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Hongwei Chuang
International University of Japan

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Hongwei Chuang†

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Abstract

We find high momentum stocks with preserving substantial "fundamental value" are more likely to rebound after unexpected financial shocks. The portfolio test show that our proposed investment strategy can inherit more portfolio downside risk, especially the momentum crash during turbulent times.

Keywords: Momentum; Financial Crisis; Fama-French Factors; Systemic Risk

JEL Codes: G11, G12, G14

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†Chuang is the corresponding author at the Graduate School of International Management, International University of Japan. Tel.: +81-25-7791531. E-mail address: hongwei@iuj.ac.jp.

1 Introduction

Value investing and momentum strategies have been successfully implemented to different financial markets and many assets; however, as Asness, Moskowitz and Pedersen (2013)'s recent empirical findings demonstrate, the two different philosophies of investing strategies work effectively at a respective time, and their portfolio returns seem to be negatively correlated. The finding is against what the modern portfolio theory has suggested – any investment strategies should not be assessed in isolation but in the context of a broader portfolio. To achieve this goal, this study proposes a way to construct an investing portfolio by decomposing the momentum return of a stock and linking it to a firm's measurement of fundamental value based on price-scaled accounting variables. Using the example of intermediate profitability in the US stock market, we show our proposed strategy can inherit more downside risk during financial crisis, especially eliminating momentum crash in turbulent times of stock market.

Equation (1) is the driving horse of this paper which shows the momentum return of a stock from $t - \tau$ to t, i.e., $r_{t-\tau,t}$, can be decomposed as:

$$r_{t-\tau,t} = (f_{t-\tau} - f_t) + \log\left(\frac{A_t}{A_{t-\tau}}\right) + ADJ_{t-\tau+1,t}, \tag{1}$$

where first and second terms are the log changes of a price-scaled accounting variable[1] and the book value for this accounting variable from time $t - \tau$ to t, respectively. The last term, $ADJ_{t-\tau+1,t}$, is this firm's unanticipated components over this period as having adjusted for dividends, stock splits, and so on.

The intuition behind our paper is from equation (1) that we can see the difference between momentum return, $r_{t-\tau,t}$, and tangible returns, $\log(b_t/b_{t-\tau})$, which can be explained by accounting performance measures, $\log(f_{t-\tau}/f_t)$ and that is related to accounting growth, i.e., some fundamental "intrinsic" value of a firm. In our empirical work below, we empirically

[1] Such as book-to-market (BM), earnings-to-price, sales-to-price, dividend-to-price, and cash-flow-to-price ratios.

investigate and test the quantity on the right-hand side of equation (1) with its future stock returns. When a firm that receives terrible news about future growth options, for example, financial crisis; this information will not affect its book value, but the market value will decrease in response to the bad news, thereby increasing the firm's fundamental value. If a firm's value (book value) remains stable within an accounting year, any unexpected shock causes a systemic risk, resulting in *every* stock's market share price falling dramatically. In such a circumstance, a stock's price trend just tentatively deviates from its predicted intrinsic values, stocks in strong firms will be more likely to resume to the "normal" after a period of high volatility in the market.

To illustrate this idea, Figure 1 demonstrates the trends of book-to-market (BM) ratio and share price of Bank of America (BAC) from 1973 through 2013.[2]

[Place Figure 1 about here]

In the aftermath of the 2009 financial crisis, when BAC's BM ratio was at a relative peak, the share prices following were more likely to be rising instead of falling. Although a high BM ratio of a stock after a financial crisis may not be surprising, it could merely reflect how low the market share price if the firm's book value doesn't change dramatically. However, the pattern observed in Figure 1 challenges standard portfolio theory. Figure 1 shows that stock prices can move for reasons that are orthogonal to current performance information. Although we know BM ratios are unusually high during recessions, financial crises and the aftermath of market crashes, when theory generally suggests investors should, if anything, be more risk averse relative to normal times. Adversely, from the perspective of investors, a widely held view was that those who reduced positions in equities were missing a once-in-a-generation buy opportunity such as Moreira and Muir (2017) they argue. Sharpening the puzzle is the fact that investors' willingness to take part in the stock market seems to be

[2]The reason why we choose a financial stock to express our idea follows the research of Daniel and Moskowitz (2016) in which they also include financial stocks in conducting the momentum portfolios. Most empirical asset pricing studies should not exclude financial stocks from their sample that will cause the issue of sample selection bias.

higher when the stock market has high BM ratios, which runs counter to most theories.

Moreover, after a financial crisis, a momentum investor is often unable to identify whether a stock belongs to a past winner/loser or not, making it difficult for such an investor to form an investment portfolio without the danger of time-varying risk. When the market rebounds, misidentified past-winner stocks admitted to high drawdown risk and misidentified past-loser stocks, tend to rise instead of fall as a result. This causes the momentum portfolio to crash (Daniel and Moskowitz (2016)), as shown in Figure 3. Researches have shown that momentum crashes are especially profound during economic recessions and clustered when the market rebounds after unexpected market shocks. Furthermore, we also show that the investment portfolios of the momentum strategy seem to be exposed to a common risk and their behaviors are positively correlated in Figure 5. If an investor implemented the momentum strategy over the period from 1927 to 2013, only 15% of investment portfolios would go in the "right" direction – stocks that have gone up (past winners) tend to continue rising, and stocks that have gone down (past losers) tend to continue sliding.

From the perspective of portfolio choice, it is particularly difficult to choose stocks when the market rebounds after a financial crisis. A standard value investor would take less risk when the market is unattractive (in collapse) and more risk when the market is attractive (in rebound). In contrast, a conventional momentum investor focuses on stocks that are misidentified because of unexpected economic shocks without recognizing the fundamental information of a stock.

Our proposed investment portfolio, value-decomposed momentum portfolio, (denoted by Ti-MOM in Section 3.1), reconciles the conflict between value investment and the momentum strategy. The proposed portfolio combines the long-only value and long/short momentum investment strategies but also eliminate the associated idiosyncratic risks. We also show that a typical investor can benefit from the long-only value-decomposed momentum portfolio. The strategy can generate a significant 2.45% monthly average portfolio return with slightly negatively skewed and less kurtosis than the conventional momentum strategy. Notably,

in the aftermath of the share price declines in the fall of 2008, our approach recommends investors to keep the stocks with high intrinsic fundamental values during unexpected systemic shocks. This strategy takes substantially less risk and earns significantly higher profits during financial crises throughout several crisis episodes, including the 1987 stock market crash, the 2000 DotCom bubble, and the recent 2009 sub-prime mortgage crisis.

In Section 4, we conduct more comprehensive tests to evaluate the robustness of our empirical results by using the nested regression models. We examine whether the time-varying price risk factors can explain the value-decomposed portfolio return. Over the past two decades, Fama and French (1993, 1996, 2015, 2018) have already offered a good description of the performances on portfolios formed by size, book-to-market ratio, and others. These models not only would have provided consistently good returns but were also mostly uncorrelated with factors in credit risk for bonds and macroeconomic values such as inflation. We find the profit of the investment portfolio cannot be entirely subsumed by existing price risk factors controlling for a recession dummy. The empirical results of nested regression models in Table 5 show that the conventional momentum portfolio is complemented by the value-decomposed momentum portfolio. We find value and profitability price risk factors significantly explain the traditional momentum portfolio returns, whereas the other three price risk factors – market excess return, size, and investment – significantly explain the value-decomposed momentum portfolio returns.

Lastly, we study a value-decomposed version of the betting-against-beta factor and show our approach can also be embedded in a cross-sectional asset pricing model. The regression results also motivate us in developing a systemic risk index, market Ti-BM, in Section 4.3. The stability of the financial system and the potential of systemic risks to alter the functioning of this system have long been famous for central banks and related research communities. For example, Ibragimov, Jaffee and Walden (2011) argue that the recent financial crisis has significant externalities and systemic risks arising from the interconnectedness of financial intermediary risk portfolios. The negative externalities occur because intermediaries' actions

to diversify, which is optimal for an individual intermediary, may prove to be suboptimal for society. Billio, Getmansky, Lo and Pelizzon (2012) introduce a methodology to construct networks of spillover effects among financial institutions. Guarding against systemic risk in the financial system is yet a new issue. However, explicitly defining this type of risk and managing it is difficult. As the time series plot in Figure 8 later shows, we find that when the market Ti-BMs are relatively low, market prices are in relative troughs, and vice versa.

The paper is organized as follows. Section 2 revisits the momentum strategy. Section 3 documents the sample for our analysis, states the methodology and presents the main empirical results. Section 4 establishes the regression analysis with existing risk factors and discusses the implication of structural asset pricing models. Section 5 concludes.

2 Revisit Momentum Investing

Our analysis starts by examining the predictability patterns in the cross-sectional stock returns. These are particularly interesting since this research has been an important building block for quantitative asset management, as witnessed by the sizable exodus of finance academics into the private sector. Over the past decades, financial economists have puzzled over two contradictory observations: one is the reversal effect – i.e., past three-to-five-year stock losers tend to outperform past three-to-five-year winners[3] – and the other is the momentum effect, i.e. recent (six-to-twelve-month) stock price winners tend to outperform recent stock price losers. The reversal and momentum findings might be seen as inconsistent at first; however, the key difference is that the reversal finding conditions on lagged returns from three to five years, while the momentum one conditions on recent lagged stock price performance from six to twelve months.[4]

[3]A related finding is a value versus growth: stocks with low price to fundamentals such as sales, earnings, cash flow and dividends (i.e., value stocks) tend to outperform those with high multiples (i.e., growth stocks). See the prominent interpretations of these effects offered by DeBondt and Thaler (1985, 1987), Fama and French (1992, 1993, 1995, 1996) and Lakonishok, Shleifer and Vishny (1994).

[4]There is considerable debate in the academic literature on the source of the momentum premium: see Daniel, Hirshleifer and Subrahmanyam (1998), Barberis, Shleifer and Vishny (1998), Hong and Stein (1999),

2.1 Momentum Portfolios Construction

The momentum strategy typically disentangles the intermediate horizon momentum effect from the short reversal effect documented by Jegadeesh (1990), Lehmann (1990) and Jegadeesh and Titman (1993). The momentum strategy is an easily implemented investment strategy which forms a hedged portfolio to buy the top 10% accumulated return stocks (winners) over the previous three to twelve months in the market and sell the bottom 10% accumulated return ones (losers) at the same time. Surprisingly, this hedged portfolio will exhibit substantial profit for up to one year.

Moreover, the momentum effect has been observed not only in the US stock market but also in other financial assets and stock markets.[5] This anomaly drives a juggernaut through one of the tenets in financial theory, the efficient market hypothesis, the weak-form of which says that past stock price movements should provide no information about future stock price changes. In a sense, investors in the market should have no logical reason to prefer recently rising stocks to recently falling ones. Although these results have been widely accepted, researchers are still in debate over the sources of the profit and the interpretation of the evidence. Also, the significant profit cannot be subsumed by controlling for other risk factors such as size and the book-to-market ratio or explained away by saying that high-performance stocks are riskier or by arguing that the trading cost would eat up all the profit.

Constructing the momentum portfolio only requires the data on stock returns from CRSP. The sample period for the momentum strategy that we examine can, therefore, go back to 1926. The data for analysis consists of all domestic, primary stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (AMEX) and Nasdaq (NASDAQ)

George and Hwang (2004) and Grinblatt and Han (2005).

[5]For example, Okunev and White (2003) find a momentum effect in currencies; Erb and Harvey (2006) find a momentum effect in commodities; and Moskowitz, Ooi and Pedersen (2012) find a momentum effect in exchange-traded futures contracts. Besides, the momentum effect is worldwide. Rouwenhorst (1998) finds evidence of momentum effects in developed stock markets and Rouwenhorst (1999) documents momentum effects in emerging markets.

stock markets. We utilize only the returns on common shares with a 10 or 11 CRSP share code. Close-end funds, real estate investment trusts (REITs), unit trusts, American depository receipts (ADRs) and foreign stocks are excluded from the analysis. To reduce the microstructure effect associated with low-priced stocks, we exclude shares with a price below $1 during the formation periods. The CRSP data covers only NYSE firms up to 1962; AMEX firms were added in 1963 and NASDAQ firms in 1973.

Following the previous literature, we assign stocks that meet the data criteria mentioned above into ten equally weighted portfolios at the end day of each formation month (individually we sort them into ten decile portfolios labeled P1 to P10 according to their cumulative returns in the ranking period). We first rank the stocks based on their past 12-month returns excluding the most recent month. This momentum definition is currently most broadly used and readily available through the PR1YR factor of Carhart (1997). The 10% of firms with the highest ranking period returns are grouped into portfolio P10, which is the "BUY"-decile portfolio, and those with the lowest 10% ranking period returns are grouped into portfolio P1, which is the "SELL"-decile portfolio. The return on a zero-investment "B-S" portfolio is the difference between the returns on the BUY- and SELL-decile portfolios in each period, denoted by (12-1) momentum. Each portfolio is held for one month following the formation month. We calculate the holding monthly returns of "B-S" portfolios by using the equally weighted returns. Decile membership does not change in a month, except for the case of delisting. We also consider the overlapping portfolio approach, which is a strategy that holds a series of portfolios selected in the current month and the previous month.

The reason we choose 12-month returns for the formation of the momentum portfolio is that, as shown in Section 3.2, the most profitable momentum portfolio is formed according to a stock's past 12-month returns. Moreover, as Benartzi and Thaler (1995) pointed out, the period over which most agents seriously evaluate their investment performance is a year because they file their taxes and receive the most comprehensive mutual fund reports once a year. Also, institutional investors scrutinize their money managers' performance most

carefully on an annual basis. Therefore, investors monitor fluctuations in the value of their stock portfolio from year to year and get utility from those fluctuations.

Table 1 presents the statistical characteristics of the decile portfolios' monthly returns from January 1927 to December 2013. For all portfolios, Mean, SE, Skew and Kurt denote the full-period realized mean, standard deviation, skewness, and kurtosis, respectively. The average monthly return is 1.76% on the BUY portfolio and 0.48% on the SELL portfolio. A market-neutral strategy, the B-S portfolio, produces a profit of 1.27% per month. The empirical results are consistent with the momentum literature.

[Place Table 1 about here]

Figure 2 calculates the compound returns[6] for investing \$1 initially in (i) the risk-free asset (RF), (ii) the market (MKT), (iii) the B-S portfolio, (iv) the BUY portfolio and (v) the SELL portfolio, from 1927 to 2013, a total of 1,044 months. On the right side of the plot, we show the final dollar values for each of the five portfolios: \$1,744,883 for the BUY, \$34,356 for the B-S, \$3,579 for the market, \$20 for the risk-free asset and \$1 for the SELL. Indeed, the momentum strategy brings a significantly high return.

[Place Figure 2 about here]

2.2 Momentum Crash

However, many investigators have argued that momentum strategies display characteristics that are often associated with factors of price risk. Chordia and Shivakumar (2002) reveal that the profits of momentum strategies exhibit strong variation across the business cycle. They show that the conventional momentum strategy earns a 14.70% annualized return during expansions and loses 8.70% during recessions over the period from January 1930 to

[6] The compound return on an implementable strategy is based on investment at time 0 and fully reinvesting at each subsequent time point. During the investment period, no cash is put in or taken out. From time t to T, the compound return is computed as $\sum_{s=t+1}^{T}(1+r_s)$, where r_s is the s-period portfolio return.

December 2009. Cooper, Gutierrez and Hameed (2004) further examine the variation in average returns to US equity momentum strategies. They find in "UP" states, which are defined by the lagged three-year return of the market, that the historical mean of returns of an equally weighted momentum strategy is 0.93% per month. In "DOWN" states, the historical mean of returns of an equally weighted momentum strategy is -0.37% per month. That means those losers often experience strong gains after the market collapses.

Table 2 presents the ten worst-month returns of the (12-1) momentum strategy from January 1927 to December 2013, which also gives the contemporaneous monthly returns of the market, as well as the lagged one-year and two-year returns on the market. We can find that the ten worst-month returns of the (12-1) momentum strategy occur in the months in which the market rose contemporaneously during the turbulent periods, often in a dramatic fashion.

[Place Table 2 about here]

Kelsey, Kozhan and Pang (2011) argue that momentum is more likely to continue for downward trends in a highly uncertain market. Chuang and Ho (2014) find the momentum effect can be substantial if low-price-risk stocks form the portfolio. Daniel and Moskowitz (2016) also characterize the strong momentum reversals that are caused by the significant negative skewness of the (12-1) momentum portfolio. It is true that in Table 1, we find the skewness of the SELL and BUY portfolios to be 2.078 and 0.669, respectively, so the SELL portfolio's skewness is triple the BUY portfolio's. Since the SELL portfolio is considerably more positively skewed than the BUY portfolio, this yields a sizable negative skewness of -2.682 for the (12-1) momentum portfolio. Moreover, the kurtosis of the SELL and BUY portfolios is 16.479 and 10.554, respectively resulting in the kurtosis of the (12-1) momentum portfolio being 23.718, which is also quite large.

Figure 3 plots the time series of (12-1) momentum portfolio returns. Due to the highly skewed returns of the momentum strategies, the market appears to under-react to public

information in "normal" environments, resulting in consistent price momentum. However, in extreme market environments, the market prices of severe past losers embody a very high premium and investors who implemented the momentum strategy would experience strings of negative returns, especially after a market collapse. For example, a momentum investor would have lost 41.89% in the US stock market at the turning-point occurrence in April 2009. Momentum crashes are even clustered to span several months.

[Place Figure 3 about here]

Figure 4 shows the compound return of momentum profit if the momentum strategy is only implemented after 2000. Compared with the compound return from investing in the market over the period, the momentum portfolio does worse. In particular, there is a massive drop during the 2009 financial crisis. When market conditions improve, these losers experience strong gains, resulting in a momentum crash, as stated in Daniel and Moskowitz (2016). They explain that, in a bear market, the SELL portfolio behaves like a call option on the market and that the value of this option is not adequately reflected in the prices of these assets. This leads to a high expected return on the losers in bear markets, and a low expected return to the (12-1) momentum portfolio that shorts these SELL portfolios. Because the value of an option on the market is increasing in the market variance, this interpretation further suggests that the expected return to the (12-1) momentum portfolio should be a decreasing function of the future variation of the market.

[Place Figure 4 about here]

Figure 5 takes one more step of our analysis to examine the portfolio return distribution of the BUY and SELL portfolios. During the sample period, the B-S portfolio returns (in red dots) less than -10% in 41 out of 1,044 months. All these red dots are distributed in quadrants I and III, which means the returns of the BUY and SELL portfolios tend to be positively correlated with each other and seem to be affected by common exposure to some risk factors. The portfolio returns of BUY and SELL are in quadrants I and III for

48.5% and 33.5% of 1,044 months, respectively. This contracts with a momentum investor's expectation, i.e., momentum investors anticipate that the BUY portfolio will rise while the SELL one will fall in the month following the formation date. Thus, the BUY and SELL portfolio returns should be located in quadrant IV; however, only 156 months out of 1,044 are in quadrant IV. It turns out that 15% of momentum portfolios are thriving, with their returns moving in the direction anticipated by the momentum strategy.

[Place Figure 5 about here]

3 Portfolio Tests

We combine several datasets to produce the sample for analysis. We use CRSP data for stock prices and returns and the merged COMPUSTAT annual data (supplied by CRSP) for all accounting information and the number of shares. To combine the CRSP and COMPUSTAT data, we use CRSPLink. Both the risk-free rate of return and the market return are from the data library of Kenneth R. French.[7] Appendix A provides the details of how we measure a firm's book and market values and how we calculate the BM ratio.

In this section, we use the decomposition of fundamental value in equation (A5) to construct a trading strategy, the Ti-momentum strategy and apply it to the CRSP data. All the stocks examined to satisfy the criteria prescribed in Section 2. Construction of our value-decomposed momentum portfolio requires accounting information from COMPUSTAT, which is available from 1950. Although we know that CRSP monthly files start from 1926 and COMPUSTAT annual data runs from 1965, in the following analysis, we start the analytical period in 1965 to ensure the reliability of the accounting information.

[7] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

3.1 Ti-Momentum Strategy

The investment strategy we propose is called the Ti-momentum strategy (Ti-MOM for short). In each formation month t, we assign the stocks to one of ten portfolios based on their cumulative returns over the previous 12 months with the most recent month excluded, as described in Section 2.1. For the momentum strategy, the 10% of firms with the highest-ranking period returns are labeled portfolio P10, the "BUY"-decile portfolio, and the 10% of firms with the lowest-ranking period returns are assigned to portfolio P1, the "SELL"-decile portfolio. Stocks are then dependently sorted by their calculated Ti-values based on equation (A5) into five equal-size portfolios within each of these deciles. The first ranking generates ten portfolios (from low to high denoted by P1 to P10) for the momentum strategy, and each of the ten portfolios produces five Ti-portfolios (from low to high indicated by B1 to B5), resulting in 10×5=50 test portfolios. Our focus is on the returns of one-month-forward portfolio returns. The empirical results are shown in Table 3.

[Place Table 3 about here]

The mean values in the last column of Table 3 show that the pattern of the momentum strategy is still preserved, with the average returns for the P portfolios ranging from 0.48% for SELL to 2.15% for BUY. We also find the portfolio returns increase as the Ti-values increase as well. The monthly average returns for the B portfolios range from 1.07% for B1 to 1.39% for B5. The investment portfolio we propose is the long-only value-decomposed momentum portfolio, the "P10-B5" portfolio, which represents the investment portfolio consisting of stock with high momentum and high tangible returns.

Indeed, we find that the Ti-momentum strategy outperforms the momentum strategy. The Ti-momentum strategy generates a significant 2.45% average monthly portfolio return with slightly negative skew and lower kurtosis than for the statistics of the momentum strategy in Table 1. Looking at the time series plots for the momentum and Ti-momentum strategies in Figure 6, we can see that the Ti-momentum portfolio returns are more stable

than the momentum portfolio returns. Our approach avoids the considerable losses in April 2009, January 2001 and November 2002 of the (12-1) momentum strategy, gaining 12.09%, 27.86%, and 8.50% instead. The approach weakens the impact of these jump events on forming an investment portfolio during the turbulent period and produces a stable performance with upward profits.

[Place Figure 6 about here]

One can put forward a rationale for focusing on the long-only investment portfolio. Asness, Moskowitz and Pedersen (2013) suggest that a value and momentum investing system, which combines pure value and pure momentum into a single portfolio, may prevent a value-only investor or a momentum-only investor from suffering through extended, long-term stretches of poor performance. Moreira and Muir (2017) also propose a volatility-managed portfolio, which scales monthly returns by the inverse of the previous month's realized variance, for decreasing the risk of exposure to volatility. Of course, not all pain can be erased, and investors must always be aware that they should expect to endure sustained stretches of volatility and relative underperformance, even with a globally diversified value and momentum equity portfolio.

A plot of the compound returns of the two momentum-type strategies from January 1965 to December 2013 is presented in Figure 7, which shows that the profits made by the Ti-momentum and momentum portfolios are $259,265 and $1,896, respectively. It also shows that the BUY portfolio earned about $4,811, the market earned $107 and the SELL portfolio lost about 36% in December 2013 with the initial investment in January 1965. Depositing the money in the bank with a risk-free compound return produces a final value of $12 in the same period.

[Place Figure 7 about here]

3.2 (J-K) Table of Momentum and Ti-Momentum Strategies

In this section, we extend the above analysis to construct investment portfolios by considering past J-month stock returns and holding the investment portfolios in the following K months for different combinations of J and K using the momentum and Ti-momentum strategies. All the stocks examined to satisfy the criteria prescribed in Section 2.

In each formation month t, the stocks are first assigned to one of the ten portfolios based on their cumulative returns over the previous J months (J =3, 6, 9, 12) with the most recent month excluded, as described in Section 2.1. The 10% of firms with the highest-ranking period returns are filed in portfolio P10, the "BUY"-decile portfolio, and the 10% of firms with the lowest-ranking period returns are in portfolio P1, the "SELL"-decile portfolio. Stocks are then sorted by the Ti-value of each stock during the same period into five equal-size portfolios within each of these deciles and labeled B1 to B5. We hold the investment portfolio "P10-B5" for the following K months (K=1, 3, 6, 9, 12). The K-month holding period return is the equally weighted average returns of the proposed investment portfolio. Table 4 shows the results.

[Place Table 4 about here]

Panel A of the table represents the results under the momentum strategy for different combinations of J and K, while the results for the Ti-momentum strategy are in Panel B. We find that the Ti-momentum portfolio returns decrease as the holding period K increases. Also, the Ti-momentum portfolio returns tend to increase as the number of months J over which past returns are assessed increases. The pattern of Ti-momentum portfolio returns is similar to the pattern of momentum portfolio returns; however, the Ti-momentum portfolios exhibit less skewness and lower kurtosis. Overall, a consistent finding is that Ti-momentum portfolios generally have a higher return than momentum portfolios.

4 Regression Tests

It has been shown that average stock returns are related to some firm characteristics ((Fama and French, 1996)). From the well-known three-factor model of Fama and French (1993) to the most recent Fama and French (2015) five-factor model, factor asset pricing models offer a good description for the returns on portfolios formed by size, book-to-market ratio, and others. These models not only would have provided consistently good returns over the past two decades but were also largely uncorrelated with factors in credit risk for bonds and macroeconomic values such as inflation. The momentum strategy has been noted as often being associated not only with time-varying risks but also with some pricing factors. The nested models that we are going to examine in the following are the capital asset pricing model (CAPM) in which $R_{m,t} - R_{f,t}$ is the only explanatory variable, the Fama and French (1993) three-factor model, which adds size (SMB_t) and value (HML_t), and the Fama and French (2015) five-factor extension, which includes investment (RMW_t) and profitability (CMA_t).

4.1 Risk Factors and Portfolios

To assess whether the returns of the zero-investment (12-1) momentum portfolio and the Ti-momentum portfolio are consistent with Fama and French's factor models, we run a time-series regression with the five Fama–French factors as independent variables and include a recession dummy:

$$\begin{aligned} r_t^p = \alpha_t + \beta_{mkt} \cdot (R_{m,t} - R_{f,t}) + \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t \\ + \beta_{RMW} \cdot RMW_t + \beta_{CMA} \cdot CMA_t + \beta_{REC} \cdot D(REC_t) + \epsilon_t. \end{aligned} \tag{2}$$

In this equation, r_t^p is the month t investment portfolio return achieved by (12-1) momentum or Ti-momentum strategies. $R_{m,t} - R_{f,t}$ represents the market excess return in which $R_{f,t}$ is the one-month US Treasury bill rate observed at the beginning of t and $R_{m,t}$ is the return on

the equal-weight (EW) portfolio of NYSE, AMEX and Nasdaq stocks. SMB_t (small minus big) and HML_t (high minus low book-to-market equity) are the size and value factors of the Fama and French (1993) three-factor model and RMW_t (robust minus weak) and CMA_t (conservative minus aggressive) are the profitability and investment factors described in Fama and French (2015). $D(REC_t)$ equals 1 if month t is in a recession period as defined by the National Bureau of Economic Research (NBER).[8] The regression results are presented in Table 5.

[Place Table 5 about here]

For models I to IV, the dependent variable is the (12-1) momentum portfolio return. For models V to VIII, the dependent variable is the Ti-momentum portfolio return. In the framework of the Fama–French three-factor model, the momentum portfolio returns are significantly negatively correlated to the value factor (HML) but not significantly associated to the market ($R_{m,t} - R_{f,t}$) and size (SMB) factors. In contrast, the Ti-momentum portfolio returns are significantly positively correlated to the market and SMB but not considerably associated with HML. This result indicates that the momentum portfolio returns and the Ti-momentum portfolio ones are orthogonally explained by the Fama–French factors. When we control for recessions in regression models II and VI, the coefficient of the recession dummy tends to be negative but not significant. Moreover, the investment factor (CMA) is positively correlated with the momentum portfolio returns, as shown in models III and IV, and the profitability factor (RMW) is negatively associated with the Ti-momentum portfolio returns, as shown in models VII and VIII.

The characteristic feature of models I to IV in Table 5 is that the five Fama–French factors cannot fully explain the momentum portfolio returns, as shown by the low R-squared values. Since the Ti-value is based on the decomposition of the book-to-market ratio, we find that the R-squared values of models V to VIII are very much higher, at close to 83%. Furthermore, the performance of our Ti-portfolios from 1965 to 2013 seems more effective

[8] http://www.nber.org/cycles.html.

than the production of the HML risk factor. As shown in models V to VIII, HML tends to be negative and not significant.

4.2 Predictive Regression Models

We further test the link between the Ti-values and future stock returns using predictive regression models. The dependent variable is one-month future stock returns and is regressed on past Ti-values (Ti_t), market excess return, other control variables as in equation (2) and also three dummies to control for recession periods, NYSE size categories and industries. Our specification is as follows:

$$\begin{aligned} r^i_{t+1} = \alpha_t &+ \beta_{Ti} \cdot Ti^i_t + \beta_{mkt} \cdot (R_{m,t} - R_{f,t}) \\ &+ \beta_{SMB} \cdot SMB_t + \beta_{HML} \cdot HML_t + \beta_{RMW} \cdot RMW_t + \beta_{CMA} \cdot CMA_t \\ &+ \beta_{REC} \cdot D(REC_t) + \beta_{SIZE} \cdot D(SIZE^i_t) + \beta_{FFI48} \cdot D(FFI48^i_t) + \epsilon_{t+1}, \end{aligned} \quad (3)$$

where the industry dummy variable $D(FFI48_t)$ is defined as the 48-industry classification code obtained from Kenneth R. French's website.[9] Table 6 reports the results from this regression analysis.

[Place Table 6 about here]

Specifications (3) and (6) in Table 6 are our main focus. We find that the coefficient estimates of Ti-values significantly predict future stock returns even after adding a number of control variables. The results are robust and imply that a one-standard-deviation increase in Ti-value predicts growth in future profits of about 0.1%, net of the effects of all control variables.

[9] http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/det_48_ind_port.html.

4.3 Ti-Systemic Risk Index

When Queen Elizabeth visited the London School of Economics in 2008, she famously asked this question: "Why did nobody see it coming?" The 2008 financial crisis was, above all else, a crisis in and of the wholesale funding markets which arose when institutional investors stopped lending to any banks at any price. Since the crisis, the banks, although more tightly regulated and less leveraged, still require massive amounts of wholesale funding to sustain their balance sheets. This borrowing creates systemic risk, and this systemic risk is backstopped not by the banks but by public authorities.

The regression results motivate us to investigate further and test whether the value-decomposed approach can produce a systemic risk index to be used as a broad indicator of risk in the market. Systemic risk represents the threat of systemic failures in a financial system spilling over into the real economy. During periods of financial crisis, such as the 2008 subprime crisis in the US and the 2011 European sovereign debt crisis, policymakers and the private sector have demonstrated that they were inadequately prepared for such systemic risk. Most central bankers around the world primarily focus on fighting inflation, on maintaining financial stability but neglect the whole system.

A group of eminent economists has written to the Queen explaining why no one foresaw the timing, extent, and severity of the recession. Basically, they concluded "the failure to foresee the timing, extent, and severity of the crisis and to head it off, while it had many causes, was principally a failure of the collective imagination of many bright people, both in this country and internationally, to understand the risks to the system as a whole." The problem in following the methodology of financial networks is that it is hard to define the connectedness among stocks. As an alternative, we develop a simple index to measure systemic risk easily. Based on the plot of average Ti-values of all stocks in Figure 8, we find that market average tangible returns being relatively low indicates that market stock prices are in troughs. In contrast, if the market average tangible returns reach a peak, the following market stock prices will more likely be rising instead of falling. This systemic index could

lead the way to a better solution for preventing financial disasters happening again in the future.

[Place Figure 8 about here]

We also compare our systemic risk index with another systemic risk index, the CBOE Volatility Index (VIX).[10] VIX was calculated and published by the Chicago Board Options Exchange (CBOE) starting from 1991. It is a popular measure of the stock market's expectation of volatility implied by S&P 500 index options and is colloquially referred to as the fear index. As shown in Figure 8, our proposed index seems to behave in a complementary way to VIX concerning the whole risk to the stock market.

5 Conclusions

In past decades, financial academics and practitioners have recognized that the momentum strategy can generate significant profit and that the momentum effect exists in many financial markets. However, people pay little attention to the fact that the collapse of momentum is profound especially after a financial crisis. Momentum has its momentum and "crash." Share prices do not rise forever. Momentum crash is often attributed to the fact that the conventional momentum strategy exhibits substantial time-varying exposures to the market.

In this study, we first revisit the conventional momentum strategy in the US stock market from January 1927 to December 2013. We find that, during the sample period, only in 15% of 1,044 months was the long/short momentum strategy successful, with stocks that have gone up tending to continue rising and stocks that have gone down tending to keep sliding. Implementing the momentum strategy could not eliminate the risk-taking and reduced the profit of momentum portfolios.

We adjust the conventional momentum strategy based on the decomposition of past stock returns into, among others, the book-to-market ratio measuring the fundamental value of

[10] Our data is from the Federal Reserve Bank of St. Louis: https://fred.stlouisfed.org/series/VIXCLS#0.

a firm in the same period. The time-varying exposures of the conventional momentum strategy can be reduced by our proposed fundamental value adjustment. The idea is that when unexpected shocks happen, a firm is more likely to be undervalued if it has high momentum; therefore the stock price tends to rise instead of fall in the following month. Conversely, if a firm is overvalued when it has low momentum, the stock price tends to fall instead of growing. The strategy that we propose can adjust the short-term deviation of fundamental values of a stock within the framework of its intermediate continuation.

This decomposition can also be applied to other price-scaled accounting variables, but data mining worries should be weighed against the potential improvements from having multiple measures of value and momentum, if for no other reason than to diverse away measurement error or noise across variables. Israel and Moskowitz (2013) show, for instance, how another measure of value and momentum can improve the stability of returns to these styles in equities.

It is true, in real-world implementations, that the literature on these strategies has a long way to go. Some issues like data snooping or transaction cost are out of the scope of this paper, but it is essential to explore them in the future. Overall, the empirical results show the modification can mostly improve the conventional momentum strategy, suggesting that our proposed investment strategy could be a better way of managing portfolios. Furthermore, we look forward to seeing whether this new concept being applied to other financial assets, such as commodities and currencies; we hope it will work well.

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Tables

Table 1: Statistics of the (12-1) Momentum Portfolios, 1927–2013

Portfolios	Mean	SE	Skew	Kurt
P1 (SELL)	0.48%	0.0032	2.0783	16.4788
P2	0.88%	0.0026	1.7486	16.2835
P3	0.97%	0.0023	1.4155	14.0145
P4	1.09%	0.0023	1.7209	17.2160
P5	1.19%	0.0022	1.2580	14.4633
P6	1.27%	0.0021	0.9012	12.2149
P7	1.41%	0.0021	0.8679	11.1855
P8	1.50%	0.0022	0.8558	11.6965
P9	1.61%	0.0023	0.5819	8.3998
P10 (BUY)	1.76%	0.0027	0.6690	10.5539
B-S	1.27%	0.0021	-2.6819	23.7182

This table reports the statistics of the momentum portfolio returns from January 1927 to December 2013. All firms that meet the data requirements are included, as described in Section 2.1. These firms are sorted into 10-decile portfolios by their past 12-month cumulative returns excluding the most recent one. The top 10% of firms, which form the "BUY"-decile portfolio, is labeled as P10 and the bottom 10% of firms, which form the "SELL"-decile portfolio, is labeled as P1. The return on a zero-investment (12-1) momentum portfolio is the difference between the returns on the BUY-decile portfolio and those on the SELL-decile portfolio in each period. The holding duration for each portfolio is one month. The monthly portfolio returns are all equal-weighted. Mean, SE, Skew and Kurt denote the realized mean, standard error, skewness and kurtosis, respectively.

Table 2: Top 10 Worst (12-1) Momentum Portfolios, 1927–2013

Rank	Month	SELL	BUY	B-S	Mkt-RF	Mkt-RF-1Y	Mkt-RF-2Y
1	1932/08	99.25%	32.57%	-66.68%	37.06%	0.41%	0.30%
2	1932/07	77.56%	15.78%	-61.78%	33.84%	-6.62%	4.12%
3	1939/09	71.62%	25.73%	-45.89%	16.88%	0.81%	-13.61%
4	2009/04	49.31%	7.42%	-41.89%	10.19%	4.60%	3.49%
5	2001/01	51.74%	14.54%	-37.20%	3.13%	-4.74%	3.50%
6	2002/11	34.27%	7.04%	-27.24%	5.96%	1.61%	1.19%
7	1938/06	38.64%	14.30%	-24.33%	23.87%	-4.21%	2.40%
8	1975/01	41.33%	19.18%	-22.15%	13.66%	-0.17%	-3.29%
9	1931/06	28.53%	9.94%	-18.59%	13.90%	-16.27%	9.70%
10	1974/01	24.64%	6.17%	-18.47%	-0.17%	-3.29%	2.49%

This table lists the ten worst monthly returns to the (12-1) momentum portfolios from 1927 to 2013 (B-S). Also tabulated are the SELL and BUY portfolios, the two-year market excess return leading up to the portfolio formation date (Mkt-RF-2Y), the one-year market excess return leading up to the portfolio formation date (Mkt-RF-1Y) and the contemporaneous market excess return (Mkt-RF).

Table 3: Statistics of the Ti-Momentum Portfolios, 1965–2013

		B1	B2	B3	B4	B5	Mean
P1 (SELL)	Mean	0.84%	0.41%	0.11%	0.31%	0.72%	0.48%
	SE	(0.0037)	(0.0028)	(0.0026)	(0.0029)	(0.0039)	
	Skew	1.6365	0.6719	0.1717	0.3654	0.9114	
	Kurt	10.6767	5.4741	3.7007	2.4641	5.7318	
P2	Mean	1.07%	0.59%	0.61%	0.53%	0.84%	0.73%
	SE	(0.0030)	(0.0023)	(0.0021)	(0.0024)	(0.0033)	
	Skew	0.7575	0.0039	-0.3453	0.0329	0.5307	
	Kurt	6.2712	4.8426	3.7833	2.7784	3.8044	
P3	Mean	0.92%	0.85%	0.79%	0.74%	1.03%	0.87%
	SE	(0.0027)	(0.0021)	(0.0020)	(0.0023)	(0.0031)	
	Skew	0.4279	-0.1203	-0.2141	0.1514	0.4006	
	Kurt	6.3575	5.2947	4.6501	3.5826	3.2500	
P4	Mean	0.88%	0.88%	0.89%	0.94%	1.08%	0.93%
	SE	(0.0026)	(0.0020)	(0.0019)	(0.0021)	(0.0029)	
	Skew	0.2405	-0.2693	-0.4327	-0.4256	0.1075	
	Kurt	5.5430	5.6920	4.2302	2.3034	3.0511	
P5	Mean	0.98%	0.86%	1.08%	1.00%	1.28%	1.04%
	SE	(0.0027)	(0.0020)	(0.0019)	(0.0021)	(0.0028)	
	Skew	0.2798	-0.4335	-0.4332	-0.4844	0.0317	
	Kurt	5.7202	4.4418	3.8817	2.4141	2.5506	
P6	Mean	1.09%	1.14%	1.23%	1.20%	1.34%	1.20%
	SE	(0.0028)	(0.0021)	(0.0019)	(0.0021)	(0.0027)	
	Skew	0.2265	-0.5012	-0.4888	-0.6123	-0.3712	
	Kurt	3.5307	4.4688	4.7171	3.2087	2.8034	
P7	Mean	1.22%	1.24%	1.46%	1.39%	1.48%	1.36%
	SE	(0.0028)	(0.0021)	(0.0020)	(0.0022)	(0.0027)	
	Skew	0.2049	-0.5205	-0.2089	-0.6648	-0.4800	
	Kurt	4.1356	3.2805	3.9754	3.1285	2.4114	
P8	Mean	1.19%	1.43%	1.46%	1.56%	1.80%	1.49%
	SE	(0.0029)	(0.0023)	(0.0021)	(0.0022)	(0.0027)	
	Skew	-0.1596	-0.4845	-0.6147	-0.7037	-0.4681	
	Kurt	3.1063	3.4048	3.1642	3.3214	2.0690	
P9	Mean	1.27%	1.81%	1.87%	1.87%	1.92%	1.75%
	SE	(0.0032)	(0.0025)	(0.0023)	(0.0024)	(0.0029)	
	Skew	-0.0579	-0.4364	-0.6675	-0.6354	-0.4579	
	Kurt	3.3007	2.2225	3.0816	2.3466	2.2665	
P10 (BUY)	Mean	1.29%	2.32%	2.38%	2.33%	2.45%	2.15%
	SE	(0.0036)	(0.0030)	(0.0027)	(0.0029)	(0.0033)	
	Skew	-0.2792	-0.1737	-0.4953	-0.4303	-0.1042	
	Kurt	2.2476	2.6282	2.1431	1.9005	3.3543	
Mean		1.07%	1.15%	1.19%	1.19%	1.39%	

This table presents the monthly equal-weight portfolio returns for the Ti-momentum strategy. The sample period is from January 1965 to December 2013. The stocks are sorted on a monthly basis into ten decile portfolios according to their past stock returns × five equal-size portfolios conditional on their calculated Ti-values based on equation (A5). Mean, SE, Skew and Kurt denote the realized mean, standard error, skewness and kurtosis, respectively.

Table 4: Momentum Versus Ti-Momentum Portfolios, 1965–2013

Panel A: Momentum

$J=$	$K=$	1	3	6	9	12
3	Mean	0.82%	0.76%	0.69%	0.60%	0.52%
	SE	(0.0020)	(0.0017)	(0.0015)	(0.0014)	(0.0011)
	Skew	-1.2526	-2.0498	-2.4157	-3.3424	-1.9497
	Kurt	15.5714	22.9580	22.9307	34.5050	15.8547
6	Mean	1.13%	1.06%	0.93%	0.84%	0.58%
	SE	(0.0024)	(0.0023)	(0.0021)	(0.0017)	(0.0015)
	Skew	-2.1478	-2.1057	-2.8726	-1.9700	-1.1574
	Kurt	18.3578	18.5980	28.2486	17.3769	8.0814
9	Mean	1.21%	1.14%	1.03%	0.76%	0.46%
	SE	(0.0026)	(0.0025)	(0.0021)	(0.0019)	(0.0017)
	Skew	-2.0261	-2.3760	-1.6259	-1.0139	-0.8698
	Kurt	18.4247	21.7794	13.3787	6.5917	5.1959
12	Mean	1.48%	1.24%	0.89%	0.57%	0.26%
	SE	(0.0025)	(0.0023)	(0.0021)	(0.0019)	(0.0018)
	Skew	-1.2473	-0.9518	-0.8065	-0.7855	-0.9940
	Kurt	10.5197	8.3440	6.2552	4.9828	5.5041

Panel B: Ti-Momentum

$J=$	$K=$	1	3	6	9	12
3	Mean	1.71%	1.58%	1.61%	1.62%	1.57%
	SE	(0.0032)	(0.0030)	(0.0030)	(0.0030)	(0.0030)
	Skew	0.1671	-0.3952	-0.4142	-0.4031	-0.3407
	Kurt	5.0580	2.1117	1.9436	1.8624	1.8510
6	Mean	2.01%	1.94%	1.90%	1.85%	1.71%
	SE	(0.0032)	(0.0031)	(0.0031)	(0.0031)	(0.0030)
	Skew	0.0029	-0.3843	-0.4011	-0.3366	-0.2903
	Kurt	4.3044	2.1722	1.9270	1.8481	1.8260
9	Mean	2.38%	2.21%	2.09%	1.91%	1.73%
	SE	(0.0033)	(0.0032)	(0.0032)	(0.0031)	(0.0031)
	Skew	0.0265	-0.3475	-0.3104	-0.2764	-0.2566
	Kurt	4.3298	2.2100	2.0821	1.9787	1.9694
12	Mean	2.45%	2.18%	1.99%	1.82%	1.63%
	SE	(0.0033)	(0.0033)	(0.0032)	(0.0032)	(0.0031)
	Skew	-0.1042	-0.3074	-0.2485	-0.2132	-0.2612
	Kurt	3.3543	2.3192	2.3365	2.3110	2.1100

This table reports the monthly portfolio returns of the momentum and Ti-momentum strategies from January 1965 to December 2013. The portfolios are constructed by assigning the stocks into one of the ten portfolios based on their cumulative returns over the previous J months with the most recent month excluded, as described in Section 2.1. For the momentum strategy, the 10% of firms with the highest-ranking period returns are assigned to portfolio P10, the "BUY"-decile portfolio, and the 10% of firms with the lowest-ranking period returns are assigned to portfolio P1, the "SELL"-decile portfolio. The K-month holding period return on a zero-investment "B-S" portfolio is the difference between the returns on the BUY-decile portfolio and those on the SELL-decile portfolio in each period. The stocks are also sorted into five equal-size portfolios within each decile conditional on their calculated Ti-values based on equation (A5). The K-month holding period return is the difference between the returns on the BUY-decile portfolio conditional on 20% of firms with the highest Ti-values in each period. Mean, SE Skew and Kurt denote the realized mean, standard error, skewness and kurtosis, respectively.

Table 5: Nested Regression Models, 1965–2013

	(12-1) MOM				Ti-MOM			
Independent variables	I	II	III	IV	V	VI	VII	VIII
Intercept	**0.017**	**0.018**	**0.016**	**0.017**	**0.016**	**0.017**	**0.018**	**0.018**
	(0.0025)	(0.0027)	(0.0025)	(0.0027)	(0.0014)	(0.0016)	(0.0014)	(0.0016)
Risk factors								
$R_{m,t} - R_{f,t}$	-0.094	-0.103	-0.028	-0.037	**1.195**	**1.193**	**1.165**	**1.163**
	(0.0567)	(0.0571)	(0.0602)	(0.0604)	(0.0330)	(0.0332)	(0.0345)	(0.0346)
SMB_t	0.010	0.011	0.021	0.022	**1.125**	**1.126**	**1.029**	**1.029**
	(0.0806)	(0.0805)	(0.0858)	(0.0857)	(0.0468)	(0.0469)	(0.0491)	(0.0491)
HML_t	**-0.489**	**-0.490**	**-0.749**	**-0.757**	-0.071	-0.072	-0.064	-0.066
	(0.0879)	(0.0878)	(0.1165)	(0.1165)	(0.0511)	(0.0511)	(0.0667)	(0.0669)
RMW_t			0.082	0.083			**-0.363**	**-0.363**
			(0.1177)	(0.1176)			(0.0674)	(0.0674)
CMA_t			**0.578**	**0.594**			-0.041	-0.038
			(0.1721)	(0.1722)			(0.0985)	(0.0988)
Recession dummies		-0.009		-0.010		-0.002		-0.002
		(0.0067)		(0.0067)		(0.0039)		(0.0038)
R-squared	0.047	0.048	0.062	0.064	0.827	0.827	0.835	0.834

This table reports the results of nested regression models of equation (2). The dependent variables are (12-1) momentum and Ti-momentum portfolio returns while the independent variables are the five Fama–French factors: the market excess return ($R_{m,t} - R_{f,t}$), size (SMB_t), value (HML_t), profitability (RMW_t) and investment (CMA_t) factors from Kenneth R. French's data library. Recession dummies control for the recession periods defined by NBER. Numbers in bold represent significance at 1%. Standard errors are given in parentheses.

Table 6: Predictive Regression Models, 1965–2013

Independent variables	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	**-0.008**	**-0.003**	**-0.002**	**-0.012**	**-0.007**	**-0.006**
	(0.0005)	(0.0005)	(0.0005)	(0.0017)	(0.0017)	(0.0017)
Tangible information	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**	**0.001**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Risk factors						
$R_{m,t} - R_{f,t}$		**0.216**	**0.178**		**0.216**	**0.178**
		(0.0025)	(0.0027)		(0.0025)	(0.0027)
SMB_t		**0.141**	**0.113**		**0.141**	**0.113**
		(0.0035)	(0.0037)		(0.0035)	(0.0037)
HML_t		**-0.010**	**0.109**		**-0.010**	**0.109**
		(0.0037)	(0.0051)		(0.0037)	(0.0051)
RMW_t			**-0.136**			**-0.136**
			(0.0049)			(0.0049)
CMA_t			**-0.241**			**-0.241**
			(0.0076)			(0.0076)
Recession dummies	Yes	Yes	Yes	Yes	Yes	Yes
NYSE size dummies	Yes	Yes	Yes	Yes	Yes	Yes
Industry dummies	No	No	No	Yes	Yes	Yes
R-squared	0.20%	0.79%	0.87%	0.21%	0.80%	0.88%

This table reports the results of predictive models in equation (3). The dependent variable is stock i's $t+1$ return, while the independent variables are at time t and are defined in Table 5 with the addition of dummy variables controlling for stock i's industry and NYSE size categories. Numbers in bold represent significance at 1%. Standard errors are given in parentheses.

Figures

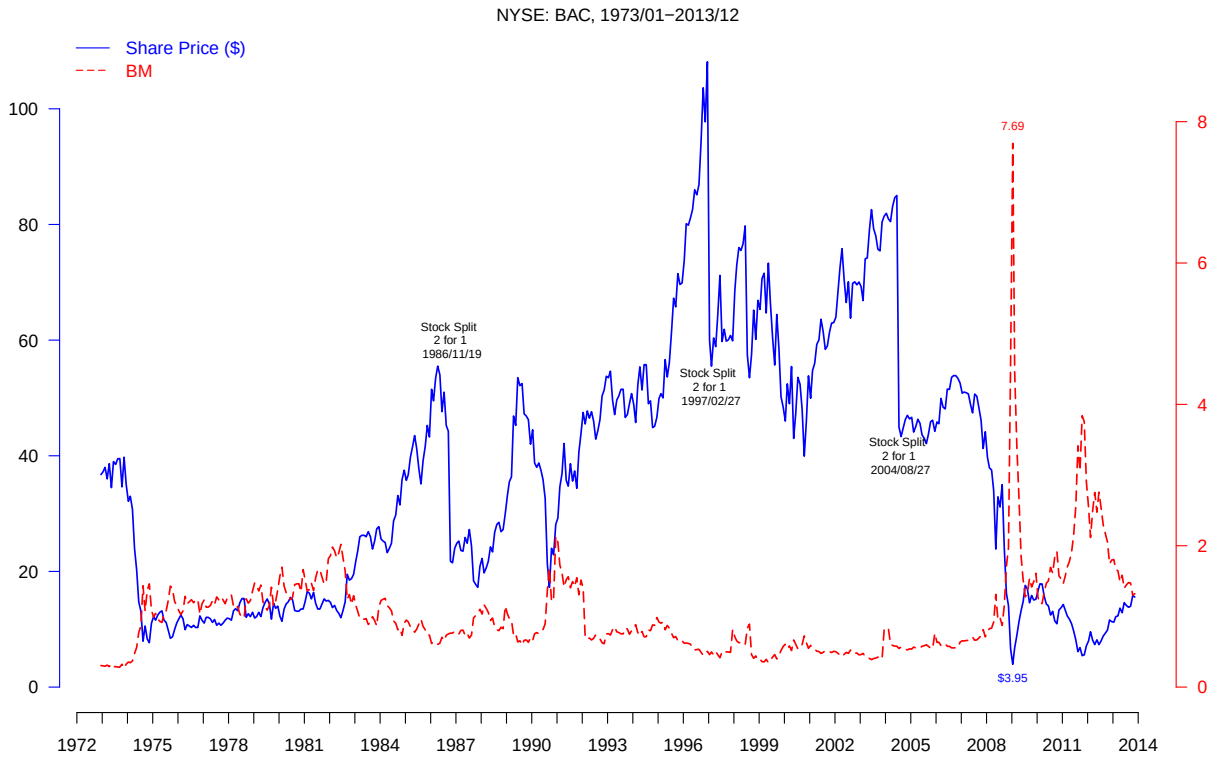

Figure 1: Bank of America, 1973/01–2013/12

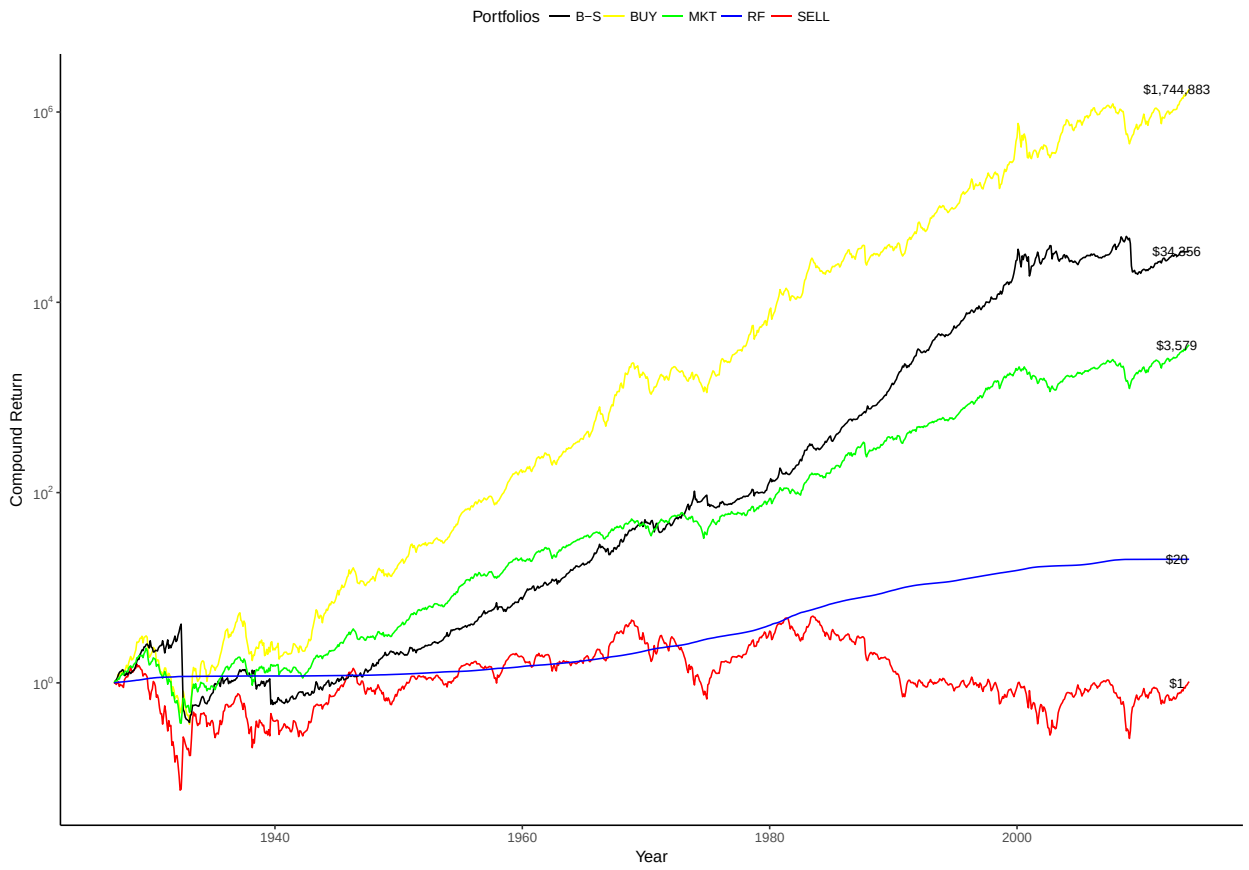

Figure 2: Compound Returns of Momentum Portfolios, 1927–2013

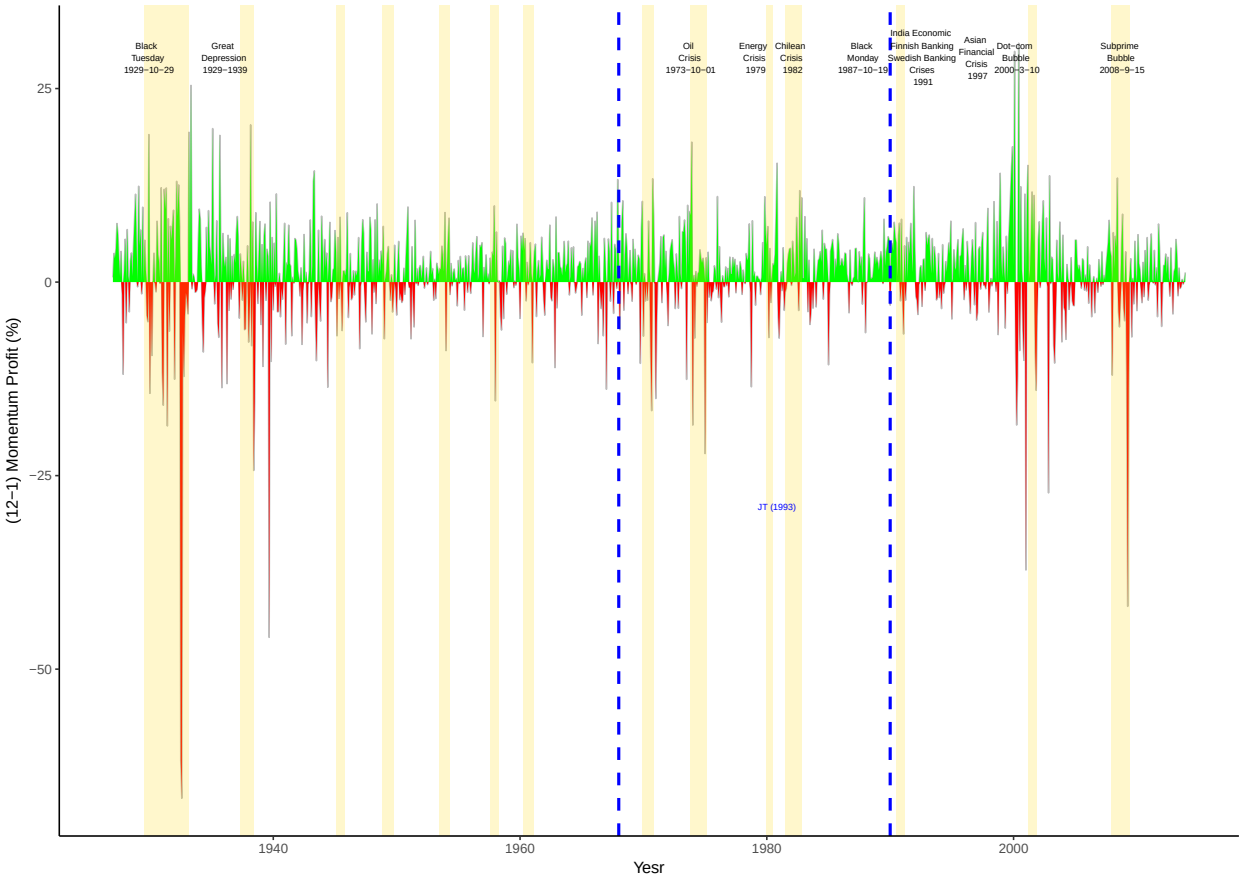

Figure 3: Momentum Crash, 1927–2013 (Jegadeesh and Titman (1993)'s sample periods are between the blue dashed lines)

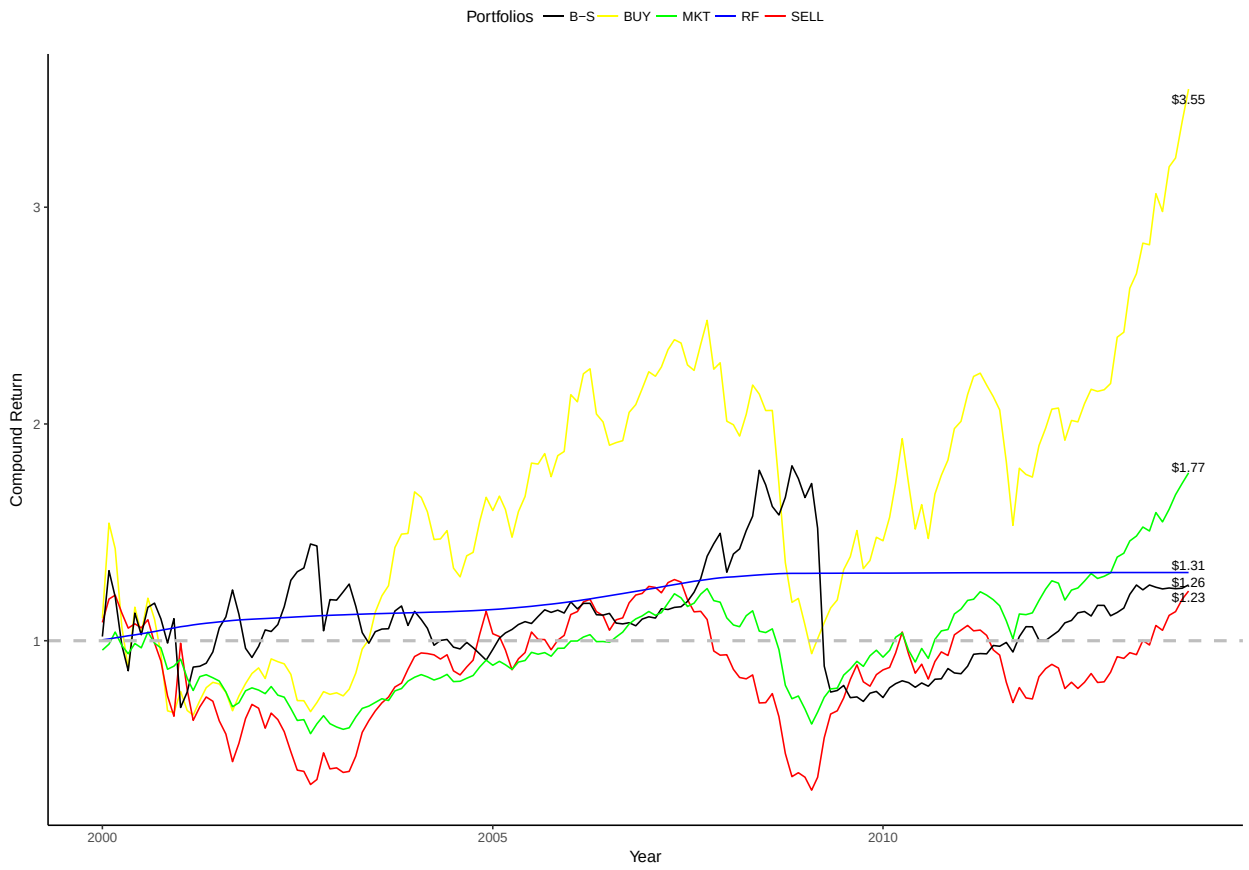

Figure 4: Compound Returns of Momentum Portfolios, 2000–2013

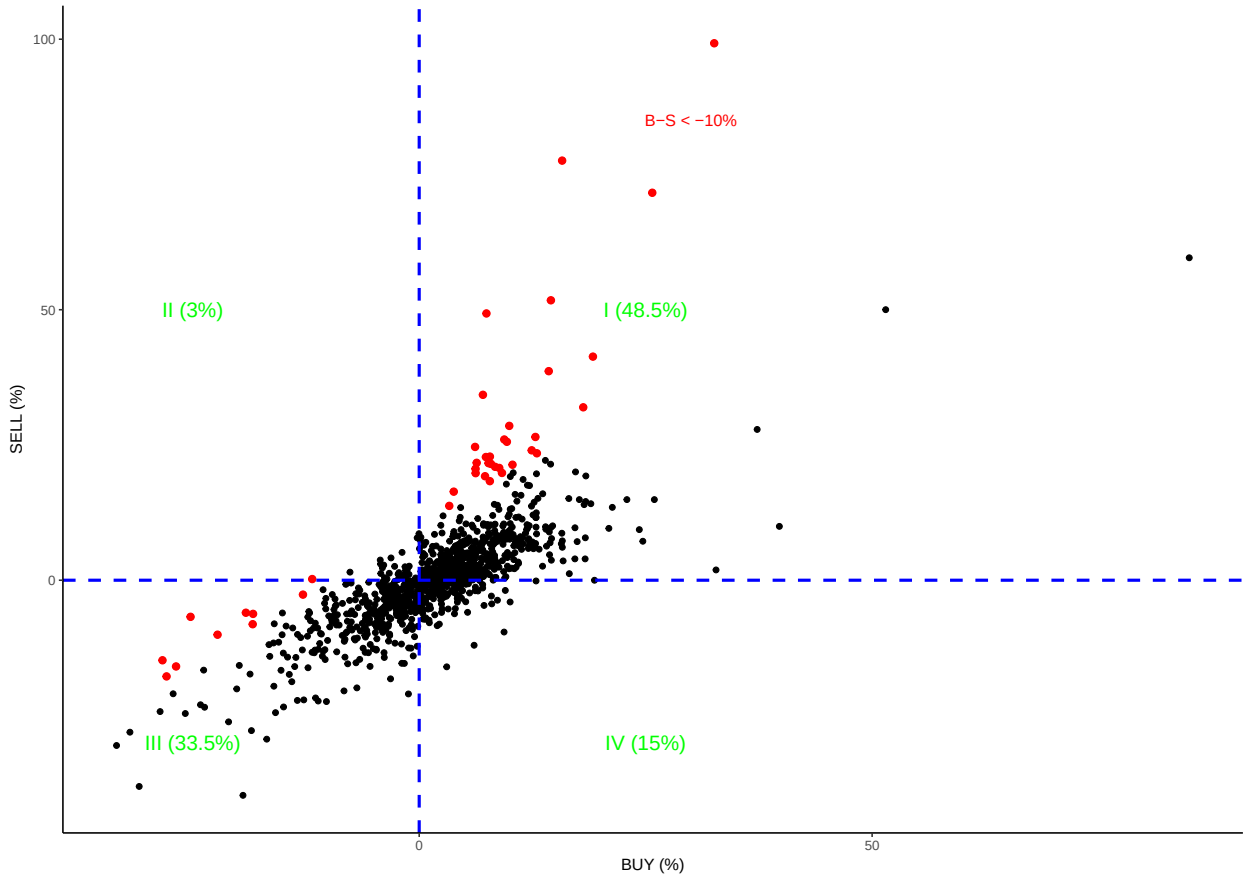

Figure 5: BUY versus SELL Portfolios, 1927–2013

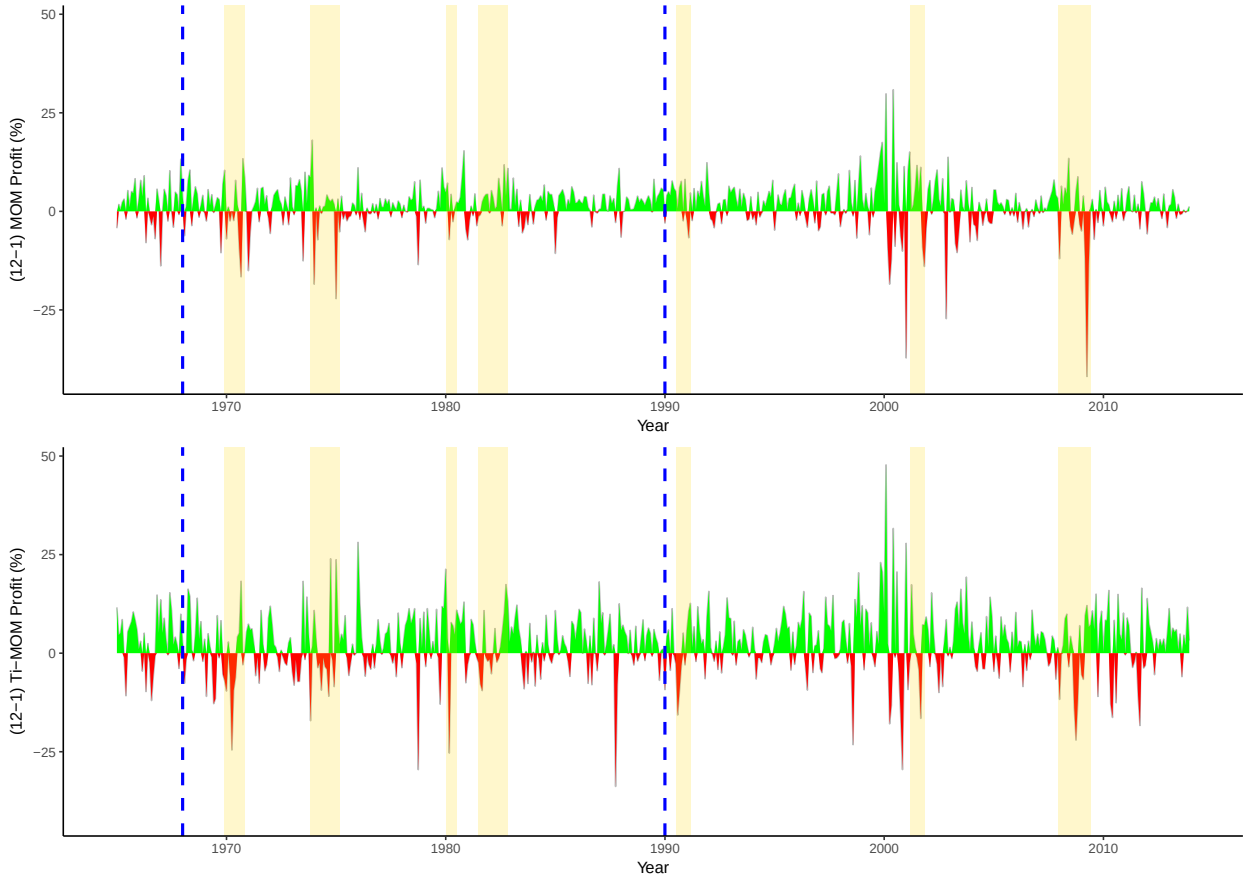

Figure 6: (12-1) Momentum (MOM) versus Ti-Momentum (Ti-MOM), 1965–2013 (Jegadeesh and Titman (1993)'s sample periods are between the blue dashed lines)

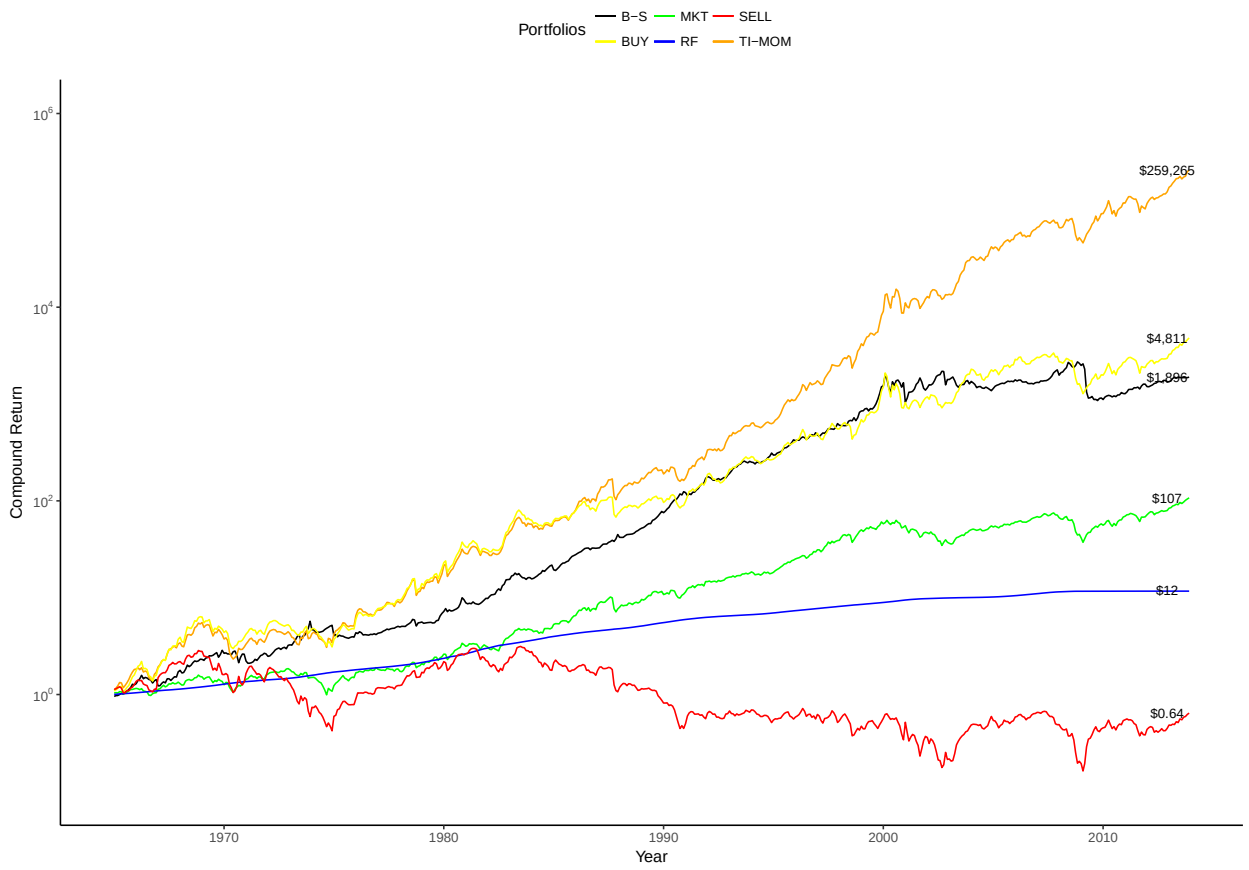

Figure 7: Compound Returns of Investment Portfolios, 1965–2013

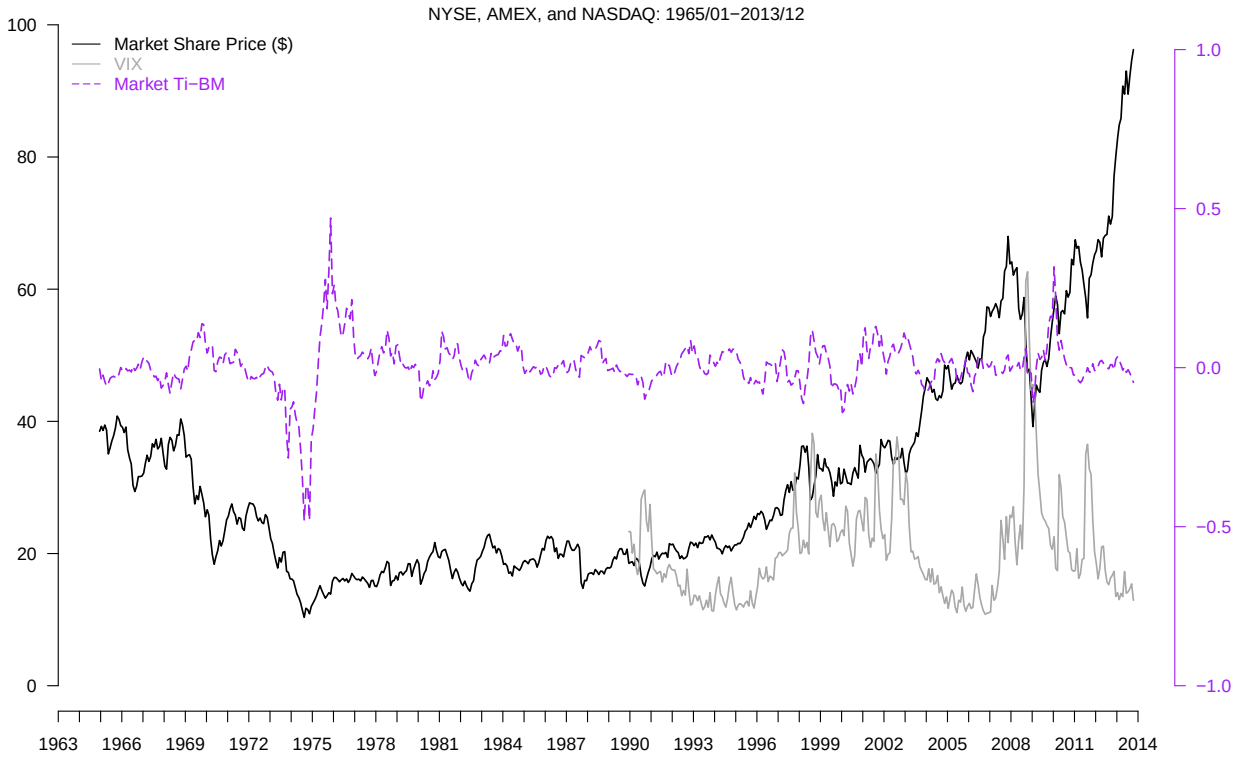

Figure 8: Ti-Systemic Risk Index, 1965–2013

Appendix A

We define a firm's log book-to-market ratio in month t (bm_t) as the log of the total book value of the firm at the end of the firm's fiscal year ending anywhere in the previous year, minus the log of total market equity on the last trading day of calendar month t, as reported by CRSP.

The market value is easy to obtain from CRSP. On the last trading day of calendar month t, we calculate the value of market equity as

$$ME = P \cdot TSO/1,000,000, \tag{A1}$$

where ME represents the issue-level market capitalization in \$ million, P is the adjusted price at the end of each month t and TSO is the adjusted total shares outstanding.

To obtain the value of book equity, we follow the definition of Daniel and Titman (1997) and use the following formula:

$$BE = SEQ + TXDB + ITCB - PREF, \tag{A2}$$

where BE is the book equity that we want, SEQ is shareholders' equity (item 144), $TXDB$ (item 74) is deferred taxes, $ITCB$ (item 208) represents investment tax credit and $PREF$ represents the preferred stock. These accounting measures are from the COMPUSTAT annual file.

The problematic part in calculating the book equity is to obtain the value of $PREF$, the preferred stock. If SEQ is positive, $PREF$ can be defined as the value of Preferred Stock/Redemption Value (item 56). If this value is missing, we replace it by using Preferred Stock/Liquidating Value (item 10) or Preferred/Preference Stock (Capital) - Total (item 130).

The monthly book-to-market ratio (BM) we use in this analysis is defined as the ratio of equation (A2) to equation (A1).

Appendix B

To understand how the relationship between the momentum return of a stock and its fundamental values is connected, it can start from the decomposing the price-scaled ratios.[11] Any log price-scaled accounting variables, f_t, can be decomposed as:

$$f_t \equiv \log\left(\frac{A_t}{P_t}\right) = \underbrace{\log\left(\frac{A_{t-\tau}}{P_{t-\tau}}\right)}_{\equiv f_{t-\tau}} + \log\left(\frac{A_t}{A_{t-\tau}}\right) - \log\left(\frac{P_t}{P_{t-\tau}}\right), \tag{A1}$$

where f_t and $f_{t-\tau}$ indicate the log of the price-scaled accounting variable and A_t and $A_{t-\tau}$ are the accounting values per share at time t and $t-\tau$, respectively. For example, the book-to-market ratio at time t, bm_t, can be decomposed as:

$$bm_t = \underbrace{\log\left(\frac{B_{t-\tau}}{P_{t-\tau}}\right)}_{\equiv bm_{t-\tau}} + \log\left(\frac{B_t}{B_{t-\tau}}\right) - \log\left(\frac{P_t}{P_{t-\tau}}\right).$$

The first and second identities say that BM ratio is basically defined as the ratio of the book value per share, B_t, to the market value per share (or share price), P_t. The log of the latter ratio can be split into the τ-period-ago log book-to-market ratio, plus the log change in its book value, minus the log change in its price.

To connect a firm's price-scaled accounting variables and its past stock returns, a good proxy for new information about firm value is the total return to a dollar invested in the firm. Thus, we must first convert the change in the per-share market value of a firm's equity into the return on its stock. If there are no splits, dividends, etc., these two measures will be the same; in general, however, some adjustment must be made. The relation between the log returns and price changes is given by:

$$r_{t-\tau,t} \equiv \sum_{s=t-\tau+1}^{t} \log\left(\frac{P_s \cdot CF_s + D_s}{P_{s-1}}\right), \tag{A2}$$

where CF_s is a cumulative factor to adjust prices from time $s-1$ to time s, adjusting for splits and rights issues, D_s is the value of all cash distributions paid between times $s-1$ and s, and P_s is the per-share value at time s.

[11] The approach to decompose price-scaled accounting variables is generalized from Daniel and Titman (2006).

A slight manipulation of equation (A2) shows:

$$
\begin{aligned}
r_{t-\tau,t} &= \sum_{s=t-\tau+1}^{t} \log\left[\frac{P_s}{P_{s-1}} \cdot CF_s \cdot \left(1 + \frac{D_s}{P_s \cdot CF_s}\right)\right] \\
&= \sum_{s=t-\tau+1}^{t} \left[\log\left(\frac{P_s}{P_{s-1}}\right) + \log(CF_s) + \log\left(1 + \frac{D_s}{P_s \cdot CF_s}\right)\right] \\
&= \sum_{s=t-\tau+1}^{t} \log\left(\frac{P_s}{P_{s-1}}\right) + \sum_{s=t-\tau+1}^{t} ADJ_s \\
&= \log\left(\frac{P_t}{P_{t-\tau}}\right) + ADJ_{t-\tau+1,t}. \qquad \text{(A3)}
\end{aligned}
$$

The log return is equal to the log price change plus a cumulative log share adjustment factor, $ADJ_{t-\tau+1,t}$, which is equal to the (log) number of shares one would have at time t, per share held at time $t-\tau$, had one reinvested all cash distributions back into the stock.

Substituting expression (A3) into equation (A1) gives the price-scaled accounting variable as the sum of the lagged log price-scaled ratio minus the log return:

$$
f_t = f_{t-\tau} + \log\left(\frac{A_t}{A_{t-\tau}}\right) - r_{t-\tau,t} + ADJ_{t-\tau+1,t}, \qquad \text{(A4)}
$$

which can be rewritten as

$$
r_{t-\tau,t} = f_{t-\tau} - f_t + \log\left(\frac{A_t}{A_{t-\tau}}\right) + ADJ_{t-\tau+1,t}. \qquad \text{(A5)}
$$