holding period during which the overall market has a high return, the high beta stocks in the winner portfolio should perform better than the low beta stocks do in the loser portfolio since winners co-move up higher with the market. Meanwhile, loser portfolio should generate a relatively lower return since the loser portfolio includes low beta stocks. However, if market reverses to a DOWN state holding period, those high beta stocks in the winner portfolio should suffer the most whereas those low beta stocks in the loser portfolio would lose less. Overall, we expect that the momentum strategy performs better if market continues from UP to UP state than market reverses from UP to DOWN state. Similarly, when formed in a DOWN market state, winner portfolio includes low beta stocks whereas loser portfolio includes high beta stocks. When market continues its DOWN state in the holding period during which the overall market has a negative return, those low beta stocks in the winner portfolio should lose less. Meanwhile, loser portfolio would perform worse since the loser portfolio includes high beta stocks which move down further together with the market. However, if market bounces back to an UP state holding period, those low beta stocks in the winner portfolio may not generate high enough returns whereas those high beta stocks in the loser portfolio would perform much better. In this case, we expect that the momentum strategy tends to perform better if market continues from DOWN to DOWN state than market reverses from DOWN to UP state. Overall, momentum strategy, which has long position in winner portfolio and short position in loser portfolio, performs better in market continuation than in market reverse.

Furthermore, the momentum portfolio is expected to have a positive return if market moves from UP to UP state or from DOWN to DOWN state since winners are expected to have a return higher than that of the losers in these two cases. Similarly, when market moves from UP to DOWN state during which winners suffer more than losers, or when market bounces from DOWN to UP state during which winners with low betas generate lower returns than losers do, momentum portfolio is expected to have a negative return. Therefore, we hypothesize that winner portfolio tends to outperform loser portfolio when market continues its state from UP to UP but not outperform when market reverses from UP to DOWN and winner portfolio tends to outperform loser portfolio when market continues its state from DOWN to DOWN but not outperform when market reverses from DOWN to UP.

Instead of defining market states by the market risk premium, we redefine the market state variables as SMB or HML positive and negative considering size and book-to-market ratio as risk factors that can be used to explain the cross sections of stock returns. The formation period is defined as SMB positive (negative) if the past six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative) and is defined as HML positive (negative) if the past six-month compound High-Minus-Low (HML) portfolio return is positive (negative). The holding period is defined as SMB positive (negative) if the next six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative) and is defined as HML positive (negative) if the next six-month compound High-Minus-Low (HML) portfolio return is positive (negative).

Similar to the ideas and hypotheses when market state is defined by market risk premium, we also propose that momentum strategy picks up winners from firms with high SMB and HML factor loadings during a positive market formation period and from firms with low SMB and HML factor loadings during a negative market formation period. At the same time, momentum strategy performs better in SMB and HML market continuation than in SMB and HML market reverse. Furthermore, winner portfolio tends to outperform loser portfolio if market continues its state from positive to positive and underperform loser portfolio if market reverses its state from positive to negative or from negative to positive market.

3. Data and Sample

The data for the study is all NYSE and AMEX (CRSP exchange code 1 and 2) common stocks (CRSP share code 10 and 11) listed on the CRSP monthly file. The sample period covers 612 months ranging from January 1965 to December 2015. Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. We exclude stocks with a price at the end of the formation period below $1 to mitigate microstructure effects associated with low-priced stocks. The sample period returns are calculated for holding periods t to t + 5. We define each momentum portfolio as long in the prior six-month winners (highest decile) and short in the prior six-month losers (lowest decile). We form a time-series of raw returns corresponding to each month of the holding period.

We then estimate beta for each stock at the end of each month based on market model using CRSP daily stock prices 252 trading days prior to the estimation date. We require that each stock have at least 252 day's trading record in order to estimate its beta.

We choose beta, size, and book-to-market ratio as potential risk factors and define market state accordingly.[3] We define the market state of month t as UP (DOWN) if the formation period

[3] I thank Ken French for providing this data for the Fama-French three-factor model. The time series of these risk premiums can be obtained from https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

six-month compound market return is higher (lower) than the contemporaneous risk-free return. We define the market state of month t as SMB positive (negative) if the formation period six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative) and define the market state of month t as HML positive (negative) if the formation period six-month compound High-Minus-Low (HML) portfolio return is positive (negative). Similarly, the holding period is defined as UP market if the next six-month holding period compound market return is greater than the contemporaneous six-month compound risk-free return and is defined as DOWN market if it is less than the six-month risk-free return. The holding period is defined as SMB positive (negative) market if the next six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative) and is defined as HML positive (negative) market if the next six-month compound High-Minus-Low (HML) portfolio return is positive (negative).

[Insert Table 1]

Table 1 shows the descriptive statistics of the data sample from January 1965 to December 2015. Momentum strategy is based on the ranking of the formation period average monthly return shown in the first column. The formation period average monthly return ranges from -5.45% for the loser portfolio up to 11.00% for the winner portfolio. The average monthly return of the holding period ranges from 0.92% for the loser portfolio and up to 1.55% for the winner portfolio, resulting in an average momentum portfolio return of 0.63% which is positive and statistically significant. This is consistent with extant literature that momentum effect still exists in the U.S. market. The pre-ranking beta is higher for loser and winner portfolio than that of the portfolios in the middle deciles. The pre-ranking beta for the momentum portfolio is -0.01 and statistically insignificant, which shows that there is no significant difference between beta for the loser portfolio and beta for the winner portfolio. As for the Fama-French three-factor model, there is a tiny difference between the winner portfolio loadings and the loser portfolio loadings for all three factors (0.03, -0.03, and 0.03 for market factor, SMB factor, and HML factor respectively).

4. Explanations based on a Single-factor Model

In this section, we investigate the relationship between market states and momentum effect and explain the momentum effect from a risk-based perspective when using beta as a single risk factor.

4.1 Simulation

Before diving into the real-world data, we apply momentum strategy on a simulated dataset and test if the hypotheses hold based on the simulated dataset. The reason for conducting a simulation is to observe the degree of momentum effect in a controlled experiment where other confounding factors are excluded.

The data generating process is based on the Capital Asset Pricing Model (CAPM) shown in Equation (1) where r_{it} is the return for individual stock i in month t, rf_t is the risk-free return in month t, rm_t is the market return in month t, β_{it} is the beta for the individual stock i in month t, and ε_{it} is a normally distributed random factor for each individual stock i in month t.

$$r_{it} = rf_t + \beta_{it} \times (rm_t - rf_t) + \varepsilon_{it} \tag{1}$$

First, we assume that the monthly risk-free rate rf_t follows an autoregressive (AR) process with an order of 1.[4] This means that the contemporaneous risk-free rate is to some degree

[4] The overall simulation results are similar if I use historical monthly risk-free rate or assume that the risk-free rate follows a normal distribution. In reality, current risk-free rate should be more or less related to its previous value. So we assume an AR(1) process which is reported.

autocorrelated with itself in the previous month. We then estimate the AR(1) model shown in Equation (2) with time-series monthly risk-free rate data from January 1965 to December 2015. The risk-free rate simulation is based on the AR(1) regression estimation result and the data generating process is described in Equation (3).

$$rf_t = \gamma + \delta \times rf_{t-1} + \epsilon_t \tag{2}$$

$$rf_t = 0.0001094 + 0.9717901 \times rf_{t-1} + \varphi_t \tag{3}$$

An initial value is needed to start the AR(1) process simulation. We assume that the first-period risk-free rate begins with a normally distributed number with a mean of 0.4029% and a standard deviation of 0.2645%, which are the historical mean and standard deviation of the risk-free rate between 1965 and 2015. 0.0001094 and 0.9717901 are the estimated regression coefficients γ and δ respectively from Equation (2) estimation. We also assume that φ_t is normally distributed with zero mean and standard deviation of 0.000765 to ensure that there are very few negative risk-free rates while keeping the mean and standard deviation of the risk-free rate close to its historical level.

In addition, we assume that the monthly market return rm_t is normally distributed with a mean of 0.8871% and a standard deviation of 4.4872%. The parameters of the normal distribution for market return simulation are the historical mean and standard deviation of market returns between 1965 and 2015. Furthermore, we assume that β_{it} is normally distributed with a mean of 1 and a standard deviation of 0.45. This ensures that on average, the overall market has a beta of 1 yet very few negative betas are observed. Finally, we assume that the random factor ε_{it} is normally distributed with a mean of zero and a standard deviation of 0.2887% (annual standard deviation of 1%). Although we use historical data as parameters in the data generating process, we could use any arbitrary but reasonable numbers as parameters.we

The simulation is designed as follows based on the distributions and parameters mentioned above. First, we simulate 600 months' (50 years') time series risk-free rate rf_t and market return rm_t data. Then, for each month, we simulate 1000 individual stock betas β_{it}. Since our goal is to explain the momentum effect from a risk-based perspective, we want to keep the individual betas time-invariant. It means that each individual stock has its own constant beta over the 600 months sample period. This allows me to control the risk factor unchanged over time and explore how the momentum effect performs. Lastly, we simulate the random factor ε_{it} for each individual stock in each month. Then based on Equation (1), we can simulate 600,000 individual stock return r_{it} observations in our final simulated dataset.

Closely follow the methodology mentioned in Section 3, we first sort simulated stock returns at the end of each month t into deciles based on their prior six-month returns. The holding period returns are calculated for time periods t to t + 5. We define each momentum portfolio as long in the prior six-month winners (highest decile) and short in the prior six-month losers (lowest decile). We form a time-series of raw returns corresponding to each month of the holding period. We also calculate portfolio beta for each decile portfolio as equal-weighted mean of each individual stock beta in the portfolio. Momentum portfolio beta is the difference between the winner portfolio beta and the loser portfolio beta.

In the last step, we run the abovementioned momentum strategy simulation 100 times. We record the average monthly returns for each decile during both formation and holding period and record the average portfolio beta for each decile portfolio.

[Insert Table 2]

Table 2 shows the average monthly returns for the formation period as well as the holding period. Loser portfolio has an average monthly return of -0.40% while the winner portfolio has an average monthly return of 2.23% during the formation period. During the holding period, the loser portfolio has an average monthly return of 0.81% while the winner portfolio has an average monthly return of 1.00% which results in a significant average monthly momentum return of 0.19%. The portfolio beta monotonically increases from 0.89 for the loser portfolio to 1.10 for the winner portfolio which produces a significant 0.21 portfolio beta for the momentum portfolio.

[Insert Table 3]

We define formation period as UP (DOWN) if the formation period six-month compound market return is higher (lower) than the contemporaneous risk-free return. Based on this definition, Table 3 shows the portfolio beta of each decile portfolio as well as the momentum portfolio in different formation period market states. The winner portfolio has a higher beta (1.68) than that of the loser portfolio (0.30) when portfolios are formed in an UP state market. This results in a positive and significant 1.38 beta for the momentum portfolio. However, when portfolios are formed in a DOWN state market, the winner portfolio has a lower beta (0.29) than that of the loser portfolio (1.73). This results in a negative and significant -1.44 momentum portfolio beta. The results shown in Table 3 are consistent with our hypothesis that momentum portfolio has a positive beta when formed in an UP market state and a negative beta when formed in a DOWN market state.

[Insert Table 4]

We define holding period as UP (DOWN) if the holding period six-month compound market return is higher (lower) than the contemporaneous risk-free return. Table 4 presents the average monthly returns for each decile portfolio as well as for the momentum portfolio in different market state combinations.

Table 4 Panel A shows that there is a positive and significant 2.33% average monthly return if the market state continues from UP to UP or from DOWN to DOWN while there is a negative and significant -2.20% average monthly return when market state reverses from UP to DOWN or bounces from DOWN to UP. The difference between the two is 4.53% which means that momentum strategy performs better in market continuation than in market reversal. This result is consistent with the hypothesis that momentum strategy performs better in market continuation that in market reverse.

Table 4 Panel B shows that when formed in UP state market, momentum portfolio has a significant average monthly return of 2.53% if followed by an UP state while it has a significant average monthly return of -1.80% if followed by a DOWN state. Table 4 Panel C shows similar results. When formed in DOWN market state, momentum portfolio has a negative and significant average monthly return of -2.60% if market reverses to an UP state while it has a positive and significant average monthly return of 1.93% if market continues to another DOWN state. These results are consistent with the hypothesis that momentum portfolio has a positive return when the market continues its state from UP to UP or from DOWN to DOWN and a negative return when the market reverses its state from UP to DOWN or from DOWN to UP.

The simulation confirms that a return generating process based on positive relationship between risk and return will create momemtum. Winners formed in bull market pick up stocks with higher beta, and formed in bear market contain stock with lower beta. Once we mixed the market condtion when they are formed, the beta difference becomes much smaller.

4.2 Empirical Results and Discussions

The simulation results in the previous section support our hypotheses. In this section, we dive into the real-world data and find that the momentum effect, to some degree, can be explained from a risk-based perspective.

[Insert Table 5]

Table 5 presents the momentum portfolio beta during both UP and DOWN formation periods. If the portfolio is formed in an UP market, momentum strategy picks winners from high beta stocks (1.29) and picks losers from low beta stocks (1.10). The momentum portfolio has a positive and significant portfolio beta (0.19). Meanwhile, if the portfolio is formed in a DOWN market, momentum strategy picks winners from low beta stocks (1.02) and picks losers from high beta stocks (1.38). The momentum portfolio has a negative and significant portfolio beta (-0.36). The overall situation for pre-ranking beta is mixed, and the momentum portfolio has a beta of -0.01 which is not significant at 10% level. The results of the pre-ranking beta in Table 5 are consistent with the hypothesis that that momentum portfolio has a positive beta when formed in an UP market state and a negative beta when formed in a DOWN market state.

[Insert Table 6]

Table 6 presents the number of months and signs of beta in different market state combinations. There are 269 months during which market continues from UP to UP state, 125 months when the market moves from UP to DOWN state, 121 months when the market bounces from DOWN to UP state, and 97 months when the market continues from DOWN to DOWN state. When the market continues its state from UP to UP, there are 68% of the time (183 of 269 months) during which the momentum portfolio has a positive beta while 32% of the time (86 of 269 months) with a negative momentum portfolio beta. When formed in UP and followed by a DOWN state, 68% (85 of 125 months) of the momentum portfolio has a positive beta while 32% (40 of 125 months) of the momentum portfolio has a negative beta. Similarly, when formed in DOWN and followed by a UP state, only 13% (16 of 121 months) of the momentum portfolio has a positive beta while 87% (105 of 121 months) has a negative beta. When market continues from DOWN to DOWN state, 15% (15 of 97 months) momentum portfolio has a positive beta while 85% (85 of 97 months) has a negative beta. These results are strong supplements to our conclusion with hypothesis that, during the majority of the time, momentum strategy picks up momentum portfolio with positive beta during UP formation period and picks up negative beta momentum portfolio during DOWN formation period.

[Insert Table 7]

Table 7 presents the momentum strategy return performance under a mix of UP or DOWN market states.

Table 7 Panel A shows that the momentum portfolio generates an average monthly return of 1.13% (t-value = 12.56) when market continues from UP to UP state or from DOWN to DOWN state. During market reversal from UP to DOWN state or DOWN to UP state, the momentum portfolio average monthly return falls to -0.11% (t-value = -0.41). A test of the difference in momentum portfolio return (1.24%) is statistically significant (t-value = 4.98). This result is consistent with the hypothesis that momentum strategy performs better in market continuation that in market reverse.

Table 7 Panel B and Panel C shows the ten decile portfolios as well as the long-short momentum portfolio average monthly return and portfolio beta when portfolios are formed in UP and DOWN market state respectively. First, the All column of Table 7 Panel B shows an overall average monthly momentum return of 1.11% (t-value = 13.34) regardless of the holding period market state. This means that if portfolios are formed in an UP market, the winner group performs better than the loser group, resulting in a positive momentum profit. However, if portfolios are formed in a DOWN market as shown in Table 7 Panel C, the momentum portfolio has an average monthly return of -0.24% which has a negative value but is not statistically significant at 10% significance level. This result is consistent with Cooper et al. (2004) that there is a positive and statistically significant average monthly momentum profit following UP market and a negative yet statistically insignificant average monthly momentum profit following DOWN market.[5]

Also, when portfolios are formed in UP market and held into UP market, the average monthly momentum return is 1.20% (t-value = 11.97) which is higher than the 0.90% (t-value = 6.16) return when market reverses to a DOWN state. At the same time, the average monthly return of the momentum portfolio is 0.91% (t-value = 4.77) when portfolios are formed in DOWN market

[5] Cooper et al. (2004) reports an average monthly momentum profit of 1.04% (t-value = 9.23) following UP market and an average monthly momentum profit of -0.08% (t-value = -0.22) with a sample period between 1929 and 1995.

and continues to DOWN market. It outperforms the momentum portfolio formed in DOWN market and held in a reversal UP market state whose return is -1.15% (t-value = -2.23). These results are also consistent with the hypothesis that momentum strategy performs better in market continuation than in market reverse.

What is more, the winner portfolio generates an average monthly return of 2.72% which is higher than the 1.51% of the loser portfolio when market continues from UP to UP state, resulting in a positive 1.20% (t-value = 11.97) momentum profit. Similarly, when market continues from DOWN to DOWN state, the winner portfolio also generates an average monthly return (-1.23%) higher than that of the loser portfolio (-2.14%), resulting in a positive and statistically significant momentum profit of 0.91% (t-value = 4.77). These results are consistent with the hypothesis that winner portfolio tends to outperform loser portfolio if market continues its state from UP to UP or from DOWN to DOWN market. When market bounces from DOWN to UP state, winners with low beta stocks generate returns (3.68%) lower than that (4.84%) of the losers with high beta stocks resulting in a negative and statistically significant momentum profit of -1.15% (t-value = -2.23). This result is consistent with the hypothesis that winner portfolio does not outperform loser portfolio if market reverses its state from DOWN to UP. During the UP-to-DOWN market state, the winner portfolio is expected to have an average monthly return lower than that of the loser portfolio as suggested by our hypothesis. However, the winner portfolio generates an average monthly return of -0.87% which is higher than that of the loser portfolio (-1.77%), resulting in a positive momentum profit of 0.90% (t-value = 6.16). This is the only result that is not consistent with the hypothesis.

[Insert Table 8]

Table 8 compares the predicted momentum profits based on CAPM with the actual momentum profits in order to further investigate whether momentum profits can be explained by risk factors such as beta. When market moves from UP to UP state, the predicted average monthly momentum profit is 0.22% which is lower than the actual momentum profit (1.20%). When market bounces from DOWN to UP state, the predicted average monthly momentum return (-0.79%) is also lower than the actual result (-1.15%). When market continues from DOWN to DOWN state, the predicted result (0.81%) is again lower but with a smaller amount than the actual result (0.91%). The results above indicate that beta, as a risk factor, can partially explain the momentum effect under different market state combinations. During the UP-to-DOWN market states, the predicted average monthly momentum profit is -0.20% while the actual momentum profit is 0.90%. The predicted result is consistent with the hypothesis that the momentum profit should be negative. However, the predicted result cannot explain why the actual momentum portfolio has a positive return during UP-to-DOWN market states.

Overall, beta as a risk factor can partially explain the momentum effect under different market state combinations. However, it cannot fully explain the actual momentum profits as well as the positive momentum profit exception during UP-to-DOWN market states. One of the potential reasons might be the following. CAPM, or beta alone, does not fully describe stock returns. There are missing risk factors in explaining stock returns. This leads to the study of two other factors which are size and valuation ratio (Book-to-market ratio) in the next section.

5. Explanations based on a Multi-factor Model

Beta, however, is not the only factor that empirical research has found affecting stock expected returns. Fama-French three-factor model implies that size and value factors also have strong explanatory power in the variations of cross-sectional stock returns. In this section, we incorporate size and value factors into our testing framework and investigate whether the risk-based explanations of momentum effect separated by market states still hold.

[Insert Table 9]

Factor loadings of Fama-French three-factor regression under different market states are reported in Table 9. If portfolios are formed during UP state market, winner portfolio (P10) tends to pick stocks with higher beta (1.28) than that of the loser portfolio (1.11). Momentum portfolio (P10-P1) has a positive and statistically significant beta (0.17). Meanwhile, if portfolios are formed during a DOWN market state, winner portfolio tends to pick stocks with lower beta (1.08) than that of the loser portfolio (1.30). Momentum portfolio has a beta of -0.22 which is negative and significant. If we ignore the market state impact and look at the overall situation, the difference between the winner portfolio beta and loser portfolio beta is very small (0.03).

Similar results are reported for the SMB and HML factor loadings. For the SMB factor, winner portfolio tends to pick higher SMB factor loadings (1.00) than that of the loser portfolio (0.76) when formed during SMB positive time period. When portfolio formed during SMB negative period, winner portfolio tends to pick stocks with lower SMB factor loading (0.66) than that of the loser portfolio (1.03). For the HML factor, winner portfolio tends to pick higher HML loadings (0.40) than that of the loser portfolio (0.17) when formed during HML positive time period. When portfolio formed during HML negative period, winner portfolio tends to pick stocks with lower HML factor loading (0.16) than that of the loser portfolio (0.44). There is no big difference between winner and loser portfolio SMB and HML factor loading overall when we ignore the impact of the market state. The momentum portfolios have SMB and HML factor loadings of -0.03 and 0.03 correspondingly. The results shown above are consistent with our hypothesis that momentum strategy picks up winners from firms with high SMB and HML factor loadings during a positive market formation period and from firms with low SMB and HML factor loadings during a negative market formation period.

[Insert Table 10]

Table 10 reports the number of months and signs of SMB factor loading in different market states defined by Small-Minus-Big (SMB) premium. There are 193 months during which market continues from SMB positive to positive state, 146 months when the market moves from SMB positive to negative state, 140 months when the market bounces from SMB negative to positive state, and 133 months when the market continues from SMB negative to negative state. When the market continues its state from SMB positive to positive, there are 73% of the time (141 of 193 months) during which the momentum portfolio has a positive SMB factor loading. When formed in SMB positive and followed by a negative state, 76% (111 of 146 months) of the momentum portfolio has a positive SMB factor loading. Similarly, when formed in SMB negative and followed by a positive state, only 11% (15 of 140 months) of the momentum portfolio has a positive SMB factor loading while 89% (125 of 140 months) has a negative SMB factor loading. When market continues from SMB negative to negataive state, 13% (17 of 133 months) momentum portfolio has a positive SMB factor loading while 87% (116 of 133 months) has a negative SMB factor loading.

[Insert Table 11]

Table 11 reports the number of months and signs of HML factor loading in different market states defined by High-minus-Low (HML) premium. There are 243 months during which market continues from HML positive to positive state, 124 months when the market moves from HML positive to negative state, 127 months when the market bounces from HML negative to positive state, and 118 months when the market continues from HML negative to negative state. When the market continues its state from HML positive to positive, there are 75% of the time (183 of 243 months) during which the momentum portfolio has a positive HML factor loading. When formed in HML positive and followed by a negative state, 72% (89 of 124 months) of the momentum portfolio has a positive HML factor loading. Similarly, when formed in HML negative and followed by a positive state, only 28% (36 of 127 months) of the momentum portfolio has a positive HML factor loading while 72% (91 of 127 months) has a negative HML factor loading. When market continues from HML negative to negataive state, 25% (29 of 118 months) momentum portfolio has a positive HML factor loading while 75% (89 of 118 months) has a negative HML factor loading.

Results presented in Table 10 and Table 11 are strong supplements to the conclusion with our hypothesis that, during the majority of the time, momentum strategy picks up momentum portfolios with positive SMB and HML factor loadings during positive formation period and picks up negative SMB and HML factor loading momentum portfolios during negative formation period.

The results highlight the importance of separating market state during formation period when we want to understand the risk characteristics of momentum portfolio and the source of momentum portfolio returns. Based on the risk characteristics of momentum portfolio discussed above, we proceed to explore the return performance of the momentum portfolio in the holding period separated by different market states.

[Insert Table 12]

Table 12 reports the average monthly returns and portfolio factor loadings of winners, losers, and momentum portfolios in mixed SMB positive and negative market states. Table 12 Panel A shows that the momentum portfolio generates an average monthly return of 1.18% (t-value = 8.57) when market continues from SMB positive to positive state or from SMB negative to negative state. During market reversal from SMB positive to negative state or SMB negative to positive state, the momentum portfolio average monthly return falls to 0.00% (t-value = 0.01). A test of the difference in momentum portfolio return (1.18%) is statistically significant (t-value = 4.82). This result is consistent with the hypothesis that momentum strategy performs better in SMB market continuation that in SMB market reverse.

Table 12 Panel B and Panel C shows the ten decile portfolios as well as the long-short momentum portfolio average monthly return and portfolio SMB factor loadings when portfolios are formed in SMB positive and SMB negative market state respectively. When portfolios are formed in SMB positive market and held into SMB positive market, the average monthly momentum return is 0.89% (t-value = 4.15) which is higher than the 0.48% (t-value = 3.67) return when market reverses to SMB negative state. However, a test of the difference in momentum portfolio return (0.41%) is not statistically significant (t-value = 1.50). At the same time, the average monthly return of the momentum portfolio is 1.60% (t-value = 12.84) when portfolios are formed in SMB negative market and continues to SMB negative market. It outperforms the momentum portfolio formed in SMB negative market and held in a reversal SMB positive market state whose return is -0.50% (t-value = -1.24). A test of the difference in momentum portfolio return (-2.10%) is statistically significant (t-value = -4.91). These results are also consistent with the hypothesis that momentum strategy performs better in SMB market continuation that in SMB market reverse.

What is more, the winner portfolio generates an average monthly return of 3.20% which is higher than the 2.31% of the loser portfolio when market continues from SMB positive to positive state, resulting in a positive 0.89% (t-value = 4.15) monthly momentum profit. Similarly, when market continues from SMB negative to negative state, the winner portfolio also generates an average monthly return (0.02%) higher than that of the loser portfolio (-1.59%), resulting in a positive and statistically significant momentum profit of 1.60% (t-value = 12.84). These results are consistent with the hypothesis that winner portfolio tends to outperform loser portfolio if market continues its state from SMB positive to positive or from SMB negative to negative market. When market bounces from SMB negative to SMB positive state, winners with low SMB factor loading stocks generate returns (2.87%) lower than that (3.37%) of the losers with high beta stocks resulting in a negative yet statistically insignificant momentum profit of -0.50% (t-value = -1.24). This result is consistent with the hypothesis that winner portfolio does not outperform loser portfolio if market reverses its state from SMB negative to positive. During the SMB positive-to-negative market state, the winner portfolio is expected to have an average monthly return lower than that of the loser portfolio as suggested by our hypothesis. However, the winner portfolio generates an average monthly return of -0.50% which is higher than that of the loser portfolio (-

0.98%), resulting in a positive momentum profit of 0.48% (t-value = 3.67). This result is not consistent with the hypothesis.

[Insert Table 13]

Table 13 reports the average monthly returns and portfolio factor loadings of winners, losers, and momentum portfolios in mixed HML positive and negative market states. Table 13 Panel A shows that the momentum portfolio generates an average monthly return of 0.97% (t-value = 9.16) when market continues from HML positive to positive state or from HML negative to negative state. During market reversal from HML positive to negative state or HML negative to positive state, the momentum portfolio average monthly return falls to 0.14% (t-value = 0.55). A test of the difference in momentum portfolio return (0.83%) is statistically significant (t-value = 3.30). This result is consistent with the hypothesis that momentum strategy performs better in HML market continuation that in HML market reverse.

Table 13 Panel B and Panel C shows the ten decile portfolios as well as the long-short momentum portfolio average monthly return and portfolio HML factor loadings when portfolios are formed in HML positive and HML negative market state respectively. When portfolios are formed in HML positive market and held into HML positive market, the average monthly momentum return is 0.84% (t-value = 7.06) which is higher than the 0.77% (t-value = 3.04) return when market reverses to HML negative state. However, a test of the difference in momentum portfolio return (0.07%) is not statistically significant (t-value = 0.27). At the same time, the average monthly return of the momentum portfolio is 1.24% (t-value = 5.88) when portfolios are formed in HML negative market and continues to HML negative market. It outperforms the momentum portfolio formed in HML negative market and held in a reversal HML positive market state whose return is -0.47% (t-value = -1.06). A test of the difference in momentum portfolio return (-1.71%) is statistically significant (t-value = -3.40). These results are also consistent with the hypothesis that momentum strategy performs better in HML market continuation that in HML market reverse.

What is more, the winner portfolio generates an average monthly return of 1.35% which is higher than the 0.51% of the loser portfolio when market continues from HML positive to positive state, resulting in a positive 0.84% (t-value = 7.06) monthly momentum profit. Similarly, when market continues from HML negative to negative state, the winner portfolio also generates an average monthly return (1.75%) higher than that of the loser portfolio (0.51%), resulting in a positive and statistically significant momentum profit of 1.24% (t-value = 5.88). These results are consistent with the hypothesis that winner portfolio tends to outperform loser portfolio if market continues its state from HML positive to positive or from HML negative to negative market. When market bounces from HML negative to HML positive state, winners with low HML factor loading stocks generate returns (1.26%) lower than that (1.73%) of the losers with high beta stocks resulting in a negative yet statistically insignificant momentum profit of -0.47% (t-value = -1.06). This result is consistent with the hypothesis that winner portfolio does not outperform loser portfolio if market reverses its state from HML negative to positive. During the HML positive-to-negative market state, the winner portfolio is expected to have an average monthly return lower than that of the loser portfolio as suggested by Hypothesis 2.6. However, the winner portfolio generates an average monthly return of 2.05% which is higher than that of the loser portfolio 1.28%), resulting in a positive momentum profit of 0.77% (t-value = 3.04). This result is not consistent with our hypothesis.

Overall, size and book-to-market ratio as proxies for risks can partially explain the momentum effect under different market state combinations. However, similar to the results when beta is used as a single risk factor, they cannot fully explain the actual momentum profits as well as the positive momentum profit exception during SMB and HML positive-to-negative market states. The reason might be that at least half of momentum return does not come from risk. This leads to further study of behavioral explanations, but beyond the scope of this paper.

5 Conclusion

Previous literature reveals a strong momentum effect in the stock market. Ever since it was first documented by Jegadeesh and Titman (1993), numerous researchers have found it across different markets and time periods. Even Fama admitted that momentum is an embarrassing challenge to the Efficient Market Hypothesis. Fama (1998) is critical of most anomalies, attributing them to methodological and other biases. However, there is no compelling evidence that the well-documented momentum profit could be attributed to risk. Very limited literature provides explanations for the momentum effect from a rational risk-based point of view under different market state combinations. We believe that previous empirical efforts to measure momentum profits and its sources are contaminated by the state of the market during both formation and holding periods.

Using beta, size, and book-to-market ratio as proxies for risk, we find that winner portfolio picks up stocks with high beta, high SMB factor loadings, and high HML factor loadings whereas loser portfolio picks up stocks with low beta, low SMB factor loadings, and low HML factor loadings when the momentum portfolio is formed during UP/positive market states. At the same time, winner portfolio picks up stocks with low beta, low SMB factor loadings, and low HML factor loadings whereas loser portfolio picks up stocks with high beta, high SMB factor loadings, and high HML factor loadings when the momentum portfolio is formed during DOWN/negative market states.

We also find that momentum portfolio formed in UP/positive and continues to UP/positive market states outperforms momentum portfolio formed in UP/positive and reveres to DOWN/negative market states. Similarly, momentum portfolio formed in DOWN/negative and continues to DOWN/negative market states outperforms momentum portfolio formed in DOWN/negative and reveres to UP/positive market states. Overall, momentum strategy, which has long position in winners and short position in losers, performs better in market continuation than in market reversal.

Furthermore, the momentum portfolio is expected to have a positive return if the market moves from UP/positive to UP/positive state or DOWN/negative to DOWN/negative state since winners are expected to have a return higher than that of the losers in these two cases. Our findings support our hypothesis that there is a 1.20% (0.89% and 0.84%) average monthly returns when the market moves from UP (SMB and HML positive) to UP (SMB and HML positive) state and that there is a 0.91% (1.60% and 1.24%) average monthly returns when market moves from DOWN (SMB and HML negative) to DOWN (SMB and HML negative) state. Similarly, when the market moves from UP/positive to DOWN/negative state during which winners suffer more than losers, or when the market bounces from DOWN/negative to UP/positive state during which winners with low betas generate lower returns than losers do, momentum portfolio is expected to have a negative return. Our finding supports the hypothesis that there is a -1.15% (-0.50% and -0.47%) average monthly return when the market bounces back from DOWN/negative to an UP/positive state. However, there is an exception that our findings do not support the hypothesis. The momentum strategy generates positive and statistically significant 0.90% (0.48% and 0.77%) average monthly return when the market moves from UP (SMB and HML positive) to DOWN (SMB and HML negative) state.

Beta, as a single risk factor, can partially explain the momentum effect under different market state combinations. However, it cannot fully explain the actual momentum profits as well as the positive momentum profit exception during UP-to-DOWN market states. One of the potential reasons might be that CAPM, or beta alone, does not fully describe stock returns. There are missing risk factors in explaining stock returns. Results are similar when size and valuation ratio (book-to-market ratio) are added as additional proxies for risk. The model can explain the momentum effect most of the time but cannot fully explain the actual momentum profits as well as the positive momentum profit exception during SMB and HML positive-to-negative market states. The reason might be that at least half of the momentum return does not come from risk. This leads to further study of behavioral explanations, but beyond the scope of this paper.

Overall, beta, size, and book-to-market ratio as proxies for risks can partially explain the momentum effect under different market state combinations.

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Table 1: Descriptive Statistics of the Sample from January 1965 to December 2015

Stock return data is from NYSE and AMEX common stocks listed on the CRSP monthly file. Sample period covers January 1965 to December 2015. Stocks with a price below $1 at the end of the formation period is excluded to mitigate microstructure effects associated with low-priced stocks. Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. The investment period returns are calculated for month t to t + 5. Winner is defined as the portfolio who has the highest past six-month return (highest decile) while loser is defined as the portfolio who has the lowest past six-month return (lowest decile). Momentum portfolio is formed with a long position in the winner portfolio and a short position in the loser portfolio at the same time. Pre-ranking beta for each stock is estimated at the end of each month based on market model using CRSP daily stock prices 252 trading days prior to the estimation date. Each stock is required to have at least 252 days' trading record in order to estimate its beta and Fama-French three-factor model factor loadings. T-statistics are in parentheses. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%.

	Formation Period Average Monthly Return	Holding Period Average Monthly Return	Pre-ranking Beta	Market Factor Loading	SMB Factor Loading	HML Factor Loading
P1 - Loser	-5.45%	0.92%	1.20	1.17	0.88	0.28
P2	-2.81%	1.06%	1.07	1.07	0.70	0.29
P3	-1.52%	1.16%	1.01	1.01	0.61	0.29
P4	-0.54%	1.20%	0.97	0.98	0.56	0.29
P5	0.33%	1.21%	0.96	0.97	0.54	0.28
P6	1.20%	1.23%	0.96	0.98	0.53	0.29
P7	2.15%	1.23%	0.97	0.99	0.54	0.29
P8	3.32%	1.27%	1.01	1.02	0.57	0.29
P9	5.10%	1.34%	1.06	1.08	0.65	0.30
P10 - Winner	11.00%	1.55%	1.19	1.21	0.85	0.31
P10-P1	16.45%***	0.63%***	-0.01	0.03**	-0.03*	0.03
	(91.08)	(5.06)	(-0.42)	(2.00)	(-1.74)	(1.46)
N	612	612	612	612	612	612

Table 2: Descriptive Statistics of the Simulated Momentum Portfolio

The data generating process is based on the Capital Asset Pricing Model (CAPM) $r_{it} = rf_t + \beta_{it} \times (rm_t - rf_t) + \varepsilon_{it}$ where r_{it} is the return for individual stock i in month t, rf_t is the risk-free return in month t, rm_t is the market return in month t, β_{it} is the beta for the individual stock i in month t, and ε_{it} is a normally distributed random factor for each individual stock i in month t. It is assumed that risk-free rate rf_t follows an autoregressive process with an order of 1 and that market return rm_t, beta β_{it}, and a random factor ε_{it} are normally distributed. I simulate 600 months' time-series risk-free rate rf_t and market return rm_t data. For each month I simulate 1000 individual stock betas β_{it}. Lastly, I simulate the random factor ε_{it} for each individual stock in each month. I simulate 600,000 individual stock return r_{it} observations in the simulated dataset. I then sort the simulated stock returns at the end of each month t into deciles based on their prior six-month returns. The investment period returns are calculated for holding periods t to t + 5. I define each momentum portfolio as long in the prior six-month winners (highest decile) and short in the prior six-month losers (lowest decile). I form a time-series of raw returns corresponding to each month of the holding period. I also calculate portfolio beta for each decile portfolio as equal-weighted mean of each individual stock beta in the portfolio. Momentum portfolio beta is the difference between the winner portfolio beta and the loser portfolio beta. I run the abovementioned momentum strategy simulation 100 times and record the average monthly returns for each decile during both formation and holding period and the average portfolio beta for each decile portfolio. T-statistics are in parentheses. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%.

	Monthly Average of Formation Period Return	Monthly Average of Holding Period Return	Portfolio Beta
P1 - Loser	-0.40%	0.81%	0.89
2	0.12%	0.85%	0.94
3	0.40%	0.87%	0.96
4	0.61%	0.88%	0.98
5	0.81%	0.90%	0.99
6	1.00%	0.91%	1.01
7	1.20%	0.93%	1.02
8	1.42%	0.94%	1.04
9	1.69%	0.96%	1.06
P10 - Winner	2.23%	1.00%	1.10
P10 - P1	2.63%***	0.19%***	0.21***
	(139.53)	(7.26)	(14.14)

Table 3: Beta for the Simulated Momentum Portfolio

The data generating process is based on the Capital Asset Pricing Model (CAPM) $r_{it} = rf_t + \beta_{it} \times (rm_t - rf_t) + \varepsilon_{it}$ where r_{it} is the return for individual stock i in month t, rf_t is the risk-free return in month t, rm_t is the market return in month t, β_{it} is the beta for the individual stock i in month t, and ε_{it} is a normally distributed random factor for each individual stock i in month t. It is assumed that risk-free rate rf_t follows an autoregressive process with an order of 1 and that market return rm_t, beta β_{it}, and a random factor ε_{it} are normally distributed. I simulate 600 months' time-series risk-free rate rf_t and market return rm_t data. Then, for each month I simulate 1000 individual stock betas β_{it}. Lastly, I simulate the random factor ε_{it} for each individual stock in each month. I simulate 600,000 individual stock return r_{it} observations in the simulated dataset. I then sort simulated stock returns at the end of each month t into deciles based on their prior six-month returns. I calculate portfolio beta for each decile portfolio as equal-weighted mean of each individual stock beta in the portfolio. Momentum portfolio beta is the difference between the winner portfolio beta and the loser portfolio beta. I run the abovementioned momentum strategy simulation 100 times and record the average portfolio beta for each decile portfolio. I define formation period as UP (DOWN) if the formation period six-month compound market return is higher (lower) than the contemporaneous risk-free return. T-statistics are in parentheses. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%.

	Formation UP	Formation DOWN	All
P1 - Loser	0.30	1.73	0.89
2	0.59	1.43	0.94
3	0.73	1.28	0.96
4	0.85	1.15	0.98
5	0.96	1.05	0.99
6	1.06	0.94	1.01
7	1.16	0.83	1.02
8	1.27	0.72	1.04
9	1.41	0.57	1.06
P10 - Winner	1.68	0.29	1.10
P10 - P1	1.38***	-1.44***	0.21***
	(300.44)	(-303.99)	(14.14)

Table 4: Simulated Momentum Portfolio Average Monthly Returns in Different Market States Defined by Market Risk Premium

The data generating process is based on the Capital Asset Pricing Model (CAPM) $r_{it} = rf_t + \beta_{it} \times (rm_t - rf_t) + \varepsilon_{it}$ where r_{it} is the return for individual stock i in month t, rf_t is the risk-free return in month t, rm_t is the market return in month t, β_{it} is the beta for the individual stock i in month t, and ε_{it} is a normally distributed random factor for each individual stock i in month t. It is assumed that risk-free rate rf_t follows an autoregressive process with an order of 1 and that market return rm_t, beta β_{it}, and a random factor ε_{it} are normally distributed. I simulate 600 months' time-series risk-free rate rf_t and market return rm_t data. Then, for each month I simulate 1000 individual stock betas β_{it}. Lastly, I simulate the random factor ε_{it} for each individual stock in each month. I simulate 600,000 individual stock return r_{it} observations in the simulated dataset. I then sort simulated stock returns at the end of each month t into deciles based on their prior six-month returns. I run the abovementioned momentum strategy simulation 100 times and record the average monthly returns for each decile during both formation and holding periods. I define formation period as UP (DOWN) if the formation period six-month compound market return is higher (lower) than the contemporaneous risk-free return and define holding period as UP (DOWN) if the holding period six-month compound market return is higher (lower) than the contemporaneous risk-free return. T-statistics are in parentheses. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%.

Panel A - Market Continuation and Reversal							
	Continuation		Reversal		All		Difference
	(A)		(B)				(A) - (B)
	Return	Beta	Return	Beta	Return	Beta	
P1 - Loser	-0.05%	0.78	1.77%	1.01	0.81%	0.89	
P2	0.43%	0.87	1.31%	1.01	0.85%	0.94	
P3	0.68%	0.92	1.07%	1.01	0.87%	0.96	
P4	0.88%	0.95	0.89%	1.00	0.88%	0.98	
P5	1.05%	0.99	0.72%	1.00	0.90%	0.99	
P6	1.22%	1.02	0.56%	1.00	0.91%	1.01	
P7	1.40%	1.05	0.40%	1.00	0.93%	1.02	
P8	1.59%	1.08	0.22%	0.99	0.94%	1.04	
P9	1.83%	1.12	-0.01%	0.99	0.96%	1.06	
P10 - Winner	2.28%	1.21	-0.43%	0.98	1.00%	1.10	
P10-P1	2.33%***	0.42***	-2.20%***	-0.03***	0.19%***	0.21***	4.53%***
	(94.13)	(16.05)	(-114.87)	(-8.83)	(7.26)	(14.14)	(123.14)

Table 4 (continued)

Panel B - Formation UP

	Holding UP		Holding DOWN		All		Difference
	(C)		(D)				(C) - (D)
	Return	Beta	Return	Beta	Return	Beta	
P1 - Loser	0.87%	0.30	0.02%	0.30	0.52%	0.30	
P2	1.39%	0.59	-0.35%	0.59	0.68%	0.59	
P3	1.66%	0.73	-0.54%	0.74	0.76%	0.73	
P4	1.87%	0.85	-0.69%	0.85	0.82%	0.85	
P5	2.06%	0.96	-0.83%	0.96	0.88%	0.96	
P6	2.25%	1.06	-0.96%	1.05	0.94%	1.06	
P7	2.43%	1.16	-1.09%	1.16	0.99%	1.16	
P8	2.64%	1.27	-1.24%	1.27	1.06%	1.27	
P9	2.90%	1.41	-1.43%	1.41	1.14%	1.41	
P10 - Winner	3.40%	1.68	-1.78%	1.67	1.29%	1.68	
P10-P1	2.53%***	1.38***	-1.80%***	1.37***	0.76%***	1.38***	4.33%***
	(77.84)	(271.13)	(-122.75)	(238.98)	(20.00)	(300.44)	(123.17)

Panel C - Formation DOWN

	Holding UP		Holding DOWN		All		Difference
	(E)		(F)				(E) - (F)
	Return	Beta	Return	Beta	Return	Beta	
P1 - Loser	3.53%	1.73	-1.82%	1.73	1.26%	1.73	
P2	2.97%	1.43	-1.42%	1.43	1.11%	1.43	
P3	2.69%	1.28	-1.21%	1.28	1.04%	1.28	
P4	2.47%	1.15	-1.05%	1.15	0.98%	1.15	
P5	2.27%	1.05	-0.90%	1.05	0.93%	1.05	
P6	2.09%	0.94	-0.76%	0.94	0.88%	0.94	
P7	1.89%	0.83	-0.62%	0.83	0.83%	0.83	
P8	1.68%	0.72	-0.46%	0.72	0.77%	0.72	
P9	1.42%	0.57	-0.26%	0.57	0.70%	0.57	
P10 - Winner	0.93%	0.29	0.10%	0.29	0.58%	0.29	
P10-P1	-2.60%***	-1.44***	1.93%***	-1.44***	-0.68%***	-1.44***	-4.53%***
	(-75.67)	(-292.92)	(74.86)	(-282.50)	(-15.72)	(-303.99)	(-95.24)

Table 5: Pre-ranking Beta for Monthly Formed Momentum Portfolio

The formation period is defined as UP market if past six-month formation period compound market return is greater than the contemporaneous six-month compound risk-free return and is defined as DOWN market if it is less than the six-month risk-free return. Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. Winner is defined as the portfolio who has the highest past six-month return (highest decile) while loser is defined as the portfolio who has the lowest past six-month return (lowest decile). Momentum portfolio is formed with a long position in the winner portfolio and a short position in the loser portfolio at the same time. Pre-ranking beta for each stock is estimated at the end of each month based on market model using CRSP daily stock prices 252 trading days prior to the estimation date. Each stock is required to have at least 252 day's trading record in order to estimate its beta. Portfolio beta is calculated as the value-weighted beta for each return decile portfolio. Portfolio beta is also calculated without considering market states (All). T-statistics are in parentheses. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%.

	Formation UP	Formation DOWN	All
P1 - Loser	1.10	1.38	1.20
2	1.00	1.20	1.07
3	0.96	1.10	1.01
4	0.95	1.01	0.97
5	0.96	0.95	0.96
6	0.98	0.92	0.96
7	1.01	0.90	0.97
8	1.07	0.90	1.01
9	1.14	0.92	1.06
P10 - Winner	1.29	1.02	1.19
P10-P1	0.19***	-0.36***	-0.01
	(9.11)	(-13.44)	(-0.42)
N	394	218	612

Table 6: Number of Months and Signs of Beta in Different Market States Defined by Market Risk Premium

The formation period is defined as UP market if the past six-month formation period compound market return is greater than the contemporaneous six-month compound risk-free return and is defined as DOWN market if it is less than the six-month risk-free return. Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. Winner is defined as the portfolio who has the highest past six-month return (highest decile) while loser is defined as the portfolio who has the lowest past six-month return (lowest decile). Momentum portfolio is formed with a long position in the winner portfolio and a short position in the loser portfolio at the same time. Beta for each stock is estimated at the end of each month based on market model using CRSP daily stock prices 252 trading days prior to the estimation date. Each stock is required to have at least 252 day's trading record in order to estimate its beta. Portfolio beta is calculated as the value-weighted beta for each return decile portfolio.

Formation Market State	Holding Market State	Number of Months	Momentum Portfolio Beta		
			Sign	#	Percentage
UP	UP	269	Positive	183	68%
			Negative	86	32%
UP	DOWN	125	Positive	85	68%
			Negative	40	32%
DOWN	UP	121	Positive	16	13%
			Negative	105	87%
DOWN	DOWN	97	Positive	15	15%
			Negative	82	85%

Table 7: Monthly Formed Momentum Portfolio Average Monthly Returns in Different Market States Defined by Market Risk Premium

The formation period is defined as UP market if the past six-month formation period compound market return is greater than the contemporaneous six-month compound risk-free return and is defined as DOWN market if it is less than the six-month risk-free return. The holding period is defined as UP market if next six-month holding period compound market return is greater than the contemporaneous six-month compound risk-free return and is defined as DOWN market if it is less than the six-month risk-free return. Stock return data is from NYSE and AMEX common stocks listed on the CRSP monthly file. Sample period covers January 1965 to December 2015. Stocks with a price below $1 at the end of the formation period is excluded. Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. The holding period returns are calculated for month t to t + 5. Winner is defined as the portfolio who has the highest past six-month return (highest decile) while loser is defined as the portfolio who has the lowest past six-month return (lowest decile). Momentum portfolio is formed with a long position in the winner portfolio and a short position in the loser portfolio at the same time. Average monthly returns are calculated for each decile portfolio as well as momentum portfolio formed and held in different market states. Average monthly returns are also calculated without considering holding period market states (All). T-statistics are in parentheses. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%.

Panel A - Market Continuation and Reversal							
	Continuation		Reversal		All		Difference
	(A)		(B)				(A) - (B)
	Return	Beta	Return	Beta	Return	Beta	
P1 - Loser	0.55%	1.18	1.48%	1.24	0.92%	1.20	
P2	0.76%	1.05	1.51%	1.10	1.06%	1.07	
P3	0.93%	0.98	1.51%	1.05	1.16%	1.01	
P4	1.01%	0.95	1.49%	1.00	1.20%	0.97	
P5	1.09%	0.94	1.40%	0.98	1.21%	0.96	
P6	1.16%	0.94	1.35%	0.98	1.23%	0.96	
P7	1.19%	0.97	1.29%	0.98	1.23%	0.97	
P8	1.28%	1.00	1.24%	1.02	1.27%	1.01	
P9	1.42%	1.07	1.24%	1.05	1.34%	1.06	
P10 - Winner	1.67%	1.21	1.37%	1.17	1.55%	1.19	
P10-P1	1.13%***	0.03	-0.11%	-0.06*	0.63%***	-0.01	1.24%***
	(12.56)	(1.25)	(-0.41)	(-1.97)	(5.06)	(-0.42)	(4.98)
N	366	366	246	246	612	612	

Table 7 (continued)

Panel B - Formation UP

	Holding UP		Holding DOWN		All		Difference
	(C)		(D)				(C) - (D)
	Return	Beta	Return	Beta	Return	Beta	
P1 - Loser	1.51%	1.11	-1.77%	1.09	0.47%	1.10	
P2	1.69%	1.00	-1.07%	0.99	0.81%	1.00	
P3	1.83%	0.95	-0.83%	0.97	0.99%	0.96	
P4	1.83%	0.95	-0.73%	0.95	1.02%	0.95	
P5	1.89%	0.95	-0.61%	0.97	1.09%	0.96	
P6	1.91%	0.97	-0.62%	1.00	1.11%	0.98	
P7	1.94%	1.01	-0.62%	1.01	1.13%	1.01	
P8	2.07%	1.06	-0.66%	1.08	1.21%	1.07	
P9	2.28%	1.13	-0.72%	1.16	1.33%	1.14	
P10 - Winner	2.72%	1.28	-0.87%	1.30	1.58%	1.29	
P10-P1	1.20%***	0.17***	0.90%***	0.21***	1.11%***	0.19***	0.30%*
	(11.97)	(7.62)	(6.16)	(5.09)	(13.34)	(9.11)	(1.73)
N	269	269	125	125	394	394	

Panel C - Formation DOWN

	Holding UP		Holding DOWN		All		Difference
	(E)		(F)				(E) - (F)
	Return	Beta	Return	Beta	Return	Beta	
P1 - Loser	4.83%	1.39	-2.14%	1.36	1.73%	1.38	
P2	4.18%	1.22	-1.80%	1.17	1.52%	1.20	
P3	3.93%	1.14	-1.59%	1.05	1.47%	1.10	
P4	3.78%	1.05	-1.27%	0.96	1.53%	1.01	
P5	3.48%	1.00	-1.13%	0.90	1.43%	0.95	
P6	3.38%	0.97	-0.93%	0.85	1.46%	0.92	
P7	3.27%	0.94	-0.90%	0.85	1.41%	0.90	
P8	3.21%	0.95	-0.91%	0.84	1.37%	0.90	
P9	3.26%	0.94	-0.99%	0.89	1.37%	0.92	
P10 - Winner	3.68%	1.04	-1.23%	0.99	1.50%	1.02	
P10-P1	-1.15%**	-0.35***	0.91%***	-0.37***	-0.24%	-0.36***	-2.06%***
	(-2.23)	(-10.04)	(4.77)	(-8.91)	(-0.77)	(-13.44)	(-3.42)
N	121	121	97	97	218	218	

Table 8: Predicted and Actual Momentum Portfolio Return in Different Market States Defined by Market Risk Premium

The formation period is defined as UP market if the past six-month formation period compound market return is greater than the contemporaneous six-month compound risk-free return and is defined as DOWN market if it is less than the six-month risk-free return. Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. Winner is defined as the portfolio who has the highest past six-month return (highest decile) while loser is defined as the portfolio who has the lowest past six-month return (lowest decile). Momentum portfolio is formed with a long position in the winner portfolio and a short position in the loser portfolio at the same time. Beta for each stock is estimated at the end of each month based on market model using CRSP daily stock prices 252 trading days prior to the estimation date. Each stock is required to have at least 252 day's trading record in order to estimate its beta. Portfolio beta is calculated as the value-weighted beta for each return decile portfolio.

Market Condition	Average of Market Return	Average of Risk-free Rate	Market Risk Premium	Momentum Portfolio Beta	CAPM Predicted Momentum Return	Actual Momentum Return
	(A)	(B)	(C)=(A)-(B)	(D)	(E)=(C)x(D)	(F)
UP-UP	1.67%	0.35%	1.32%	0.17	0.22%	1.20%
UP-DOWN	-0.55%	0.42%	-0.97%	0.21	-0.20%	0.90%
DOWN-UP	2.70%	0.43%	2.27%	-0.35	-0.79%	-1.15%
DOWN-DOWN	-1.69%	0.49%	-2.18%	-0.37	0.81%	0.91%

Table 9: Factor Loadings of Fama-French Three-Factor Regression in Different Market States

Stock return data is from NYSE and AMEX common stocks listed on the CRSP monthly file. Sample period covers January 1965 to December 2015. Stocks with a price below $1 at the end of the formation period is excluded. Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. The holding period returns are calculated for month t to t + 5. Winner is defined as the portfolio who has the highest past six-month return (highest decile) while loser is defined as the portfolio who has the lowest past six-month return (lowest decile). Momentum portfolio is formed with a long position in the winner portfolio and a short position in the loser portfolio at the same time. The formation period is defined as UP (DOWN) if past six-month formation period compound market return is greater (less) than the contemporaneous six-month compound risk-free; defined as SMB positive (negative) if the past six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative); and defined as HML positive (negative) if the past six-month compound High-Minus-Low (HML) portfolio return is positive (negative). Fama-French three-factor model regression factor loadings are reported for each decile and the momentum portfolio under different market states. Portfolio beta is the weighted average of individual stock beta weighted by its market value. Portfolio SMB and HML loading is the mean of all the stocks in the portfolio. T-statistics are in parentheses. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%.

	Beta			SMB			HML		
	Formation UP	Formation DOWN	Overall	Formation Positive	Formation Negative	Overall	Formation Positive	Formation Negative	Overall
P1 - Loser	1.11	1.30	1.17	0.76	1.03	0.88	0.17	0.44	0.28
2	1.01	1.18	1.07	0.59	0.84	0.70	0.23	0.38	0.29
3	0.97	1.10	1.01	0.52	0.73	0.61	0.25	0.35	0.29
4	0.96	1.01	0.98	0.51	0.64	0.56	0.27	0.32	0.29
5	0.97	0.98	0.97	0.51	0.57	0.54	0.27	0.30	0.28
6	0.99	0.96	0.98	0.54	0.52	0.53	0.29	0.28	0.29
7	1.01	0.94	0.99	0.59	0.48	0.54	0.30	0.26	0.29
8	1.06	0.96	1.02	0.65	0.47	0.57	0.32	0.24	0.29
9	1.14	0.98	1.08	0.77	0.51	0.65	0.36	0.22	0.30
P10 - Winner	1.28	1.08	1.21	1.00	0.66	0.85	0.40	0.16	0.31
P10-P1	0.17***	-0.22***	0.03**	0.24***	-0.37***	-0.03*	0.23***	-0.27***	0.03
	(8.86)	(-9.33)	(2.00)	(11.63)	(-19.15)	(-1.74)	(12.51)	(-9.56)	(1.46)
N	394	218	612	339	273	612	367	245	612

Table 10: Number of Months and Signs of SMB Factor Loading in Different Market States Defined by Small-Minus-Big (SMB) Premium

The formation period is defined as SMB positive (negative) market if the past six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative). The holding period is defined as SMB positive (negative) market if the next six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative). Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. Winner is defined as the portfolio who has the highest past six-month return (highest decile) while loser is defined as the portfolio who has the lowest past six-month return (lowest decile). Momentum portfolio is formed with a long position in the winner portfolio and a short position in the loser portfolio at the same time. Fama-French three-factor model regression SMB factor loading is reported for each decile and the momentum portfolio under different market states. Portfolio SMB loading is the mean of all the stocks SMB factor loadings in the portfolio.

Formation Market State	Holding Market State	Number of Months	Momentum Portfolio SMB Factor Loading		
			Sign	#	Percentage
Positive	Positive	193	Positive	141	73%
			Negative	52	27%
Positive	Negative	146	Positive	111	76%
			Negative	35	24%
Negative	Positive	140	Positive	15	11%
			Negative	125	89%
Negative	Negative	133	Positive	17	13%
			Negative	116	87%

Table 11: Number of Months and Signs of HML Factor Loading in Different Market States Defined by High-Minus-Low (HML) Premium

The formation period is defined as HML positive (negative) market if the past six-month compound High-minus-Low (HML) portfolio return is positive (negative). The holding period is defined as HML positive (negative) market if the next six-month compound High-minus-Low (HML) portfolio return is positive (negative). Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. Winner is defined as the portfolio who has the highest past six-month return (highest decile) while loser is defined as the portfolio who has the lowest past six-month return (lowest decile). Momentum portfolio is formed with a long position in the winner portfolio and a short position in the loser portfolio at the same time. Fama-French three-factor model regression HML factor loading is reported for each decile and the momentum portfolio under different market states. Portfolio HML loading is the mean of all the stocks HML factor loadings in the portfolio.

Formation Market State	Holding Market State	Number of Months	Momentum Portfolio HML Factor Loading		
			Sign	#	Percentage
Positive	Positive	243	Positive	183	75%
			Negative	60	25%
Positive	Negative	124	Positive	89	72%
			Negative	35	28%
Negative	Positive	127	Positive	36	28%
			Negative	91	72%
Negative	Negative	118	Positive	29	25%
			Negative	89	75%

Table 12: Monthly Formed Momentum Portfolio Average Monthly Returns in Different Market States Defined by Small-Minus-Big (SMB) Premium

The formation period is defined as SMB positive (negative) market if the past six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative). The holding period is defined as SMB positive (negative) market if the next six-month compound Small-Minus-Big (SMB) portfolio return is positive (negative). Stock return data is from NYSE and AMEX common stocks listed on the CRSP monthly file. Sample period covers January 1965 to December 2015. It is required that each stock has at least 252 trading days return history in order to calculate its SMB factor loading. Stocks with a price below $1 at the end of the formation period is excluded. Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. The holding period returns are calculated for month t to t + 5. Winner is defined as the portfolio who has the highest past six-month return (highest decile) while loser is defined as the portfolio who has the lowest past six-month return (lowest decile). Momentum portfolio is formed with a long position in the winner portfolio and a short position in the loser portfolio at the same time. Average monthly returns are calculated for each decile and momentum portfolio formed and held in different size market states. Average monthly returns are also calculated without considering holding period market states (All). T-statistics are in parentheses. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%.

Panel A - Market Continuation and Reversal

	Continuation		Reversal		All		Difference
	(A)		(B)				(A) - (B)
	Return	SMB	Return	SMB	Return	SMB	
P1 - Loser	0.72%	0.87	1.15%	0.89	0.92%	0.88	
P2	0.83%	0.70	1.32%	0.70	1.06%	0.70	
P3	0.96%	0.62	1.39%	0.61	1.16%	0.61	
P4	1.05%	0.57	1.38%	0.56	1.20%	0.56	
P5	1.14%	0.55	1.30%	0.53	1.21%	0.54	
P6	1.19%	0.54	1.29%	0.52	1.23%	0.53	
P7	1.26%	0.56	1.19%	0.52	1.23%	0.54	
P8	1.41%	0.59	1.10%	0.55	1.27%	0.57	
P9	1.52%	0.67	1.14%	0.63	1.34%	0.65	
P10 - Winner	1.90%	0.87	1.15%	0.82	1.55%	0.85	
P10-P1	1.18%***	0.00	0.00%	-0.07***	0.63%***	-0.03*	1.18%***
	(8.57)	(-0.08)	(0.01)	(-2.58)	(5.06)	(-1.74)	(4.82)
N	326	326	286	286	612	612	

Table 12 (continued)

Panel B - Formation SMB positive

	Holding SMB Positive		Holding SMB Negative		All		Difference
	(C)		(D)				(C) - (D)
	Return	SMB	Return	SMB	Return	SMB	
P1 - Loser	2.31%	0.76	-0.98%	0.76	0.89%	0.76	
P2	2.12%	0.60	-0.39%	0.58	1.04%	0.59	
P3	2.09%	0.54	-0.11%	0.50	1.14%	0.52	
P4	2.05%	0.52	0.01%	0.49	1.17%	0.51	
P5	2.06%	0.52	-0.02%	0.50	1.17%	0.51	
P6	2.06%	0.55	0.07%	0.53	1.20%	0.54	
P7	2.16%	0.60	-0.02%	0.57	1.22%	0.59	
P8	2.36%	0.66	-0.13%	0.64	1.29%	0.65	
P9	2.59%	0.78	-0.16%	0.76	1.40%	0.77	
P10 - Winner	3.20%	1.01	-0.50%	0.98	1.61%	1.00	
P10-P1	0.89%***	0.25***	0.48%***	0.22***	0.71%***	0.24***	0.41%
	(4.15)	(8.80)	(3.67)	(7.60)	(5.30)	(-11.63)	(1.50)
N	193	193	146	146	339	339	

Panel C - Formation SMB negative

	Holding SMB Positive		Holding SMB Negative		All		Difference
	(E)		(F)				(E) - (F)
	Return	SMB	Return	SMB	Return	SMB	
P1 - Loser	3.37%	1.02	-1.59%	1.03	0.95%	1.03	
P2	3.12%	0.83	-1.03%	0.85	1.10%	0.84	
P3	2.95%	0.72	-0.67%	0.74	1.19%	0.73	
P4	2.81%	0.63	-0.41%	0.64	1.24%	0.64	
P5	2.68%	0.56	-0.20%	0.58	1.28%	0.57	
P6	2.56%	0.52	-0.08%	0.52	1.27%	0.52	
P7	2.45%	0.47	-0.04%	0.49	1.24%	0.48	
P8	2.39%	0.46	0.03%	0.48	1.24%	0.47	
P9	2.50%	0.50	-0.03%	0.52	1.27%	0.51	
P10 - Winner	2.87%	0.65	0.02%	0.67	1.48%	0.66	
P10-P1	-0.50%	-0.37***	1.60%***	-0.37***	0.53%**	-0.37***	-2.10%***
	(-1.24)	(-15.07)	(12.84)	(-12.23)	(2.36)	(-19.15)	(-4.91)
N	140	140	133	133	273	273	

Table 13: Monthly Formed Momentum Portfolio Average Monthly Returns in Different Market States Defined by High-Minus-Low (HML) Premium

The formation period is defined as HML positive (negative) market if the past six-month compound High-Minus-Low (HML) portfolio return is positive (negative). The holding period is defined as HML positive (negative) market if the next six-month compound High-Minus-Low (HML) portfolio return is positive (negative). Stock return data is from NYSE and AMEX common stocks listed on the CRSP monthly file. Sample period covers January 1965 to December 2015. It is required that each stock has at least 252 trading days return history in order to calculate its HML factor loading. Stocks with a price below $1 at the end of the formation period is excluded. Stocks are sorted at the end of each month t into deciles based on their prior six-month returns. The holding period returns are calculated for month t to t + 5. Winner is defined as the portfolio who has the highest past six-month return (highest decile) while loser is defined as the portfolio who has the lowest past six-month return (lowest decile). Momentum portfolio is formed with a long position in the winner portfolio and a short position in the loser portfolio at the same time. Average monthly returns are calculated for each decile and momentum portfolio formed and held in different size market states. Average monthly returns are also calculated without considering holding period market states (All). T-statistics are in parentheses. Significance levels are indicated as follows: * = 10%, ** = 5%, *** = 1%.

Panel A - Market Continuation and Reversal

	Continuation		Reversal		All		Difference
	(A)		(B)				(A) - (B)
	Return	HML	Return	HML	Return	HML	
P1 - Loser	0.51%	0.28	1.51%	0.27	0.92%	0.28	
P2	0.80%	0.29	1.44%	0.29	1.06%	0.29	
P3	0.94%	0.29	1.49%	0.29	1.16%	0.29	
P4	0.97%	0.30	1.54%	0.27	1.20%	0.29	
P5	1.02%	0.30	1.50%	0.27	1.21%	0.28	
P6	1.01%	0.30	1.55%	0.26	1.23%	0.29	
P7	1.05%	0.31	1.49%	0.26	1.23%	0.29	
P8	1.11%	0.31	1.49%	0.26	1.27%	0.29	
P9	1.19%	0.33	1.56%	0.26	1.34%	0.30	
P10 - Winner	1.48%	0.34	1.65%	0.25	1.55%	0.31	
P10-P1	0.97%***	0.06**	0.14%	-0.02	0.63%***	0.03	0.83%***
	(9.16)	(2.53)	(0.55)	(-0.84)	(5.06)	(-1.46)	(3.30)
N	361	361	251	251	612	612	

Table 13 (continued)

Panel B - Formation HML positive

	Holding HML Positive (C)		Holding HML Negative (D)		All		Difference (C) - (D)
	Return	HML	Return	HML	Return	HML	
P1 - Loser	0.51%	0.20	1.28%	0.12	0.77%	0.17	
P2	0.82%	0.24	1.41%	0.21	1.02%	0.23	
P3	0.96%	0.26	1.55%	0.22	1.16%	0.25	
P4	1.00%	0.28	1.60%	0.23	1.20%	0.27	
P5	1.02%	0.29	1.61%	0.25	1.22%	0.27	
P6	1.04%	0.31	1.66%	0.26	1.25%	0.29	
P7	1.08%	0.32	1.66%	0.26	1.28%	0.30	
P8	1.14%	0.35	1.67%	0.27	1.32%	0.32	
P9	1.20%	0.38	1.78%	0.30	1.39%	0.36	
P10 - Winner	1.35%	0.44	2.05%	0.33	1.58%	0.40	
P10-P1	0.84%***	0.24***	0.77%***	0.20***	0.81%***	0.23***	0.07%
	(7.06)	(10.90)	(3.04)	(6.31)	(7.03)	(-12.51)	(0.27)
N	243	243	124	124	367	367	

Panel C - Formation HML negative

	Holding HML Positive (E)		Holding HML Negative (F)		All		Difference (E) - (F)
	Return	HML	Return	HML	Return	HML	
P1 - Loser	1.73%	0.42	0.51%	0.46	1.14%	0.44	
P2	1.47%	0.37	0.76%	0.39	1.13%	0.38	
P3	1.43%	0.35	0.88%	0.35	1.16%	0.35	
P4	1.48%	0.31	0.91%	0.33	1.21%	0.32	
P5	1.39%	0.29	1.01%	0.31	1.21%	0.30	
P6	1.45%	0.27	0.96%	0.29	1.21%	0.28	
P7	1.32%	0.25	0.98%	0.28	1.16%	0.26	
P8	1.32%	0.24	1.04%	0.24	1.19%	0.24	
P9	1.35%	0.22	1.18%	0.22	1.27%	0.22	
P10 - Winner	1.26%	0.17	1.75%	0.15	1.50%	0.16	
P10-P1	-0.47%	-0.25***	1.24%***	-0.30***	0.35%	-0.27***	-1.71%***
	(-1.06)	(-6.83)	(5.88)	(-6.73)	(1.38)	(-9.56)	(-3.40)
N	127	127	118	118	245	245	