# Market volatility and momentum

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**A B S T R A C T**

We investigate the predictive power of market volatility for momentum. We find that (1) market volatility has significant power to forecast momentum payoffs, which is robust after controlling for market state and business cycle variables; (2) market volatility absorbs much of the predictive power of market state; (3) after controlling for market volatility and market state, other variables do not have incremental predictive power; (4) the time-series predictive power of market volatility is centered on loser stocks; and (5) default probability helps explain the predictive power of market volatility for momentum. These findings jointly present a significant challenge to existing theories on momentum.

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## 1. Introduction

We examine the predictive power of market volatility for momentum profitability. A direct motivation for our study arises from the observation that the high stock market volatility in late 2008 is followed by a string of dramatic losses of momentum strategies. After the bankruptcy of Lehman Brothers in September, market volatility skyrocketed, which was followed by strikingly large momentum losses. In the first half of 2009, the momentum strategy performed miserably, producing a monthly average payoff of −17% (Fig. 1).[2] The momentum strategy also performs poorly following other periods of skyrocketed volatility, such as in the early 1930's, the middle 1970's, and around the turn of the century after the burst of the NASDAQ bubble. These drastic episodes suggest that market volatility may predict momentum profits.

While there exists an extensive literature on the momentum effect of Jegadeesh and Titman (1993), empirical studies are overwhelmingly aimed at cross-sectional features of the anomaly. Time-variation in momentum profits has received relatively less attention. Important exceptions include Chordia and Shivakumar (2002; hereafter CS), who find that momentum varies with business cycles, Cooper, Gutierrez, and Hameed (2004; hereafter CGH), who find that momentum exists only in the "UP" market state, and Stivers and Sun (2010), who find that cross-sectional return dispersion negatively predicts momentum payoff.[3] In this paper, we investigate whether market volatility has predictive power for time-variation in momentum payoff.

Our tests reveal a set of interesting findings. First, market volatility indeed has significant and robust power to forecast momentum payoffs. Unlike market state and business cycle variables, market volatility has significant explanatory power even when the

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[1] Tel.: +1 416 946 5059.
[2] The strategy's monthly payoffs for January through June 2009 are −17.02%, 3.40%, −23.49%, −40.62%, −23.23%, and −1.85%, respectively.
[3] Cooper, Gutierrez, and Hameed (2004) define that it is an "UP" ("DOWN") market state if the past three-year market return is non-negative (negative). For convenience, we will use a positive market state instead of a non-negative market state. Unless noted otherwise, this definition is used throughout our paper.
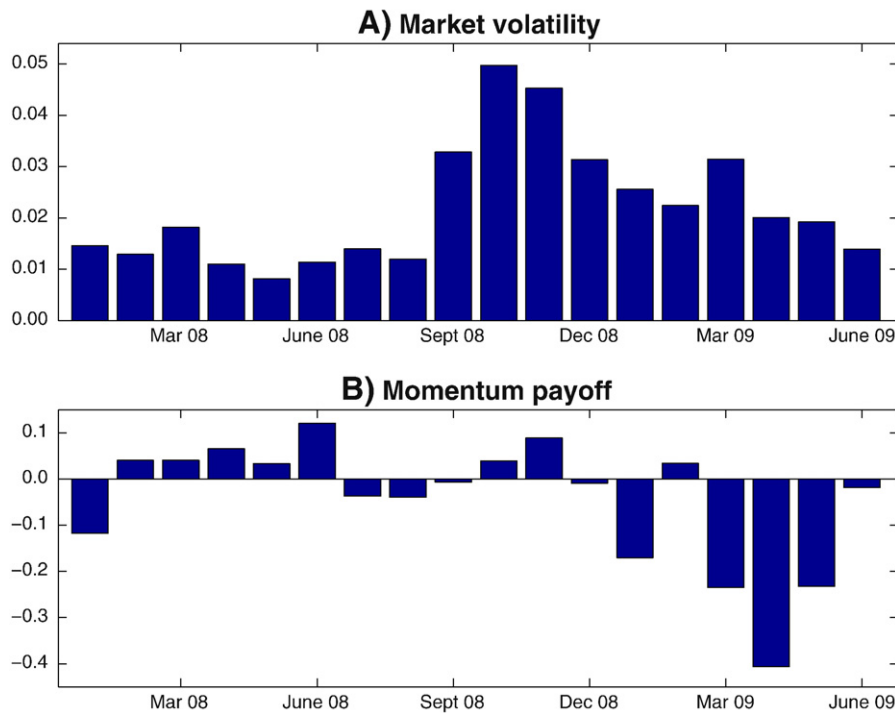
## A) Market volatility



## B) Momentum payoff



**Fig. 1.** Market volatility and momentum payoff in the 2008–2009 episode. Panel A plots market volatility (standard deviation of daily market returns) in the month. Panel B plots the payoffs to a momentum strategy. The data for momentum payoffs are from the Ken French data library. Specifically, stocks are sorted into deciles based on returns from month t − 12 to month t − 2, where month t is the holding period. The momentum payoff is the difference between equal-weighted returns of the winner and loser portfolios.

momentum portfolios are constructed using relatively large stocks. Second, the predictive power of market volatility persists after controlling for market states and business cycle variables. In contrast, these other variables lose much of their explanatory power in the presence of market volatility. Only market state continues to have predictive power for momentum profitability. Third, the predictability of momentum profits arises mainly from loser stocks. Performance of the winner stocks does not deviate from the overall market performance in a predictable way. We use the market index and the Fama and French three-factor model as the benchmark to adjust the performance of winners and losers. Finally, inspired by the fact that market volatility is related to default probability and that the predictability is loser-centered, we explore the role of default probability and find that default probability can absorb much of the predictive power of market volatility for momentum profitability.[4]

We also examine other potentially important variables in predicting momentum profitability, including investor sentiment (Baker and Wurgler (2006)), cross-sectional stock return dispersion (Stivers and Sun (2010)), and Chicago Board Options Exchange Volatility Index (VIX). Cross-sectional return dispersion and VIX are highly correlated with market volatility. The correlation coefficients are 0.52 and 0.71, respectively. We confirm Stivers and Sun (2010)'s finding that cross-sectional return dispersion negatively predict momentum performance. We also find that investor sentiment and VIX can predict momentum profitability. In the presence of these variables, the predictive power of market volatility remains robust. In contrast, the predictive power of these variables is not robust in the presence of market volatility.

Our study extends previous work on time-series features of momentum in three aspects. First, existing work aims at testing certain theories. For example, CGH (2004) aim at testing the models of Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999). CS (2002) focus on the role of business cycles in explaining momentum. In contrast, our goal is to establish the predictive power of a particular variable (market volatility) for momentum profitability. Second, our new findings, centered on market volatility, are challenging for existing theories. They are not readily reconciled with the studies of CS and CGH that are motivated by the business cycle risk explanation and the behavioral theories. Third, our findings are intriguing when compared with numerous cross-sectional studies. The results of Jiang, Lee, and Zhang (2005) and Zhang (2006), for example, show that momentum payoffs are higher among firms with higher information uncertainty. However, we find that over time high volatility periods are followed by low momentum payoffs.

Although momentum is largely a cross-sectional effect, our study shows that the time-series dimension is important as well for developing a convincing theory of momentum. Overall, our findings present a significant challenge to existing research on

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[4] With data from January 1971 to June 2008, we use the approach of Hillegeist et al. (2004), which is based on the Black–Scholes–Merton option-pricing model, to estimate bankruptcy probabilities of firms (hereafter referred to as BSM probs). We find that the average BSM probs across all stocks is significantly correlated with market volatility. Our tests that focus on down markets show that both the all-stock average BSM probs and the loser-winner difference in BSM probs have significant predictive power for momentum. These default risk proxies take away the explanatory power of market volatility.

momentum. Using several recent papers on momentum, we discuss (in Section 2.4) why implications from our empirical results are challenging. We also suggest two directions to explore theories that can account for the time-series features of the momentum effect.

Our focus on volatility also relates our study to the literature on stock market volatility and return predictability. Earlier research has examined the time-series relation between market volatility and the expected market return.[5] Our study extends this line of research by examining the time-series relationship between market volatility and momentum profitability. Our finding that default risk helps explain the momentum predictive power of market volatility suggests that default risk may play an important role in predicting stock returns, especially in volatile down markets.

The rest of the paper is organized as follows. Section 2 presents the empirical analysis. Section 2.1 describes the setup and data. Section 2.2 presents the main results on predictive power of market volatility for momentum profitability. Section 2.3 explores potential explanations. Section 2.4 discusses implications of our findings, emphasizing that they present a challenge to existing theories. Section 3 concludes.

## 2. Market volatility and momentum

### 2.1. Setup and data

We aim at establishing the role of market volatility in predicting momentum profits in the presence of other important variables. Toward this end, we run predictive regressions of the following form:

$$MOM_t = a + bx_{t-1} + \varepsilon_t$$

where $MOM_t$ is the momentum payoff of month t. To calculate momentum, stocks are ranked into portfolios based on past returns. The ranking period is from 3 to 12 months. The portfolio with the highest (lowest) past return is the winner (loser) portfolio. Momentum payoff is winner–loser return difference in month t. $x_{t-1}$ is a vector of predictors measured at the end of month $t - 1$.[6]

We organize the results into two parts. The first part aims at establishing the main results (Section 2.2). The performance of market volatility is presented together with the findings from two most related studies (CGH and CS). In addition to market state of CGH, this part has involved the macroeconomic variables of CS: dividend yield of the CRSP value-weighted index (DIV), yield spread between Baa-rated bonds and Aaa-rated bonds (DEF), yield spread between ten-year Treasury bonds and three-month Treasury bills (TERM), and yield on a T-bill with three months to maturity (YLD). We obtain monthly observations on these four variables from the CITIBASE database. The sample period is from April 1953 to June 2009.

The second part explores robustness and potential explanations of our key findings (Section 2.3). We test whether cross-sectional stock return dispersion, option implied volatility, or Baker–Wurgler sentiment index can account for market volatility's explanatory power. We construct the return dispersion measure following exactly the procedure of Stivers and Sun (2010). We obtain data on VIX from the web site of Chicago Board Options Exchange. The data on Baker–Wurgler sentiment index is obtained from Jeffrey Wurgler's web site (http://www.stein.nyu.edu/~jwurgler). We further explore whether default risk can explain the predictive power of market volatility. Hillegeist et al. (2004) and Vassalou and Xing (2004) have used Merton's (1974) option-pricing model to compute default measures for firms. We implement the procedure of Hillegeist et al. (2004) to estimate default probabilities of firms.

The rest of this section explains how we construct momentum, market state, and market volatility and how we use alternative definitions of these variables for robustness checks. In Appendix A, we provide a list summarizing all the variables used in our analysis.

The momentum strategy is constructed following Fama and French (1996). Specifically, the ranking period is from month $t - 12$ to month $t - 2$. The holding period is month t. Stocks are sorted into deciles using their ranking period returns. The top (bottom) return decile is defined as the winner (loser) portfolio. Equal-weighted portfolios are formed for the deciles. Momentum payoff is the holding month return difference between the winner and loser portfolios.

We focus on this momentum strategy for three reasons. First, the data for the strategy is publicly available at the French's web site. This makes it easy to replicate most of our results, since it is straightforward to obtain the predictors such as market volatility and market state. Second, Fama and French (1996) show that this momentum strategy is as tough as the ones constructed by Jegadeesh and Titman (1993). Their three-factor model fails to explain the payoff to this strategy. Third, the one-month holding period in this construction makes it well suited for studying time-series predictability. Extending the holding period beyond one month would artificially introduce a strong autocorrelation in monthly observations of momentum payoffs. A highly autocorrelated dependent variable also creates concerns of spurious regressions and makes it unclear how to interpret the adjusted R-squares of the regressions.

For robustness concerns, we examine a widely used alternative momentum measure, MomFF, constructed by Fama and French (1996). This factor is constructed using six value-weighted portfolios formed on size and past returns. The portfolios, denoted as Small High, Small Medium, Small Low, Big High, Big Medium, and Big Low, are the intersections of two portfolios formed on size and three portfolios formed on prior return (from month $t - 12$ to month $t - 2$). To be size-balanced, MomFF is the average return

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**Table 1**

Market states, market volatility, and momentum profits.

Monthly momentum returns are from the Ken French data library. Stocks are sorted into deciles based on returns from month t − 12 to month t − 2, where month t is the holding period. Momentum returns are the holding month return differences between equal-weighted winner and loser portfolios. A month is in positive (negative) market states if the lagged three-year market return is positive (negative). A month is of high (low) volatility if the lagged 12-month market volatility is larger (smaller) than the lagged 36-month market volatility. The average monthly payoff for each of the four categories of positive (negative) market state and high (low) volatility is reported. In parenthesis are robust t-statistics. All the payoffs are in percentage terms.

| MOM | Positive market state | | Negative market state | |
|---|---|---|---|---|
| | High vol | Low vol | High vol | Low vol |
| *Aug 1929–July 2009* | | | | |
| 0.79 | 0.89 | 1.56 | −3.01 | −1.29 |
| (3.60) | (4.40) | (9.27) | (−1.94) | (−0.94) |
| *Aug 1929–July 1969* | | | | |
| 0.63 | 0.75 | 1.45 | −3.25 | −2.28 |
| (1.95) | (3.31) | (5.97) | (−1.87) | (−1.75) |
| *Aug 1969–July 2009* | | | | |
| 0.95 | 1.00 | 1.70 | −2.86 | 1.16 |
| (3.33) | (3.29) | (8.75) | (−1.33) | (2.56) |

**Table 2**

Predictive power of market volatility.

We regress momentum payoff on a set of variables including market volatility, market state, and business cycle variables. All regressions are of the form:

$$y_t = a + bx_{t-1} + \varepsilon_t$$

where $x_{t-1}$ is the vector of predictors measured at the end of month t − 1. MKT is the lagged three-year market return in annual terms. Vol is the lagged 12-month (month t − 12 to month t − 1) market volatility in percentage terms. Vol+ (Vol−) is equal to Vol if the lagged three-year (month-36 to month t − 1) market return is positive (negative) and otherwise equal to 0. DIV is the dividend yield of the CRSP value-weighted index. DEF is the yield spread between Baa-rated bonds and Aaa-rated bonds. TERM is the yield spread between ten-year Treasury bonds and three-month Treasury bills. YLD is the yield on a T-bill with three months to maturity. We use different time windows to calculate market state and volatility (in Panel A) and alternative measures of momentum profitability (in Panel B) for robustness checks. For each regression, we report regression coefficients, robust t-statistics (in parentheses), and adjusted R-squares. We omit the intercepts for brevity.

Panel A. Market state and volatility

| MKT | Vol | Vol+ | Vol− | Adj-R$^2$ |
|---|---|---|---|---|
| *I. Market state and market volatility* | | | | |
| 7.95 | −1.64 | | | 0.029 |
| (2.38) | (−2.38) | | | |
| 1.78 | | −0.71 | −2.68 | 0.035 |
| (0.33) | | (−1.64) | (−2.34) | |
| *II. Market volatility calculated over past six months* | | | | |
| 7.92 | −1.59 | | | 0.030 |
| (2.28) | (−2.10) | | | |
| 7.03 | | −0.90 | −1.84 | 0.032 |
| (2.13) | | (−1.15) | (−2.61) | |
| *III. Both state and volatility calculated over past six months* | | | | |
| 0.42 | −2.27 | | | 0.022 |
| (0.42) | (−3.56) | | | |
| −3.85 | | −0.78 | −3.53 | 0.032 |
| (−2.83) | | (−1.14) | (−3.93) | |

Panel B. Market state, market volatility, and business cycles

| MKT | Vol | Vol+ | Vol− | DIV | DEF | TERM | YLD | Adj-R$^2$ |
|---|---|---|---|---|---|---|---|---|
| *I. Regular momentum construction* | | | | | | | | |
| 3.68 | −2.09 | | | −0.24 | −1.86 | 0.49 | 0.38 | 0.056 |
| (1.99) | (−2.44) | | | (−1.02) | (−2.14) | (2.06) | (3.69) | |
| | | −1.38 | −2.91 | −0.21 | −1.52 | 0.43 | 0.32 | 0.060 |
| | | (−2.02) | (−3.18) | (−0.97) | (−1.81) | (1.93) | (3.05) | |
| *II. Size-balanced momentum profit* | | | | | | | | |
| 1.98 | −1.41 | | | −0.14 | −0.77 | 0.25 | 0.15 | 0.029 |
| (1.14) | (−2.60) | | | (−0.91) | (−1.54) | (1.57) | (2.07) | |
| | | −0.88 | −1.95 | −0.12 | −0.51 | 0.21 | 0.10 | 0.034 |
| | | (−2.06) | (−3.13) | (−0.79) | (−1.01) | (1.35) | (1.35) | |
| *III. Large-cap momentum profit* | | | | | | | | |
| 1.06 | −1.70 | | | −0.10 | −0.37 | 0.11 | 0.02 | 0.016 |
| (0.51) | (−3.46) | | | (−0.64) | (−0.77) | (0.66) | (0.29) | |
| | | −1.10 | −2.20 | −0.06 | −0.06 | 0.06 | −0.04 | 0.022 |
| | | (−2.37) | (−3.93) | (−0.43) | (−0.12) | (0.39) | (−0.49) | |

**A)**

Market volatility of the past twelve months



**B)**

Market state defined by past three-year return



**C)**

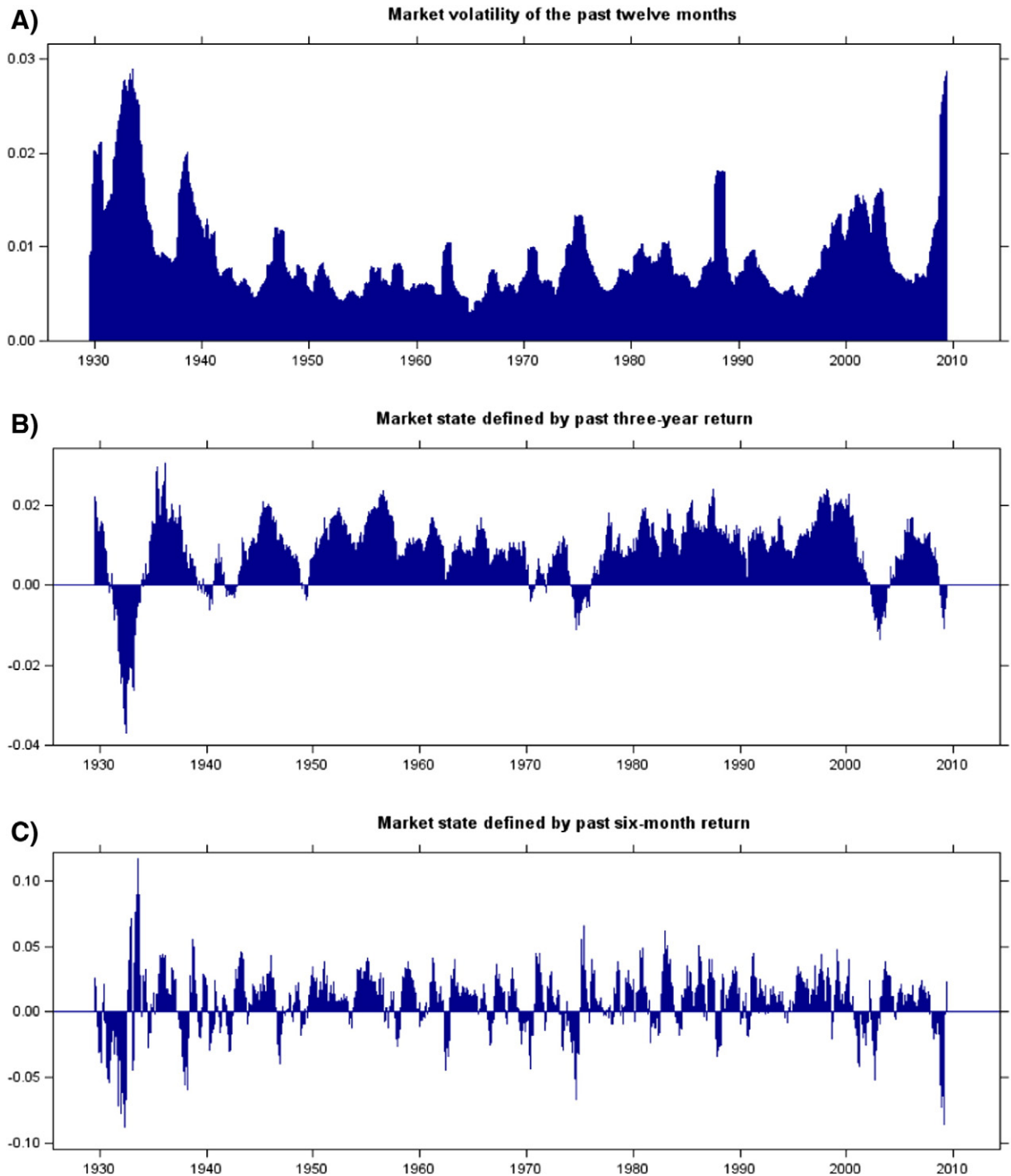Market state defined by past six-month return



**Fig. 2.** Market volatility and market state. In Panel A, market volatility is the standard deviation of daily market returns in the last 12 months. In Panel B, market state is the lagged three-year market return, measured in terms of the monthly average. In Panel C, market state is the lagged six-month market return.

on the two high prior return portfolios (Small High and Big High) minus that on the two low prior return portfolios (Small Low and Big Low). In addition to MomFF, we also use MomBig, the return difference between Big High and Big Low. This helps to show whether the predictive power is limited to small stocks. For brevity, the results based on MomFF and MomBig are reported only in Table 2.[7]

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[7] We have also considered the momentum strategy with a six-month ranking period and a six-month holding period. Both the overlapping construction approach of Jegadeesh and Titman (1993, 2001) and the non-overlapping approach are applied. The results (reported in an earlier version of this paper) are similar and hence omitted.

We employ the value-weighted CRSP market index to calculate market state and market volatility. Following CGH (2004), we calculate the past three-year market return as a measure of market state (MKT hereafter). We compute the lagged 12-month (month t − 12 to month t − 1) daily return standard deviation as a measure of market volatility (Vol hereafter). Two alternative measures are checked for robustness.[8] In addition, we consider the up and down market volatility, Vol + and Vol−, which equal to Vol in positive and negative market states, respectively, and otherwise equal to 0.

Fig. 2 plots time-variations in market volatility and market state. Panel A shows that market volatility jumped in late 2008 to the highest level in the post-war period, comparable to the level in the early 1930's. Panel B shows that, using the lagged three-year market return, the market is rarely in negative states. Only 13.6% of the months in the sample period are in negative market states. There is not a single month in the negative market state during the 1980's and 1990's. Since 1980, market state is negative only during the internet crash period and the 2008–2009 recession. To address this issue, we consider an alternative definition of up and down markets, which is based on past six-month returns (Panel C). The six-month return is more sensitive to sudden changes in market returns. With this measure, about 30% of the months in the sample period are in negative market states. For a robustness check, we have used the lagged six-month market return to define up and down market volatility (see Table 2).

### 2.2. Market volatility and momentum profitability

In this subsection, we present evidence that market volatility can predict momentum profitability. We proceed in two steps. First, we show that market volatility can predict momentum. Because market state and business cycle variables are found important by existing studies, we control for these variables. Second, we check whether the time-series predictability is symmetric between the winner and loser portfolios.

#### 2.2.1. Predictive power of market volatility

We start with a two-way sort. The purpose is to make an intuitive comparison showing whether market volatility matters after controlling for market state. All the months in the sample period are sorted into four subsets, depending on whether the market state is positive or negative and whether the market volatility is high or low. Following CGH (2004), we define a month to be in the UP (DOWN) market state if the lagged three-year market return is positive (negative). The UP (DOWN) market state is also referred to as the positive (negative) market state. A month is of high (low) volatility if the lagged 12-month volatility is larger (smaller) than the lagged 36-month volatility. Over the full sample period, there are 829 months in positive market states, 358 (471) of which are of high (low) volatility. There are 131 months in negative market states, 75 (56) of which are of high (low) volatility. Since this is an independent two-way sorting, it does not matter whether we first sort on market state or market volatility.

Table 1 presents results from the two-way sort. The average monthly momentum payoff is 0.79% for the full sample period. The average payoffs over the subsets show that both market state and market volatility matter. Consistent with CGH, momentum profits are higher in positive market states. Within positive (negative) market states, momentum profits are higher in low volatility months. Within positive market states, low volatility months outperform high volatility months by 0.67% (=1.56% − 0.89%). Within negative market states, the difference is 1.72% (=−1.29% − (−3.01)%). It seems that volatility matters more in negative market states. Jointly, market state and market volatility create a very large return spread. Positive-market-state-low-volatility months outperform negative-market-state-high-volatility months by an astonishing 4.57% (=1.56% − (−3.01)%).

The eighty-year sample period is divided into two equal-length subperiods, from 1929 to 1969 and from 1969 to 2009. Consistent with various earlier studies, the momentum payoff is higher in the more recent subperiod. Volatility also matters more in the more recent period but this difference is limited to negative market state. The return spread between high and low market volatility months in negative market states is −0.97% and −4.02% for the first and second subperiods, respectively. In comparison, the return spread in positive market states is 0.7% for both subperiods. Overall, Table 1 suggests market volatility matters and it matters more in negative market states.

The results from Table 1 suggest a simple way to improve momentum profitability. Given the large negative payoff in volatile down markets, it is natural to reverse the momentum-trading rule in these volatile periods. Specifically, one takes a long position in the loser portfolio and a short position in the winner portfolio in negative market states with high volatility. In other months, one carries out the regular momentum strategy. It should be noted that the increase in transaction costs due to the modification should not be a major concern, given that the negative market states of high volatility are relatively infrequent (75 out of 960 months, or 7.8%) and tend to cluster together.[9] The gain from the modified strategy is highly significant.[10]

#### 2.2.2. Market state and macroeconomic variables

Table 2 presents predictive regressions. In Panel A, we include only market state and market volatility. In Panel B, we further add business cycle variables. In both panels, we try different measures of market volatility, market state, and momentum profitability. The purpose is to establish the robustness of the basic results.

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[8]  For alternative measures, we have considered using the standard deviation of daily returns from month t − 6 to month t − 1 or from month t − 12 to month t − 2. The results are robust.

[9]  In every month, both the regular and modified strategies need to buy one portfolio and short-sell another. It is not even clear whether the modified strategy is more costly.

[10]  For example, if in late 2008 one canceled the short position in the loser portfolio in a regular momentum strategy, she would have avoided the large losses in 2009 as depicted in Fig. 1. Of course, she would have gained tremendously if she reversed the momentum trading rule instead of just unwinding the short position in the loser portfolio.

In Panel A, we present three pairs of regressions, differing in the number of months used to calculate MKT and Vol. In each pair, we first use MKT with Vol and then use MKT with Vol + and Vol−. In the first pair, MKT is the lagged three-year market return. Vol is the lagged 12-month market volatility. In the first regression, both MKT and Vol are significant, indicating that both variables have independent power to forecast momentum profits. In the second regression, MKT becomes insignificant.[11] It should be emphasized that since MKT is used in defining Vol− and Vol+, one cannot conclude from the second regression that MKT has no power. Throughout this paper, we do not dispute the predictive power of market state. Our view is that market volatility and market state fit well with each other so that combined together, they provide a useful indicator of market conditions. Consistent with Table 1, the predictive power of market volatility is more evident in down markets. Although Vol + and Vol − both have negative signs, Vol − is dominant in terms of the magnitudes of the coefficient and the t-statistic.

In Pairs II and III, we present robustness checks using alternative time windows to calculate market state and market volatility. That is, we calculate MKT and Vol as market returns and volatility in the past 6, rather than 36 and 12 months. In Pair II, only volatility is changed into the new measure. In Pair C, we replace both market state and market volatility with new measures. The results show that it does not matter whether to use 12 or 6 months to measure volatility. Vol keeps its sign and remains significant. Vol − continues to be stronger than Vol +. In contrast, the results about market state change significantly. It is significantly positive in Pair II, but significantly negative in the second regression of Pair III.[12]

In Panel B, we examine whether the macroeconomic variables of CS can take away the explanatory power of market volatility. Panel B also consists of three pairs of regressions that differ in the dependent variable. In Pair I, the dependent variable is the same momentum payoff as in previous tables. In Pairs II and III, the dependent variables are the size-balanced momentum factor of Fama and French (MomFF) and momentum payoff using large stocks only (Mombig), respectively. Pairs II and III are used to check whether the predictive variables perform well when the portfolio construction is size-balanced or tilted toward large stocks.

The results from Pair I show that these macroeconomic variables do have predictive power for time-variation in momentum profits. For example, DEF, TERM and YLD are all statistically significant in the first regression. However, the predictive power of the macroeconomic variables becomes considerably weaker when the momentum factor is size-balanced. For the regressions in Pair II, only YLD has a robust t-statistic that is above 2.0 in absolute value. In Pair III, the predictive power of the macroeconomic variables disappears completely, with the t-statistics ranging from −0.77 to 0.66. Similar to the macroeconomic variables, MKT is statistically significant in Pair I, but not in Pairs II and III. That is, the predictive power of the market state is also not robust when the portfolio construction is tilted toward large stocks. In contrast, market volatility remains significant throughout all the cases. As a matter of fact, the t-statistic of Vol increases in absolute value when moving from Pairs I to Pairs III. The t-statistics of Vol − and Vol + in Pair III are also larger in absolute value than those in Pairs I and II.

In sum, Table 2 shows that market volatility has robust predictive power in the presence of market state and macroeconomic variables. Unlike the market state and macroeconomic variables, market volatility retains its significant predictive power when the momentum portfolios are constructed to be size-balanced or with large stocks.[13] We also notice that in all cases, the predictive power of market volatility is more pronounced in down markets.

### 2.2.3. Asymmetric predictability

We proceed to examine whether the predictability of momentum payoff comes from the winner or the loser portfolios. Toward this end, we separately run the regressions for the loser and winner portfolio returns. Table 3 reports the results. In Panels A1 and A2, the dependent variable is the return difference between the loser (winner) portfolio and the market index. Using the performance relative to the market, we avoid the issue that returns of the winner and loser portfolios consist of a market component that is predictable (e.g., by DIV). In Panels B1 and B2, we adjust the loser and winner portfolio returns by the Fama and French three factor (FF3F) model. For example, the dependent variable in Panel B1 is $r_L − r_f − b_L$RMF $− s_L$SMB $− h_L$HML, where $r_L$ is the return on the loser portfolio, $r_f$ is the riskless rate, and $b_L$, $s_L$, and $h_L$ are the three factor loadings of the loser portfolio. RMF, SMB, and HML are the three factors of Fama and French.

The contrast between Panels A1 and A2 is impressive. It clearly shows that the predictability mainly comes from the loser portfolio. In predicting the loser's relative performance over the market, Vol and Vol − are statistically significant. The adjusted R-squares are as large as 5.3%. In contrast, in predicting the winner's relative performance over the market, none of the variables are statistically significant. The robust t-statistics range between −0.72 and 0.68 and the adjusted R-squares are negative. The macroeconomic variables also show some predictive power for the loser's performance. The t-statistics of DEF, TERM, and YLD show signs of statistical significance. In particular, YLD has t-statistics of −3.62 and −2.92 in the two regressions. In contrast, the macroeconomic variables do not have any predictive power for the winner's performance.

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[11] For this reason, we do not include MKT in the presence of Vol− and Vol+ in the following tables.

[12] CGH have used the squared term of the market state. It is difficult to explain and apply a nonlinear relation. Nonetheless, we have checked it for different subsamples and different constructions. We find that the conclusion about the squared term is not robust. It is statistically insignificant for the more recent subperiods, for example, for the August 1969 to July 2009 subsample.

[13] We conduct various subsample analyses and find the predictive power of market volatility to be robust across time. Motivated by the concern that the results could be driven by the 2008–2009 financial crisis period, we run the regression in Table 2 excluding the 2008 and 2009 (ending in December 2006 or 2007). We find the predictive power of market volatility to be less pronounced but remain significant. In unreported results, we split the whole sample of 1929 to 2009 into three approximately equal-length sub-periods and run the regression on each subsample. The results remain robust. The results are more evident in more recent subsamples. We also split the 1953–2009 period (the period we have business cycle data) into two approximately equal length period and run the regression on each subsample. The results remain robust and are more evident in the more recent subsample.

**Table 3**

Asymmetric predictability.

We regress winner and loser portfolio returns on market state, market volatility, and business cycle variables. The definition of these variables is the same as in Table 2. In Panels A1 and A2, portfolio returns are adjusted by the market index. In Panels B1 and B2, portfolio returns are adjusted by the Fama-French three factor model (FF3F). The sample period is from April 1953 to June 2009. We report regression coefficients, robust t-statistics (in parentheses), and adjusted R-squares.

| DIV | DEF | TERM | YLD | MKT | Vol | Vol+ | Vol− | Adj-R$^2$ |
|---|---|---|---|---|---|---|---|---|
| *A1. Loser (relative to the market)* | | | | | | | | |
| 0.35 | 1.95 | −0.45 | −0.43 | −2.86 | 2.12 | | | 0.053 |
| (1.17) | (2.21) | (−1.90) | (−3.62) | (−0.98) | (2.30) | | | |
| 0.34 | 1.79 | −0.42 | −0.40 | | | 1.76 | 2.62 | 0.053 |
| (1.16) | (1.84) | (−1.72) | (−2.92) | | | (1.73) | (2.73) | |
| *A2. Winner (relative to the market)* | | | | | | | | |
| 0.11 | 0.09 | 0.04 | −0.05 | 0.82 | 0.03 | | | −0.009 |
| (0.58) | (0.10) | (0.19) | (−0.44) | (0.38) | (0.05) | | | |
| 0.13 | 0.27 | 0.01 | −0.08 | | | 0.38 | −0.28 | −0.006 |
| (0.68) | (0.30) | (0.05) | (−0.72) | | | (0.55) | (−0.42) | |
| *B1. Loser (adjusted by FF3F)* | | | | | | | | |
| 0.04 | 1.60 | −0.51 | −0.31 | −2.08 | 1.31 | | | 0.046 |
| (0.23) | (2.11) | (−2.49) | (−3.96) | (−1.26) | (1.92) | | | |
| −0.01 | 1.14 | −0.44 | −0.23 | | | 0.40 | 2.11 | 0.057 |
| (−0.10) | (1.78) | (−2.34) | (−3.36) | | | (0.82) | (3.42) | |
| *B2. Winner (adjusted by FF3F)* | | | | | | | | |
| −0.08 | −0.39 | 0.06 | 0.05 | 0.97 | −0.44 | | | 0.010 |
| (−0.75) | (−0.78) | (0.53) | (0.80) | (0.74) | (−1.12) | | | |
| −0.09 | −0.40 | 0.06 | 0.05 | | | −0.43 | −0.53 | 0.009 |
| (−0.77) | (−0.75) | (0.50) | (0.78) | | | (−1.04) | (−1.26) | |

The contrast remains evident between Panels B1 and B2 when the performance is relative to the FF3F benchmark. In B2, none of the variables is statistically significant in predicting the performance of winners and the regressions have adjusted R-squares around 1%. In B1, several of the variables have the robust t-statistics above 2.0 in absolute value and the regressions' adjusted R-squares are 4.6% and 5.7%. In sum, using the FF3F benchmark, we still find that loser stocks are dominant in generating time-series predictability of momentum.

In the regressions for loser stocks, the coefficients of Vol are positive and significant. The results indicate that volatile markets forecast high returns on loser stocks and hence low momentum payoffs. On the contrary, low volatility forecasts low returns on loser stocks and hence high momentum payoffs. These patterns suggest that loser stocks are over-sold in volatile markets but over-bought in good market conditions.

Two notes are at demand here. First, the asymmetric predictability is conditional on the benchmark for measuring the relative performance. For example, if we set the average of the winner and loser portfolios to be the benchmark, the relative performances of the winner and loser portfolios would be perfectly symmetric. We argue that the asymmetry is meaningful because they are with respect to two prevalent benchmarks. Second, the asymmetric predictability does not imply that momentum profits come mainly from loser stocks. It is possible that both winner and loser stocks have quite large abnormal returns but the time-varying performance of the loser stocks is (much) more predictable. This appears to be the case. Using the Fama-French three factor model, we find that the alphas of the winner and loser portfolios over the 1929–2009 period are 0.73% and −0.64%, with t-statistics of 7.58 and −4.83, respectively. Thus, a successful explanation of momentum should account for not only the asymmetric time-series predictability but also the average abnormal returns of both winner and loser stocks.

### 2.3. Potential explanations

In this subsection we explore potential explanations for the predictive power of market volatility for momentum profitability. We consider four variables: the cross-sectional stock return dispersion (Stivers and Sun (2010)), option implied volatility (VIX), the Baker and Wurgler (2006) investor sentiment index, and default risk.

#### 2.3.1. Return dispersion

Stivers and Sun (2010) find that cross-sectional return dispersion negatively predict momentum performance. Following them, we calculate the three-month moving average of the cross-sectional standard deviation of the 100 size and book-to-market portfolio returns, denoted by $RD_{1-3}$. Over the full sample period, this measure has a correlation of 0.52 with Vol. While the two variables are highly correlated, market volatility and return dispersion are conceptually different. Market volatility measures time-series variation of the overall market return. Return dispersion measures cross-sectional variation in stock returns.

Our results, reported in Panel A of Table 6, confirm that $RD_{1-3}$ has predictive power with the right sign. When used alone, it has a robust t-statistic of −2.21. The adjusted R-square is 0.4%. However, when MKT and Vol are included, the t-statistic of $RD_{1-3}$ drops to 0.35. Adding business cycle variables does not save the predictive power of $RD_{1-3}$. Similarly, in the presence of Vol+ and Vol−, the significance of $RD_{1-3}$ also disappears. Therefore, although market volatility is significantly and positively correlated with return dispersion, the predictive power of market volatility is not derived from return dispersion.

**Table 4**

Potential explanations: return dispersion, VIX, and investor sentiment.

We examine whether stock return dispersion ($RD_{1-3}$), VIX, and investor sentiment (Sent) can absorb the predictive power of market volatility on momentum profitability. Monthly returns on the 100 size and book-to-market portfolios are from the data library of Ken French. $RD_{1-3}$ is the three-month moving average of the cross-sectional standard deviation of the 100 portfolio returns. VIX is the Chicago Board Options Exchange (CBOE) Volatility Index. The data are available from the web site of CBOE. Baker–Wurgler sentiment index (Sent) is from the web site of Jeffrey Wurgler (http://www.stein.nyu.edu/~jwurgler). $RD_{1-3}$, VIX, and Sent are available for the period of 1929–2009 (the whole sample), 1990–2009, and 1966–2009, respectively. The regressors MKT, Vol, Vol+ and Vol− are the same as in Table 2. We report regression coefficients, robust t-statistics (in parentheses), and adjusted R-squares.

| Panel A. return dispersion | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| DIV | DEF | TERM | YLD | MKT | Vol | Vol + | Vol− | $RD_{1-3}$ | Adj-R$^2$ |
| | | | | | | | | −0.11 (−2.21) | 0.004 |
| | | | | 8.03 (2.29) | −1.76 (−2.07) | | | 0.02 (0.35) | 0.028 |
| −0.24 (−1.03) | −1.86 (−2.13) | 0.50 (1.94) | 0.38 (3.65) | 3.64 (2.00) | −2.16 (−1.99) | | | 0.05 (0.20) | 0.056 |
| −0.02 (−0.98) | −1.53 (−1.80) | 0.43 (1.79) | 0.32 (3.02) | | | −1.41 (−1.58) | −2.93 (−2.70) | 0.02 (0.09) | 0.060 |
| Panel B. VIX | | | | | | | | | |
| DIV | DEF | TERM | YLD | MKT | Vol | Vol + | Vol− | VIX | Adj-R$^2$ |
| | | | | | | | | −0.08 (−1.05) | −0.002 |
| | | | | 6.80 (1.72) | −5.78 (−3.13) | | | 0.18 (2.77) | 0.071 |
| −5.37 (−3.00) | 3.22 (1.01) | 2.57 (2.54) | 1.82 (2.05) | −1.34 (−0.20) | −7.56 (−3.88) | | | 0.10 (1.01) | 0.112 |
| −4.97 (−2.61) | 3.51 (1.16) | 2.50 (2.43) | 1.59 (1.81) | | | −6.36 (−2.74) | −7.83 (−3.65) | 0.09 (1.08) | 0.116 |
| Panel C. Investor sentiment | | | | | | | | | |
| DIV | DEF | TERM | YLD | MKT | Vol | Vol + | Vol− | Sent | Adj-R$^2$ |
| | | | | | | | | 0.46 (2.52) | 0.003 |
| | | | | 3.59 (1.65) | −1.68 (−2.43) | | | 0.38 (2.22) | 0.009 |
| −0.98 (−1.73) | −1.05 (−1.06) | 0.67 (2.29) | 0.69 (2.37) | −2.04 (−0.68) | −2.14 (−2.10) | | | 0.08 (0.36) | 0.015 |
| −0.85 (−1.71) | −0.93 (−0.92) | 0.60 (2.17) | 0.60 (2.32) | | | −1.91 (−1.97) | −2.06 (−1.96) | 0.07 (0.34) | 0.015 |

### 2.3.2. VIX

The Chicago Board Options Exchange Volatility Index (VIX) is popular among investors. VIX is a measure of expected future market volatility. In comparison, Vol measures realized past market volatility. The regression results for VIX are interesting (Panel B of Table 4). When used alone, VIX has the negative sign but insignificant. When MKT and Vol are included, VIX becomes positive and significant.[14] When business cycle variables are included, VIX becomes insignificant again. This is not surprising since it is well known that VIX changes with macroeconomic status. In short, VIX cannot absorb the power of market volatility.

### 2.3.3. Baker–Wurgler sentiment index

It seems possible that our market volatility measure may be linked to the investor sentiment measure of Baker and Wurgler (2006; BW hereafter). BW study how investment sentiment affects the cross-section of stock returns.[15] They construct a composite sentiment index based on the first principal component of the following six proxies: the close-end fund discount, NYSE share turnover, the number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. To reduce the potential link to systematic risk, they also form an index based on the six proxies that have been orthogonalized to a set of macroeconomic indicators that include industry growth, consumption growth, and a dummy variable for NBER recessions.

In Panel C of Table 4, we present results using the orthogonalized index. The results are similar when using the unorthogonalized index and hence omitted. When business cycle variables (DIV, DEF, TERM, and YLD) are not included, the BW index shows up significantly with a positive sign. However, the predictive power disappears after controlling for the business cycle variables. It seems that

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[14] The change of sign for VIX when MKT and VOL are included is intriguing. There is a simple explanation. On the one hand, when market volatility is tapering off after volatile down markets, low momentum payoffs tend to occur (e.g., the 2008–2009 episode). Since VIX measures expected future market volatility, a drop in VIX in volatile down markets tends to precede the tapering-off of the market volatility and thus forecasts low momentum payoffs. This conditional predictive power gives rise to the positive sign of VIX in the presence of Vol. On the other hand, VIX is highly correlated with Vol. VIX has a correlation coefficient of 0.71 with Vol. Combined together, the conditional predictive power of VIX in high volatility states and the high unconditional correlation of VIX with Vol can explain why VIX is insignificantly negative in the single-predictor regression.

[15] Baker and Wurgler (2007) point out that their sentiment index also has some predictive power for the aggregate stock market.

**Table 5**
Black–Scholes–Merton probabilities of bankruptcy.

We employ the approach of Hillegeist et al. (2004) to estimate the Black–Scholes–Merton default probabilities of firms (denoted as BSM probs). Avg denotes the average BSM probs across all stocks. Diff denotes the difference in BSM probs between the loser and winner portfolios. Avg and Diff are in percentage terms. Vol denotes the lagged 12-month market volatility. Vol+, Avg+, and Diff+ are equal to Vol, Avg, and Diff, respectively, if the lagged three-year market return is positive and otherwise equal to 0. Vol−, Avg−, and Diff− are defined similarly when the lagged three-year market return is negative. The dependent variable in the predictive regressions is the momentum payoff. The sample period is from January 1971 to June 2008. We report regression coefficients, robust t-statistics (in parentheses), and adjusted R-squares.

| corr(Avg,Vol) = 0.42 | | corr(Avg+,Vol+) = 0.36 | | | corr(Avg−,Vol−) = 0.84 | | |
| --- | --- | --- | --- | --- | --- | --- | --- |
| corr(Diff,Vol) = 0.25 | | corr(Diff+,Vol+) = 0.35 | | | corr(Diff−,Vol−) = 0.35 | | |
| Avg | Avg+ | Avg− | Adj-$R^2$ | Diff | Diff+ | Diff− | Adj-$R^2$ |
| −0.20 | | | 0.001 | −0.09 | | | 0.000 |
| (−2.33) | | | | (−1.44) | | | |
| | −0.14 | −0.57 | 0.008 | | −0.06 | −0.36 | 0.003 |
| | (−1.77) | (−3.49) | | | (−0.82) | (−3.20) | |

although investor sentiment positively forecasts high momentum payoffs, the predictive power is derived from business cycle variations. Such predictive power is not captured by industry growth, consumption growth, and NBER recession, but is captured by measures from capital markets (DIV, DEF, TERM, and YLD).[16] Furthermore, we find that the correlation between market volatility and the BW index is only 0.05. Clearly, the BW sentiment index is not closely linked to market volatility and its predictive power does not absorb that of market volatility.

### 2.3.4. Default risk

Our earlier finding that the predictive power of market volatility is 1) more pronounced in negative market states, and 2) is centered on loser stocks is inspiring. Intuitively, volatile down markets are associated with uncertainty about the stock market and the overall economy. During such times, investors are more concerned about default risk, especially for stocks in the loser portfolio. It is natural to ask whether default risk can account for the predictive power of market volatility for momentum profits.

Applying the approach of Hillegeist et al. (2004), we compute the Black–Scholes–Merton default probabilities (denoted as BSM probs) for all stocks with available data.[17] We focus on two summary measures: the average BSM probs across all stocks, denoted as Avg, and the difference in BSM probs between the loser and winner portfolios, denoted as Diff. To verify our conjecture that market volatility may be related to default probability, we start with their correlations in up and down markets. When computing correlations in up (down) markets, we remove all observations in down (up) market states and use the remaining time series. This ensures that the correlations are not inflated. For example, if we do not remove the zeros in the series for Vol− and Avg−, their correlation will be pushed up since a large faction of observations in the two time series have the value of 0 in the same months.

Table 5 shows that these default risk measures are positively correlated with market volatility. In particular, Avg and Vol have a correlation of 0.84 in down markets. In comparison, the correlation is much smaller at 0.36 in up markets, which is still very high in magnitude. The regressions show that both Avg− and Diff− are significant in explaining momentum payoff, with robust t statistics of −3.49 and −3.20, respectively. In comparison, Avg+ and Diff+ are not significant in predicting momentum payoff. This is consistent with the intuition that default risk matters only in down markets.

While the results in Table 5 are consistent with our conjecture, we realize that there is a potential test power problem. When market state is defined by the lagged three-year market return, the market is rarely in negative states. During 1980's and 1990's, as mentioned earlier when examining Fig. 2, the market was never in negative states. Thus, the regression tests may have low power. To improve the test power, we use the lagged six-month return to define market states, which drastically raises the number of negative states during the 1971–2008 period. Using this alternative definition of markets, we regress momentum payoffs on market state, volatility, business cycle variables, and default probability measures in up and down markets separately.

The results are presented in Table 6. Panel A is for down markets. When Avg and Diff are not included, Vol shows up significantly in predicting momentum profitability. However, this predictive power disappears when either Avg or Diff is included. Both Avg and Diff show up significantly when the other variables are present. Diff seems to have more predictive power than Avg. This is not surprising since we are predicting the return difference between winner and loser portfolios. In contrast, none of the variables are significant in predicting momentum payoff in up markets (Panel B).

The main point of Table 6 is that the default risk proxies, Avg and Diff, take away the predictive power of market volatility in down markets. These results are intuitive. In fearful times default risk is likely to be a major concern for investors and loser stocks are likely to be perceived as having high default risk. However, this time-series finding is contradicting to the cross-sectional result of Avramov,

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[16] In unreported results, we find that when using value-weighted rather than equal-weighted returns, sentiment does not predict momentum even without controlling DIV, DEF, TERM, and YLD. The sensitivity to the weighting scheme suggests that the role of BW sentiment index in forecasting momentum profits is limited to small-cap stocks.

[17] We note that the number of stocks with available data is unstable before 1971. So we focus on period from January 1971 to June 2008. We have verified different starting points (e.g., January 1980) to check for robustness of the results.

**Table 6**
Predictive power of BSM probabilities in UP and DOWN markets.
We regress momentum payoff on market state (MKT), market volatility (Vol), business cycle variables (DIV, DEF, TERM, and YLD), and default probability measures (Avg and Diff). MKT and Vol are the same as in previous tables such as Table 2. Avg and Diff are the same as in Table 5. UP (DOWN) markets are defined as the months when the lagged six-month market return is positive (negative). In Panel A (B), we include only months in UP (DOWN) markets. The sample period is from January 1971 to June 2008. We reported regression coefficients, robust t-statistics (in parentheses), and adjusted R-squares.

| DIV | DEF | TERM | YLD | MKT | Vol | Avg | Diff | Adj-R² |
|---|---|---|---|---|---|---|---|---|
| *Panel B. DOWN market* | | | | | | | | |
| −1.26 | −1.41 | 1.15 | 0.67 | −3.93 | −3.34 | | | −0.020 |
| (−2.30) | (−0.79) | (1.89) | (1.55) | (−0.52) | (−2.47) | | | |
| −1.85 | −2.62 | 1.55 | 0.86 | −7.16 | −0.86 | −0.76 | | −0.009 |
| (−2.95) | (−1.62) | (1.97) | (2.06) | (−1.11) | (−1.14) | (−3.31) | | |
| −2.21 | −0.86 | 1.03 | 0.82 | −1.60 | −1.10 | | −0.44 | 0.019 |
| (−3.67) | (−0.57) | (1.69) | (2.01) | (−0.21) | (1.57) | | (−4.52) | |
| −2.21 | −0.79 | 1.01 | 0.81 | −1.41 | −1.17 | 0.03 | −0.45 | 0.010 |
| (−3.55) | (−0.56) | (1.62) | (2.00) | (−0.20) | (−1.21) | (0.12) | (−4.44) | |
| *Panel B. UP market* | | | | | | | | |
| −0.84 | −0.22 | 0.43 | 0.55 | 1.75 | −1.71 | | | 0.020 |
| (−1.37) | (−0.26) | (1.95) | (1.59) | (0.47) | (−1.64) | | | |
| −0.87 | −0.54 | 0.52 | 0.58 | 1.78 | −1.34 | −0.12 | | 0.019 |
| (−1.45) | (−0.50) | (2.08) | (1.60) | (0.48) | (−1.18) | (−1.04) | | |
| −0.87 | −0.31 | 0.46 | 0.59 | 1.96 | −1.71 | | −0.03 | 0.018 |
| (−1.25) | (−0.31) | (1.56) | (1.33) | (0.52) | (−1.57) | | (−0.34) | |
| −0.88 | −0.55 | 0.53 | 0.59 | 1.87 | −1.38 | −0.11 | −0.02 | 0.016 |
| (−1.29) | (−0.49) | (1.82) | (1.34) | (0.49) | (−1.10) | (−0.79) | (−0.15) | |

Chordia, Jostova, and Philipov (2007) that momentum profits are higher among firms with higher default risk. Thus, although the results in Tables 5 and 6 suggest that the predictive power of market volatility for momentum is related to default risk in down markets, they do not explain the puzzling contrast between the cross-sectional and the time-series results.

### 2.4. Implications and discussions

#### 2.4.1. Existing theories

In this section we put our findings in the light of existing theories to search for plausible explanations. The literature on momentum is extensive. However, the existing literature focuses on cross-sectional features of momentum. Numerous studies aim at explaining why winner stocks earn higher average returns than loser stocks. For example, Fama and French (1996), Grundy and Martin (2001), Lewellen and Nagel (2006), and Liu and Zhang (2008), among others, have explored whether factor models can explain the average winner–loser return difference. In contrast, time-series variations in momentum have received much less attention and have not yet challenged the existing theoretical literature. The findings of CGH, for instance, are interpreted as supportive evidence for the models of Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999). Unlike CGH, we emphasize that our findings are not readily explicable by existing theories, whether behavioral or risk-based.

For example, Garlappi and Yan (2011) propose an elegant model in which there is a hump-shaped relationship between equity beta and default probability due to potential shareholder recovery. For firms with high default probabilities, the model implies a downward sloping relationship between beta and default probability. Loser stocks have higher default risks, lower equity betas, and hence lower future expected returns. This is opposite to our finding that loser stocks earn high returns following volatile down markets.

Sagi and Seasholes (2007) propose a model of firms with mean-reverting revenues and growth options. They show that firms with high revenue growth volatility, low cost, and good growth options become riskier after positive shocks and thus command higher expected returns. Empirically, they find that momentum payoffs are indeed higher among firms with high revenue growth volatility, low costs, and valuable growth options. These firms tend to have higher information uncertainty and thus their finding is consistent with those of Jiang, Lee, and Zhang (2005) and Zhang (2006). However, their model cannot explain our findings, particularly why loser stocks have good returns following volatile down markets.

Liu and Zhang (2008) employ industrial production (IP) growth rate, which they consider as a priced risk factor, to explain momentum. They show that winner stocks have higher loadings on IP than loser stocks, suggesting that risk plays an important role in generating momentum. However, it is unclear whether such a factor model can be extended to explain time series variations in momentum profits. In fact, the macroeconomic variables described in Table 2 are popular stock market predictors and widely used instruments in conditional asset pricing models (e.g., see Ferson and Harvey (1999)). The finding that the power of these variables is not robust in predicting momentum casts doubts on whether risk-based models are capable of explaining time-series predictability of momentum (see CGH, Griffin, Ji, and Martin (2003), and our results reported in Tables 2).

Grinblatt and Han (2005) show that the disposition effect can generate momentum in stock returns. Li and Yang (2013) propose a general equilibrium model to show that the S-shaped value function of prospect theory can give rise to the disposition effect and hence the momentum effect. These models cannot explain our finding that loser stocks reverse after volatile down markets. It seems possible to construct a model of loss aversion to explain the asymmetric predictability. However, it is challenging for such a

theory to account for both cross-sectional and time-series patterns and to link investors' concern about individual stocks to aggregate market volatility in a loss aversion framework.

Several other papers, including Hong, Lim, and Stein (2000) and Jegadeesh and Titman (2001), suggest that the empirical evidence obtained from their tests is in favor of behavioral explanations. Cremers and Pareek (forthcoming), for example, find that momentum payoffs (and some other anomalies) are much stronger for stocks that have greater proportions of short-term institutional investors. Their test results are not consistent with the smart money hypothesis but consistent with behavioral biases. While all these studies argue that momentum is behavioral, their findings do not explain ours.

### 2.4.2. An intuitive interpretation

The above discussion shows that our findings are not easily captured by existing theories.[18] Since existing theories are focused on the cross-sectional without paying much attention to time series variations in momentum profitability, it is not surprising that these theories do not satisfactorily explain our time-series findings. Here we provide an intuitive explanation for our findings. It is not a rigorous theory but helps organize our findings and invite future research. Our intuitive explanation rests on time-varying investor sentiment and may be intuitively described as a "loser-centered" conjecture. In volatile down markets, investors are afraid of holding loser stocks, especially those with low credit ratings or high information uncertainty. As investors over-sell loser stocks, the subsequent loser reversal gives rise to low momentum payoffs. In contrast, investors tend to be overly optimistic in good market conditions. They ignore negative aspects of loser stocks. As investors aggressively search for cheap stocks, they over-buy loser stocks, generating high momentum profits. Consistent with this conjecture, we find that volatile down markets precede high returns on loser stocks. We also find that high market states forecast low returns on loser stocks, which is consistent with the conjecture that loser stocks are over-bought in good times.

This loser-centered conjecture is different from all existing behavioral theories on momentum. It assumes that investors react differently to negative information in different market conditions. Investors overreact to negative news about loser stocks in bad times but underreact to them in good times. Essentially, it is a story of time-varying investor sentiment. The challenge for future research is to find out whether the required time-variation in investor sentiment is consistent with basic patterns of investor behaviors and whether the argument can be established in a rigorous model.

Alternatively, future research can explore a rational explanation based on time-varying risk or risk-aversion. The base line here is that in bad times loser stocks become significantly riskier than winner stocks. Or alternatively, investors become more risk-averse. In both cases, investors run away from (all stocks but particularly) loser stocks. At a quick glance, it does not seem difficult to build such a model. However, it is ad hoc to cope with only the time-series dimension. The challenge is to account for both the cross-sectional and the time-series variations in momentum profitability.

## 3. Conclusion

Volatility is an important indicator in capital markets. In this paper, we investigate the role of market volatility in characterizing time series variations in momentum payoffs. We carry out various tests and reveal a significant and robust link between market volatility and momentum. The tests generate a comprehensive overview of time-varying momentum performance, showing that the time series predictability of momentum is rather different from aggregate stock market predictability (e.g., one may compare our findings with those of Henkel, Martin and Nardari (2011)). The time-variation patterns complement cross-sectional studies and provide important clues for understanding the sources of momentum profits.

We further find that market volatility is intimately linked to default risk in predicting momentum profitability. This is consistent with that default risk is a more serious concern in volatile down markets. However, default risk alone does not account for all of our findings. A possible explanation of our results is that in different market conditions investors act differently toward loser stocks. Such an explanation could be either behavioral or rational. As discussed in the previous section, one plausible direction is to explore time-varying investor sentiment centered on the fear factor that rules investors in volatile down markets. Alternatively, one may search for a completely rational, risk-based explanation. It is intuitive that in bad times loser stocks have higher default risk and investors are more risk-averse in such times. However, it is challenging how such a rational theory can be extended to account for both the time-series and the cross-sectional patterns of momentum.

## Appendix A. Variable descriptions

In this appendix, we briefly describe variable definitions and how they are calculated.

- MOM: Momentum payoff in month t. The ranking period is from month t − 12 to month t − 2. The holding period is month t. Stocks are sorted into deciles. Equal-weighted portfolios are formed for the deciles. The momentum payoff is the holding month return difference between the winner and loser portfolios.
- MomFF: An alternative momentum payoff measure for robustness constructed using six value-weighted portfolios formed on size and past returns, denoted as Small High, Small Medium, Small Low, Big High, Big Medium, and Big Low. MomFF is the average return

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[18] For brevity, we do not include all existing theories of momentum. For example, Barberis, Shleifer, and Vishny (1998), Berk, Green, and Naik (1999), and Johnson (2002) are among those that are not included. To our knowledge, none of the existing theories is readily capable of explaining our findings.

on the two high prior return portfolios (Small High and Big High) minus the average return on the two low prior return portfolios (Small Low and Big Low).
- MomBig: The return difference between Big High and Big Low portfolios.
- MKT: market state defined as past three-year market return on the value-weighted CRPS market index.
- UP (DOWN): Equals 1 if the past three-year market return, MKT, is non-negative (negative) and zero otherwise.
- Vol: market volatility calculated as the standard deviation of daily returns from month $t − 12$ to month $t − 1$. We used month $t − 6$ to $t − 1$ and $t − 12$ to $t − 2$ for robustness check. It is in percentage terms (i.e., multiplied by 100).
- Vol+ (Vol−): UP (DOWN) market volatility, equal to Vol in UP (DOWN) market states and otherwise equal to 0.
- DIV: Lagged dividend yield of the CRSP value-weighted index. This and the next three variables are lagged by one month (i.e., measured at the end of month $t − 1$).
- DEF: Lagged yield spread between Baa-rated bonds and Aaa-rated bonds.
- TERM: Lagged yield spread between ten-year Treasury bonds and three-month Treasury bills.
- YLD: Lagged yield on a T-bill with three months to maturity.
- RD: Cross-sectional stock return dispersion. Following Stivers and Sun (2010), we focus on the 3-month moving average of the market's monthly RD. Monthly RD is the cross-sectional standard deviation of the 100 stock portfolios formed on size and book-to-market equity ratios.
- VIX: Option implied volatility obtained from the web site of Chicago Board Options Exchange.
- Baker–Wurgler sentiment index: A sentiment index of Baker and Wurgler (2006), obtained from the Wurgler's web site (http://www.stein.nyu.edu/~jwurgler).
- BSM probs: Default probabilities of firms based on the Black–Scholes–Merton option-pricing model. We follow Hillegeist et al. (2004) to calculate this probability. It is in percentage terms (i.e., multiplied by 100).
- Avg: Average BSM probs across all stocks.
- Diff: The difference in the BSM probs between the loser and winner portfolios.
- Avg+ (Avg−): UP (DOWN) market average default probability, which equals Avg if the lagged three-year market return is non-negative (negative) and equals 0 otherwise.
- Diff+ (Diff−): Difference in the BSM probs between the loser and winner portfolios in UP (DOWN) market states, which equals Diff if the lagged three-year market return is non-negative (negative) and otherwise equal to 0.

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