Time-Varying Momentum Profitability

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ABSTRACT

Despite the extensive literature on cross-sectional aspects of momentum, time-variation in momentum profitability receives little attention. We present a comprehensive examination of the time-series predictability of momentum profits. We uncover a list of intriguing features of time-variation in momentum profits: (1) market volatility has significant power to forecast momentum payoffs, which is even more robust than that of market state or business cycle variables; (2) the time-series predictability is centered on loser stocks; and (3) the time-series patterns appear to be at odds with the cross-sectional results. These new findings jointly present a tough challenge to existing theories on momentum.

1. Introduction

The high stock market volatility in late 2008 is followed by a string of dramatic losses of momentum strategies. Figure 1 shows monthly observations of market volatility and payoffs to a momentum strategy from January 2008 to June 2009.[1] After the bankruptcy of Lehman Brothers in September, market volatility skyrocketed in the last few months of 2008 before it tapered off over the first half of 2009. Also striking are the large negative momentum profits following the dramatic rise in market volatility. In the first half of 2009, the momentum strategy performed miserably, producing a monthly average payoff of −17%! Specifically, the strategy's monthly payoffs for January through June are −17.02%, 3.40%, −23.49%, −40.62%, −23.23%, and −1.85%, respectively. The drastic 2008-2009 episode suggests that market volatility may be linked to momentum.[2]

Cross-sectional studies have recently shown that momentum profitability is related to default risk and information uncertainty. Avramov, Chordia, Jostova, and Philipov (2007; hereafter ACJP) identify a cross-sectional link between momentum and credit rating. They find that profitability of momentum investing is highly significant among low-grade firms, but nonexistent among high-grade firms. Jiang, Lee, and Zhang (2005) and Zhang (2006) find that momentum payoffs are higher among firms with higher information uncertainty. If concerns of investors about default risk and information uncertainty are cross-sectionally linked to momentum profitability, they may also be important in the time-series dynamics of momentum. Intuitively, volatile markets are generally time periods of high information uncertainty. These are also times when default risk grabs attention. For example, the perceived default risk of many financial firms (e.g., AIG) increased dramatically after the

[1] In Figure 1, market volatility is computed as the standard deviation of daily returns in the month. Monthly returns of the momentum strategy are downloaded from the Ken French data library. Profitability of the momentum strategy, usually referred to as the momentum payoff or momentum profit, is measured by the winner-loser return difference.

[2] The momentum strategy also performed poorly in the early 1930's, which is a well-known period of highly volatile stock market performance. Specifically, the monthly average momentum payoff from January 1930 to December 1934 is −1.42%.

breakdown of Lehman Brothers. In general, volatile down markets could be the "show time" to demonstrate that the concerns about default risk and information uncertainty can impact time-variation in momentum profitability.

Motivated by the 2008-2009 episode and the cross-sectional results, we investigate time-series predictability of momentum, with the focus on predictive power of market volatility. There is an extensive literature on the momentum effect of Jegadeesh and Titman (1993).[3] However, empirical studies on the momentum effect are overwhelmingly focused on cross-sectional aspects of the anomaly. Time-variation in momentum profits has received much less attention. The study of Cooper, Gutierrez, and Hameed (2004; hereafter CGH) is an important exception. CGH provide the most well-known time-series analysis of momentum, and hence it is the one that is most related to our study. CGH aim at testing behavioral theories and their key finding is that momentum profits depend on market states.[4]

Our tests uncover a set of intriguing features of time-variation in momentum profits. First, using monthly stock returns and other data from the 1929-2009 sample period, we find that 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 momentum portfolios are constructed using stocks with relatively large market capitalization. Second, time-series predictability is asymmetric between the winner and loser portfolios. 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. When the relative performance is measured using the Fama and French three factor model, the loser stocks are still the dominant source of the time-series predictability. Third, the time-series results from our study appear to be contradicting to

[3]For a partial list of explanations on momentum, see Barberis, Shleifer, and Vishny (1998), Berk, Green, and Naik (1999), Harvey and Siddique (2000), Chordia and Shivakumar (2002), Johnson (2002), Grinblatt and Han (2005), Avramov and Chordia (2006), Chen and Zhang (2008), Garplappi and Yan (2008), Liu and Zhang (2008), and Li and Yang (2009).

[4]Following CGH, we define market state as the lagged three-year market return. Down (up) markets are the negative (positive) market states which are the periods when the lagged three-year market return is negative (positive). We use the lagged 12-moth market volatility in our tests.

the cross-sectional patterns identified by ACJP, Jiang, Lee, and Zhang (2005), and Zhang (2006). The cross-sectional relation is that momentum profitability is higher among firms with higher default risk or higher information uncertainty. We find that high market volatility forecasts low momentum payoffs, especially in negative market states. This is puzzling since volatile down markets should be the time periods in which investors are more concerned about default risk and information uncertainty.

Our study extends the work of CGH in two important aspects. First, the objective of CGH is to test the models of Daniel, Hirshleifer, and Subrahmanyam (1998) and Hong and Stein (1999). We aim for a systematic investigation of the time-series predictability, and our results present a comprehensive overview of the time-varying momentum profits. Second, the findings of CGH, which are interpreted as supportive evidence for the above models, do not challenge the existing literature. In contrast, our empirical results raise tough questions to a variety of theories, both behavioral and risk-based, that have been proposed to explain the momentum effect. Daniel, Hirshleifer, and Subrahmanyam (1998), for example, assume that investors are overconfident about their private information and overreact to it. Like many models, this behavioral model generates implications that are symmetric between positive and negative information, which is inconsistent with the asymmetric predictability. Another example is the behavioral theory developed by Hong and Stein (1999). They assume that private information diffuses gradually in the marketplace, which leads to underreaction. Hong, Lim, and Stein (2000) provide evidence that information diffusion is slow for bad news. However, our finding that high volatility in down markets forecasts high returns on loser stocks is consistent with investor overreaction, not underreaction, to negative information associated with loser stocks in volatile down markets.

Our results demonstrate that features of the time-series predictability are important for understanding the sources of momentum profits. Our findings show that the time-series predictability of momentum raises three challenging issues. Why does market volatility have robust power for predicting time-varying momentum payoffs? Why is the time-series predictability asymmetric and centered on loser stocks? Why do the time-series predictability and cross-sectional predictability appear to be at odds with each other? Combined together, these questions present a three-piece puzzle, creating a tough challenge to all existing theories of the momentum effect.[5]

In searching for an explanation of the market volatility's predictive power, we examine whether default risk plays a significant role. 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 of the BSM probs across all stocks has a correlation coefficient of 0.84 (0.36), in down (up) markets, with our market volatility measure. Our tests that focus on down markets show that both the all-stock average of 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. However, default risk alone does not resolve the three-piece puzzle. In particular, it does not explain the puzzling contrast between the time-series and cross-sectional patterns.

One possible explanation of our findings is a loser-centered, irrationality-based story. This is a conjecture about time-varying sentiment in different market conditions. 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 to avoid high default risk or high uncertainty in such fearful times, the subsequent loser reversal gives rise to low momentum payoffs. In good market conditions, investors are overconfident and to some extent they ignore negative aspects of loser stocks including particularly credit risk and information uncertainty. Investors are aggressive in searching for relatively cheap stocks such that they over-buy loser stocks associated with high credit risk or high information uncertainty, generating high momentum profits.[6] Consistent with the conjecture that loser

[5]Section 2.4 provides examples and discussions to show that recently proposed theories on momentum, either behavioral or risk-based, do not explain the puzzle.

[6]Interestingly, the cross-sectional analysis of ACJP finds that among the low-grade firms, loser stocks are

stocks are relatively over-sold in bad times, we find that volatile down markets precede high returns, relative to the market return over the same period, on the loser stocks. We also find that consistent with the conjecture that loser stocks are relatively over-bought in good times, high market states forecast low returns on the loser stocks.

This irrationality-based explanation is different from all existing behavioral theories on momentum. It is loser-centered and it assumes that investors react differently to negative information in different market conditions. Investors overreact to negative aspects associated with loser stocks in bad times but underreact to them in good times. Being a simple story, it presents a tantalizing invitation to future research for resolving the three-piece puzzle. Clearly, this loser-centered, irrationality-based explanation is a conjecture. We highlight it for three reasons. First, it is an intuitive interpretation of our empirical results. Second, it helps us to see clearly why the existing behavioral theories fail to explain our results. Third, we hope that this loser-centered irrational explanation will serve as a stimulating benchmark for developing alternative explanations.

Our findings suggest a simple way to enhance the profitability of momentum investing. We define a month to be of high (low) volatility if the lagged 12-month volatility is larger (smaller) than the lagged 36-month volatility. The monthly average payoff of the momentum strategy in Figure 1 is 0.79% over the 1929-2009 sample period, while in contrast that average is -3.01% over negative market states that have high volatility. Thus, there is an obvious way to modify the momentum strategy for enhancing the profitability. One can simply reverse the momentum trading rule in volatile down markets by taking a long position in the loser portfolio and a short position in the winner portfolio. The increase in transaction costs of the modified strategy should not be a major concern, given that volatile down markets are relatively infrequent.[7] The gain from the simple modification could be highly significant. For example, if in late 2008 one canceled the short position in the loser portfolio in a regular

the dominant source of momentum profits.

[7] 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.

momentum strategy, she would have avoided the large losses in 2009 as depicted in Figure 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 (e.g., see Figure 3).

Chordia and Shivakumar (2002; hereafter CS) show that a set of commonly applied macroeconomic instruments for measuring market conditions, such as the dividend yield of the market index and the term premium, can explain a significant portion of momentum profits. Being related to the business cycle, these variables are popular return predictors that are widely used in conditional asset pricing models. CS conclude that time-variation in the momentum profitability can be attributed to variations in the macroeconomic variables (and therefore presumably to risk). However, CGH show that the explanatory power of the macroeconomic variables is sensitive to methodological adjustments that take account of microstructure concerns. We examine whether these popular return predictors can take away the explanatory power of market volatility. We confirm the findings of both CS and CGH that the macroeconomic variables have certain predictive power but their performance is not robust when the momentum strategy is constructed using larger-cap stocks. In contrast, the predictive power of market volatility remains significant in all the cases.

We find similar results when using the Baker-Wurgler investor sentiment index to predict momentum profits. Baker and Wurgler (2006) construct a composite index based on the first principal component of six variables that are regarded as proxies for investor sentiment. They show that the index has predictive power for the cross-section of stock returns. We find that the sentiment index has significant predictive power for momentum profits, but only in the equal-weighting scheme. For the same sorting procedure, the predictive power disappears when we use value-weighted momentum portfolios.

The predictor that we focus on is the realized market volatility. We examine robustness of our findings with two related variables, the cross-sectional stock return dispersion and the Chicago Board Options Exchange Volatility Index (VIX). Stivers and Sun (2009) find that the cross-sectional dispersion in stock returns is negatively related to the subsequent momentum premium. Consistent with their study, we confirm that the cross-sectional dispersion forecasts momentum profits. The correlation between the return dispersion and our market volatility measure is 0.52. The predictive power of the return dispersion, however, becomes insignificant in the presence of the market volatility measure. VIX is a measure of future volatility, but it is significantly correlated to the realized market volatility. In the 1990-2009 period, a time period in which we have data on VIX, the correlation coefficient between our volatility measure and VIX is 0.71. We find that our volatility measure remains robust in the presence of VIX. VIX has incremental explanatory power conditional on the presence of the realized volatility measure. Thus, the cross-sectional return dispersion and VIX do not capture the predictive power of the realized market volatility measure.

Our focus on volatility 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 (e.g., see Campbell and Hentschel (1992) and Glosten, Jagannathan and Runkle (1993)). Recently, Ang, Hodrick, Xing, and Zhang (2006, 2009) investigate how market volatility affects the cross-sectional variation in stock returns. They find that stocks with high sensitivities to innovations in aggregate volatility have low average returns and that stocks with high idiosyncratic volatilities have low average returns. Our study extends this line of investigation by examining the time-series relationship between market volatility and momentum profitability. Our finding that default risk helps explain the predictive power of market volatility for momentum suggests that default risk, especially in volatile down markets, may play an important role in predicting stock returns.

The rest of the paper is organized as follows. Section 2 presents the empirical analysis of the time-series predictability of momentum. Section 2.1 describes the setup and data. Section 2.2 presents the main results on characterizing time-variation in momentum profits. Section 2.3 explores potential explanations about the predictive power of market volatility. Section 2.4 discusses implications of our findings, using examples to show that the three-piece puzzle is a challenge to the existing theories on momentum. Section 3 concludes the paper.

2. Time-Series Predictability of Momentum

2.1. Setup and Data

Most of the studies on momentum aim at cross-sectional features of the anomaly. Our study provides a time-series analysis. We aim to present a characterization of time-variation in momentum profits. We run regressions of the momentum payoff on various predictors. These predictive regressions are of the form:

$$\mathrm{MOM}_t = a + b' x_{t-1} + \varepsilon_t,$$

where MOM_t is the month t momentum payoff or the winner-loser month t return difference, which is observed at the end of month t, and x_{t-1} is the vector of predictors, which is measured at the end of month t-1. It should be noted that the time-series predictability of momentum is different from the aggregate stock market predictability. For the momentum effect, the focus is on whether (and why) the relative performances of the winner and loser portfolios vary over time in a predictably different way.

Monthly returns on momentum portfolios, from August 1929 to July 2009, are obtained from the data library of Ken French. The momentum strategy is constructed following Fama and French (1996). Specifically, the ranking period of the strategy is from month t-12 to month t-2 while 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, and stocks in the top (bottom) return decile are referred to as winner (loser) stocks. Equally-weighted portfolios are formed for the deciles. The momentum payoff is the holding month return difference between the winner and loser portfolios.

We focus on this momentum strategy, which is used throughout all of the reported tests, 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) such that their three-factor model fails to explain the payoff to this strategy. In addition to the momentum deciles, Fama and French construct a widely used momentum factor, denoted as MomFF in our subsequent discussions, which we use for a robustness check. Third, the one-month holding period in the Fama-French construction makes it well suited for studying time-series predictability. If the holding period is more than one month (e.g., six months), one can replace the dependent variable MOM_t by the payoff over the multi-month holding period (e.g., the payoff over the period from month t to month t+5). Extending the holding period beyond one month, however, would artificially introduce a strong autocorrelation in monthly observations of the momentum payoff. A highly autocorrelated dependent variable creates concerns of spurious regressions, and also makes it unclear how to interpret the adjusted R-squares of the regressions.

For robustness concerns, we have put the MomFF factor as the dependent variable in the regressions. 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, the momentum factor is the average return 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). In addition to the momentum factor, we have used the return difference between Big High and Big Low, which is the momentum payoff among stocks with larger market capitalization. This helps to show whether the predictive power is limited to only small stocks. For brevity, the results based on the MomFF factor and Big High minus Big Low are reported only in Table 4. 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.

The value-weighted CRSP market index is obtained for measuring market volatility and market state. For each month in the period from August 1929 to July 2009, we compute the lagged 12-month (month t-12 to month t-1) market volatility which is the standard deviation of daily returns in the 12-month period. This is the volatility measure in our predictive regressions. Two alternative measures are checked for robustness.[8] Following CGH, we use the lagged three-year (month t-36 to month t-1) market return to define market states. Time-variations in the measures are plotted in Figure 2.

Panel A in Figure 2 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 variation in market state. 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. For example, there is not a single month of 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 way to define up and down markets. Panel C depicts variation in the lagged six-month market return, a different measure that we have checked for defining market state. The six-month return is more sensitive to sudden changes in market sentiment. 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 down market volatility (see Table 3).

We center our empirical analysis on market volatility and divide the results into two parts. Here we briefly point out certain data sources and/or the construction approaches in each part. The first part aims to establish an empirical characterization of the time-series predictability of momentum. This part has involved the macroeconomic variables of CS: the lagged dividend yield of the CRSP value-weighted index (DIV), the lagged yield spread between Baa-rated bonds and Aaa-rated bonds (DEF), the lagged yield spread between ten-year Treasury bonds and three-month Treasury bills (TERM), and the lagged yield on a

[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.

T-bill with three months to maturity (YLD). We obtain monthly observations on these four variables from the CITIBASE database in the period from April 1953 to June 2009.

The second part aims to explore potential explanations about the findings on the time-series predictability. We test whether the cross-sectional stock return dispersion, VIX, or the Baker-Wurgler sentiment index can account for the market volatility's explanatory power. We construct the return dispersion measure following exactly the procedure of Stivers and Sun (2009) and obtain data on VIX from the web site of Chicago Board Options Exchange. The former is available for the full sample period, but the latter is only since 1990. The data on the Baker-Wurger sentiment index is obtained from the Jeffrey Wurgler's web site (http://www.stein.nyu.edu/~jwurgler). The monthly observations range from January 1966 to December 2005. We explore whether default risk is linked to 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 individual firms. We implement the procedure of Hillegeist et al. (2004) to estimate default probabilities of firms, using the SAS code provided in their paper.

2.2. Time-Variation in Momentum Profits

What characterizes time-variation in momentum profits? In this subsection, we present tests that aim at this issue, with the focus on the role of market volatility. We proceed in three steps. First, we evaluate the significance of the link between market volatility and momentum. Next, we examine the robustness of market volatility in the presence of market state and macroeconomic variables of CGH and CS. Finally, 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. All the months in the sample period are sorted into four subsets, depending whether the market state is positive or negative and whether the market volatility is high or low. A month is in a negative (positive) market state if the lagged three-year market return is negative (positive). In other words, the market state for month t is determined by the 36-month market return from month t-36 to month t-1. 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, and 358 (471) of them are of high (low) volatility. There are 131 months in negative market states, with 75 (56) of them being of high (low) volatility. It should be noted that this is an independent two-way sort such that it does not matter whether we first do the sorting on market state or market volatility.

Table 1 presents results from the two-way sort. For the full sample period, the average monthly momentum payoff is 0.79%. The average payoffs over the subsets show that both market state and market volatility matter. Momentum profits are higher in positive market states while they are lower in months of high volatility. Among positive market states, the average payoff over the low volatility months outperforms that over the high volatility months by 0.67% (= 1.56% − 0.89%). In negative market states, the average payoff over the high volatility months is −3.01%. The payoff over the low volatility months outperforms that over the high volatility months by 1.72% (= −1.29% − (−3.01)%). The monthly average payoff differs by 4.57% (= 1.56% − (−3.01)%) between the low volatility positive market states and the high volatility negative market states.

The eighty-year sample period is divided into two equal-length subperiods. The results for the two subsamples show that consistent with the results from various studies, the momentum payoff is higher in the second period. The predictive power of market volatility in negative market states is stronger in the more recent four decades. For the 1969-2009 subperiod, the average payoff difference between the sets of high and low volatility months in negative market states is −4.02% (= −2.86% − 1.16%). In particular, the low volatility months in negative market states have a positive average payoff of 1.16%, which is even slightly higher than that average (1.00%) of the high volatility months in positive market states.

The results from Table 1 suggest a simple way to improve the momentum profitability. Given the large negative payoff in volatile down markets, it is nature 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 with a long position in the winner and a short position in the loser. It should be noted that the increase in transaction costs due to the modification should not be a serious concern, given that the negative market states of high volatility are relatively rare (75 out of 960 months, or a frequency of 7.8%) and tend to be clustered together. The gain from the modified strategy is highly significant.

To illustrate, Panel A of Figure 3 plots the cumulative payoffs to the modified and regular momentum strategies from the past decade (from August 1999 to July 2009).[9] Panel B shows the two variables for constructing the modified trading rule: the volatility ratio, the lagged 12-month market volatility divided by the lagged 36-month market volatility, and the lagged three-year market return. If the volatility ratio is above (below) 1.0, it is a month of high (low) volatility. There are only two intervals that are relevant for the modified rule. One of them is from October 2002 to July 2003 and the other is from October 2008 to the end of the period. The modifications make quite a difference for the strategy's payoff. The decade's cumulative payoff to the modified strategy is 299.85%, while the payoff to the regular momentum strategy is 22.61%! This example highlights the economic significance of the time-series predictability of momentum.

Table 2 presents results from regressions of the momentum payoff on the 12-month market volatility measure (hereafter Vol). In addition, we consider the up market volatility (Vol+) and the down market volatility (Vol−), which are equal to Vol in positive (negative) market

[9] Apparently, the performance difference between the two strategies would be more impressive if we increase the length of the time period. We have verified that this is indeed the case. Such results are available upon request.

states and otherwise equal to 0. The full sample period is divided into three subperiods of equal length. The results for the full sample period and the subperiods indicate that market volatility has significant predictive power, especially in negative market states. In all cases, Vol has a negative coefficient that is statistically significant, with the robust t-statistics ranging between -3.60 and -2.04. There is quite a difference between the up market volatility and the down market volatility. In all the cases, Vol+ and Vol$-$ have negative signs, but Vol$-$ is dominant in terms of the magnitudes of the coefficient and the t-statistic. For the full sample period, the regression with Vol+ and Vol$-$ has an adjusted R-square of 3.6%, while the regression with Vol has an adjusted R-square of 2.2%. The findings indicate that the predictive power of market volatility is more evident in down markets. The predictive power is particularly impressive in the most recent subperiod. This is not surprising given that we have seen in Figure 3 that the modified momentum strategy worked quite well over the internet crash and the 2008-2009 bear market. While all the three subperiods provide supportive evidence, the results from the middle one or the 1956-1982 period are less strong. This is consistent with the fact that the middle subperiod, as shown in Panel A of Figure 2, is relatively much less volatile than the other two subperiods.

2.2.2. Market State and Macroeconomic Variables

Table 3 presents predictive regressions that include both market volatility and market state. It also presents results from a robustness check that uses the lagged six-month market return to define market state and the lagged six-month market volatility as the volatility measure. In Panel A, the market state and volatility measures are the same as in Tables 1 and 2. In the first regression, both MKT and Vol are statistically significant, indicating that both variables have independent power to forecast momentum profits. In the second regression, MKT becomes insignificant.[10] The adjusted R-square increases slightly, and Vol$-$ is statistically

[10] For this reason, in Tables 4 through 7 we do not include MKT in the presence of Vol$-$ and Vol+.

significant. This result is consistent with those from Table 2. It should be emphasized that since MKT is used in defining Vol− and Vol+, one cannot conclude that the result from the second regression shows 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 such that combined together, they provide a useful indicator of market conditions and/or market sentiment.

The results from Panels B and C show that the predictive power of market volatility passes the robustness check when the lagged six-month market return defines market state and the volatility measure is the lagged six-month market volatility. In these two panels, the lagged six-month market return is used to define the up market volatility, Vol+, and the down market volatility, Vol−. The result from the first regression in Panel B is similar to that in Panel A, showing that it does not matter significantly whether to use the 12-month volatility measure or the six-month one. In the second regression, we still use the lagged three-year market return for MKT. As expected, Vol− is stronger than Vol+. Panel C shows that when MKT is replaced by the lagged six-month return, the results about market state change significantly. It is insignificant in the first regression and has the negative sign in the second regression.[11]

We examine whether the macroeconomic variables of CS can take away the explanatory power of market volatility. The results are presented in Table 4, which consists of three panels that differ in terms of the dependent variable of the regressions. In Panel A, the dependent variable is the payoff to the strategy used in the previous tables. In Panel B, the dependent variable is the momentum factor of Fama and French (MomFF) that is constructed using six value-weighted portfolios. This factor is size-balanced. In Panel C, the dependent variable is the return difference between Big High and Big Low, which is the payoff to a momentum

[11] 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.

strategy using larger-cap stocks. The momentum payoffs in Panels B and C are described in Section 2.1. Panels B and C are used to check whether the predictive variables perform well when the portfolio construction is tilted to emphasize larger-cap stocks.

The results from Panel A show that these popular conditioning variables do have some 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 in Panel B. For the regressions in Panel B, only YLD has a robust t-statistic that is above 2.0 in absolute value. In Panel C, the predictive power of the macroeconomic variables disappears completely, with the t-statistics ranging from -0.77 to 0.66. Similarly as the macroeconomic variables, MKT is statistically significant in Panel A, but not in Panels B and C. These results suggest that predictive power of the market state MKT is also not robust when the portfolio construction is tilted to the larger-cap 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 Panel A to Panel C. The t-statistics of Vol$-$ and Vol$+$ in Panel C are also larger in absolute value than those in Panels A and B.

In sum, Tables 3 and 4 show that market volatility has robust predictive power in the presence of the market state and the macroeconomic variables. Unlike the market state and the macroeconomic variables, market volatility retains its significant predictive power when the momentum portfolios are constructed with the larger market-cap stocks.

2.2.3. Asymmetric Predictability

Table 5 presents our finding of asymmetric predictability. We separately run the predictive regressions for the loser and winner portfolios. For the dependent variable, we use the return difference between the loser (winner) portfolio and the market index in Panel A1 (A2). 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). It is natural to remove the market component since the objective of our study is not about the stock market predictability. For the momentum effect, it is interesting to find whether the time-varying performances of loser and winner stocks deviate from the overall market performance in a predictable way.

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 $r_L - r_f - b_L\text{RMRF} - s_L\text{SMB} - h_L\text{HML}$, 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. RMRF, RMRF, and HML are the three factors of Fama and French. All the returns and factors are over the holding month (month t). Other than the dependent variables, the setup in Panels A1, A2, B1, and B2 is similar to that of Panel A in Table 3. In Panels C1, C2, D1, and D2, the macroeconomic variables are included, and other than the dependent variables, the setup of these panels is identical to that of Panel A in Table 4.

The contrast between Panels A1 and A2 is impressive. In predicting the loser's relative performance over the market, MKT, Vol, and Vol$-$ show up significantly. The adjusted R-squares of these full sample regressions range from 2.1% to 3.5%. In predicting the winner's relative performance over the market, however, all the variables are statistically insignificant. The robust t-statistics range between -1.20 to 0.01 and all the adjusted R-squares are negative, about -0.2% or -0.1%. In Panels C1 and C2, the sharp contrast remains evident. For the loser's performance in Panel C1, the adjusted R-squares are about 5.3%. Vol and Vol$-$ are significant. The macroeconomic variables also show certain predictive power. 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 respectively. The regressions in Panel C2 give the opposite conclusion. None of the variables is statistically significant, and the adjusted R-squares of the two regressions are -0.9% and -0.6%.

In terms of the performance relative to the FF3F benchmark, Panels B1 and B2 show that the adjusted R-squares in B1 are 2.1% and 3.3%, which are considerably higher than those in B2. MKT is significant in B1 but not in B2. Also, the coefficients for Vol and Vol$-$ in B1 are much higher than those in B2 in terms of the absolute value. The contrast is even stronger between Panels D1 and D2. None of the variables are statistically significant in D2 and the regressions have adjusted R-squares around 1%. In D1, 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 the time-series predictability of momentum.

It should be emphasized that 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. Thus, the asymmetric or loser-centered predictability that we identify is with respect to the two popular benchmarks, the overall market and the Fama-French three factor model.

The separate regressions for loser and winner stocks provide support for the loser-centered explanation of momentum. In the regressions for loser stocks, the coefficients of Vol and MKT are positive and negative, respectively. The results indicate that volatile down markets lead to high returns on loser stocks and hence low subsequent momentum payoffs. The low volatility positive market states forecast low returns on loser stocks and hence high subsequent momentum payoffs. These patterns suggest that loser stocks are over-sold in volatile down markets but over-bought in good market conditions.

The asymmetric time-series predictability does not imply that the abnormal component of momentum profits should come mainly from loser stocks. It is possible that both winner and loser stocks have quite large average 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 (the average abnormal returns) of the winner and loser portfolios from the monthly return regressions 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

Why does market volatility have power for predicting time-variation in momentum profits? We discuss this issue in this subsection. In the first three steps, we examine whether the cross-sectional stock return dispersion, VIX, or the Baker-Wurgler investor sentiment index can take away the explanatory power of market volatility. We then check whether default risk plays a role in explaining the link between market volatility and momentum.

2.3.1. Return Dispersion

Our market volatility measure reflects the realized volatility during the ranking period of the momentum strategy. Over the full sample period, this measure has a correlation of 0.52 with RD_{1-3}, the three-month moving average of the cross-sectional return standard deviation of the 100 size and book-to-market portfolios. While the two are significantly correlated, market volatility and return dispersion are conceptually quite different. Market volatility is a measure of time-series variation of the overall market, but return dispersion is a measure of cross-sectional variation in stock returns. For example, the return dispersion increases when two of the portfolios have extreme returns of opposite signs (hypothetically, say 30% and -30% respectively). But in this case the market return may not even be affected as the two extreme returns are canceled out in the aggregation.

Our results, reported in 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. Similarly, in the presence of Vol+ and Vol−, the significance of RD_{1-3} disappears.

The conclusion from Table 6 is obvious. Although Vol is significantly correlated with the return dispersion, the predictive power of market volatility is clearly not derived from that of the return dispersion.

2.3.2. VIX

The Chicago Board Options Exchange Volatility Index (VIX) is popular among investors. VIX is a measure of future market volatility, but the measure Vol that we focus on is the realized market volatility. The regression results for VIX, reported in Table 7, are interesting. When it is being used alone, VIX has the negative sign but it is statistically insignificant, with a robust t value of -1.05. The adjusted R-square is -0.2%. When MKT and Vol are included, VIX becomes significant, but it has the positive sign. The result is similar in the last regression that includes Vol+ and Vol−. Compared to the regressions without VIX, the inclusion of VIX leads to a moderate increase in the adjusted R-square.

These results are intriguing. Why does VIX have positive sign in the multiple-predictor regressions and why is VIX insignificant when used alone? 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 is a measure of expected future market volatility, it is natural that 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.

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.[12] 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 Table 8, we present results using the orthogonalized index. The results are similar when using the unorthogonalized index and hence omitted. As shown in Panel A, the BW index shows up significantly in the predictive regressions, with robust t-statistics of 2.22 and 2.38. The results suggest that high investor sentiment forecasts high momentum payoffs. In Panel A, the regression dependent variable is the momentum payoff based on the equally-weighted portfolios. In Panel B, the regression dependent variable is the momentum payoff based on the value-weighted portfolios. The change of the weighting scheme matters for the BW index. In both regressions in Panel B, the coefficients of the BW index are much smaller than those in Panel A, and are statistically insignificant, with robust t-statistics of 0.12 and 0.17. In contrast, the significance of Vol or Vol$-$ is robust across all the cases, with the t-statistics ranging from -3.88 to -2.43.

The sensitivity to the weighting scheme suggests that the role of the BW sentiment index in forecasting the momentum profits is limited to small-cap stocks. Furthermore, we find that the correlation between our market volatility measure and the BW index is only 0.05. Clearly, these results give rise to the conclusion that the BW sentiment index is not linked

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

to our market volatility measure and the predictive power of the BW sentiment index does not capture that of market volatility.

2.3.4. Default Risk

Intuitively, volatile down markets are generally associated with great uncertainty about the overall economy. During such times, investors are more concerned about default risk of stocks, especially those in the loser portfolio. Thus, it is a natural hypothesis that default risk in down markets may play a role in explaining the predictive power of market volatility for momentum profits.

Applying the approach of Hillegeist et al. (2004), we compute the BSM probs for all stocks with available data.[13] We focus on two summary measures: the average of the BSM probs across all stocks, denoted as Avg, and the difference in BSM probs between the loser and winner portfolios, denoted as Diff. To compute correlations in down markets (reported in Table 9), we remove all the observations in positive market states and take the time series of the remaining observations in down markets.[14] This ensures that the correlations in down markets 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 over the same time periods.

Table 9 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! The regressions show that both Avg$-$ and Diff$-$ are statistically significant, with robust t statistics of -3.49 and -3.20 respectively. While the results are consistent with our conjecture, we realize that there is a potential test power problem. When market state is defined by the

[13] 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.

[14] Similarly, to compute correlations in up markets, we remove all the observations in negative market states and use the time series of only observations in up markets.

lagged three-year market return, the market is rarely in negative states. During 1980's and 1990's, as mentioned before when looking at Figure 2, the market was never in negative states. Thus, the regression tests in Table 9 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. We also remove the observations in positive states and run the regressions over the time series of observations in negative states. The results are presented in Table 10.

For each of the four variables: MKT, Vol, Avg, and Diff, Panel A of Table 10 shows the single-predictor regressions.[15] When used alone, Vol, Avg, and Diff are statistically significant. Among the three, Diff has an adjusted R-square of 2.3%, much better than the other two. In the multiple-predictor regressions reported in Panel B, the statistical significance of Vol disappears when we include Avg and/or Diff. Again, Diff performs better than Avg. In the third regression that have MKT, Avg, and Diff as the explanatory variables, Diff has a robust t-statistic of -3.23 while in contrast the t-value for Avg is 1.67. Similarly, in the last regression, Diff is significant but Avg is not. The main point of Table 10 is that the default risk proxies, Avg and Diff, take away the predictive power of market volatility in the regressions that focus on down markets.

These results on the default risk proxies suggest that high default risk in down markets leads to low momentum profits. This finding is intuitive, since in fearful times default risk is likely to be a major concern of investors and loser stocks are likely to have high perceived default risk. However, this time-series finding is contradicting to the cross-sectional result of ACJP that momentum profits are higher among firms with higher default risk. Thus, although the results in Tables 9 and 10 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 time-series results.

[15] Note that the notations are simplified. For example, Vol represents the down market volatility, since only the down market months are included in this table. In other words, Vol stands for Vol$-$ in this table. Similar remarks applied to the other variables.

2.4. Challenges and Implications

Our empirical findings present three challenging questions. First, a basic finding of our study is that market volatility is linked to momentum. Why does market volatility have power to forecast the momentum payoff? Second, the asymmetric predictability is another key finding of ours. Why is the time-series predictability centered on loser stocks? Third, the time-series relation that we find is that volatile down markets forecast low momentum payoffs. The cross-sectional relation, as shown by ACJP, Jiang, Lee, and Zhang (2005), and Zhang (2006), is that stocks with higher default risk or higher information uncertainty (higher stock return volatility in particular) generate higher momentum profits. Volatile down markets are periods of high perceived default risk and high information uncertainty, but they forecast low momentum profits. Why do the time-series and cross-sectional findings appear to be at odds with each other?

The literature on momentum is extensive, but the focus of the research efforts is on cross-sectional differences among winner and loser stocks. Numerous studies aim to explain why winner stocks earn higher average return 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. Time-series predictability of momentum has not yet challenged the existing 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 the time-series predictability of momentum raises tough questions. Specifically, the three questions listed above present a three-piece puzzle, which is a tough challenge to all the existing theories, whether behavioral or risk-based.

For example, Garlappi and Yan (2008) 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 a high level of default probability, the relationship is downward sloping. Thus, since loser stocks have higher default risk, they have lower equity betas and hence lower expected returns. While this model provides an interesting explanation for the puzzling cross-sectional results of ACJP, its time-series prediction is that loser stocks should have low returns following periods of high default risk. This is opposite to our finding that volatile down markets are followed by high returns on loser stocks.

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. Focusing on cross-sectional effects, they perform various two-way sorts in empirical analyses. They find that enhanced payoffs arise from momentum strategies that use firms with high revenue growth volatility, low costs, and valuable growth options. It is interesting to note that 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). Since firms with these characteristics are associated with higher return volatility, their model does not explain our findings. In particular, their model does not explain why loser stocks tend to have good returns following volatile down markets.

Harvey and Siddique (2000) incorporate conditional skewness in an asset pricing model. Their results suggest that the momentum effect is related to systematic skewness. Motivated by a neoclassical reasoning, Chen and Zhang (2008) propose a multifactor model that include factors based on investment and productivity. They show that the model performs well in explaining the momentum effect. Liu and Zhang (2008) focus on the growth rate of industrial production, which is considered a priced risk factor in asset pricing. They show that winner stocks have higher loadings on the growth rate of industrial production than loser stocks, giving rise to the conclusion that risk plays an important role in generating momentum profits. However, the success of these explanations is measured in terms of the ability to price the cross-sectional return differences. It is unclear whether the factor models can be extended to explain the patterns of time-variation in momentum profits.

In particular, the macroeconomic variables described in Table 4 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 explanatory power of these variables is not robust in predicting momentum profits (see CGH, Griffin, Ji, and Martin (2003), and our results reported in Panel C of Table 4) casts doubts about whether rational factor-based pricing models are able to succeed in explaining the time-series predictability of momentum.

Grinblatt and Han (2005) show that the disposition effect can generate momentum in stock returns. Li and Yang (2009) 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. The disposition effect states that investors have a tendency to hold loser stocks for too long, which does not explain our time-series finding of loser reversal after volatile down markets. It seems possible to construct a model of loss aversion to explain the asymmetric predictability. However, it remains unclear how such a theory can account for both the cross-sectional and time-series patterns. Another challenge is how to link investors' concern about aspects of individual stocks (e.g., individual stock return volatility) to the 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 (2010), for example, recently find that momentum payoffs (and some other anomalies) are much stronger for stocks that have greater proportions of short-term institutional investors. This suggests that stocks dominated by short-term focused investors are more subject to anomalous pricing. 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.

Our discussion of these recently proposed explanations of momentum aims to illustrate that the three-piece puzzle is not captured by the existing theories on momentum.[16] Since

[16] For brevity, we do not include all the existing theories of momentum. But to our knowledge, none of the

the existing theories are focused on explaining cross-sectional differences between winner and loser stocks, it is not surprising that the puzzling contrast between the cross-sectional and time-series predictability results is a particularly tough challenge to these theories.

Our findings complement the existing results from various cross-sectional studies and call for a thorough theoretical exploration of both time-series and cross-sectional properties of the momentum effect. Although a rigorous theory remains to be uncovered, we have proposed a loser-centered, irrationality-based conjecture (stated in the introduction) for the purpose to highlight the three-piece puzzle, stimulate further critiques and invite comprehensive theoretical investigations. Our findings on the time-series predictability provide important clues for future work. The finding of asymmetric predictability, for example, suggests that a convincing model of momentum should treat positive and negative information differently. Clearly, a convincing model of momentum should also address why the cross-sectional and time-series findings are seemingly contradicting to each other.

3. Conclusion

The stock market in late 2008 was so fearful that market volatility jumped to the highest post-war level. As the fear wore off, the market rebounded. In particular, loser stocks put up a drastic reversal along with the market recovery, creating large negative momentum payoffs. For the momentum strategy used in Figure 1, for instance, the loser portfolio's monthly returns for March, April, and May of 2009 are 30.34%, 46.10%, and 26.02%, beating the market by a wide margin. This fearful episode is a good example to illustrate high default risk and great aggregate information uncertainty in volatile down markets.[17]

The focus of the momentum literature has been on cross-sectional differences among stocks in the winner and loser portfolios. Less attention has been paid to the time-series

existing theories is readily capable of explaining our findings.

[17] For anecdotal evidence, one may take a look at the Associated Press article "2009 Was One of the Worst Years on Record for Bankruptcies" at http : //www.cnbc.com/id/34690872.

dynamics. Stimulated by the impressive loser reversal in early 2009, we investigate the time-series predictability of momentum, with the focus on the predictive power of market volatility. We carry out various tests and the results indicate that there exists a significant and robust link between market volatility and momentum. The tests have generated a comprehensive overview of time-varying momentum profits, showing that the time-series predictability of momentum is rather different from the aggregate stock market predictability (e.g., one may compare our findings with those of Henkel, Martin, and Nardari (2009)). We summarize the findings from our time-series analysis as a three-piece puzzle, which is a tough challenge to all the existing theories on the momentum effect.

Loser stocks have higher default risk but lower holding period returns than winner stocks (see ACJP, Dichev (1998), and Campbell, Hilscher, and Szilagyi (2008)). This finding makes it hard to imagine that momentum can be fully explained by a risk-based rational theory. Our findings make it much harder, since the time-series and cross-sectional patterns appear to be contradicting to each other. For instance, Garlappi and Yan (2008) provide a model to rationalize the puzzling findings on momentum and default risk. While it shows a way to explain the cross-sectional relation between loser stocks and default risk, the model's time-series prediction is opposite to our finding of loser stock reversal following volatile down markets. This example shows that evidence from the time-series dimension is important. Complementing cross-sectional findings on momentum, the time-variation patterns provide important clues for understanding the sources of momentum profits.

We find evidence that the predictive power of market volatility is intimately related to default risk. This is consistent with the common sense that default risk is more likely to be a serious concern of investors in volatile down markets. However, default risk alone does not account for all of our findings. A possible explanation of our empirical results is that in different market conditions investors act differently with loser stocks, especially those with high default risk and high information uncertainty. The fear factor rules investors in volatile down markets. The flight to safety drags equity prices down, particularly for the loser stocks. In contrast, optimism and overconfidence prevail in good market states. Downplaying default risk and information uncertainty, investors in good times are more likely to aggressively search for bargains such that they tend to over-buy the loser stocks. This time-varying sentiment explanation is rather simple, but it can intuitively account for the above puzzle. It remains to be seen whether the three-piece puzzle together with other findings on momentum can be successfully explained in a rigorous model.

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Table 1: Momentum Profits, Market States and Market Volatility

Monthly returns of the momentum strategy are from the Ken French data library. Stocks are sorted into deciles using returns over the ranking period from month t-12 to month t-2, where month t is the holding period. The momentum profits or payoffs are measured by the holding month return differences between the equal-weighted portfolios of the winner and loser deciles. The monthly average momentum profits, denoted by MOM, are reported for the sample period and two subperiods. Market state is defined by the lagged three-year market return. Negative (positive) market states, or down (up) markets, are the times when the lagged three-year market return is negative (positive). A month is of high (low) volatility if the lagged 12-month market volatility is larger (smaller) than the lagged 36-month market volatility. An independent two-way sort for the months in the sample is carried out. Every month in the period is put into one of four categories depending whether the market state is positive or negative and whether the market volatility is high or low. The average monthly payoff for each of the four categories is reported. Robust t-statistics (in parentheses) are provided. All the payoffs are in percentage terms, with the monthly observations ranging from August 1929 to July 2009. The data and construction of the momentum strategy are used throughout all the other tables.

MOM	Positive Market State		Negative Market State	
	High Vol	Low Vol	High Vol	Low Vol
		August 1929 - July 2009		
0.79	0.89	1.56	−3.01	−1.29
(3.60)	(4.40)	(9.27)	(−1.94)	(−0.94)
		August 1929 - July 1969		
0.63	0.75	1.45	−3.25	−2.28
(1.95)	(3.31)	(5.97)	(−1.87)	(−1.75)
		August 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

This table reports predictive regressions in which the dependent variable is the momentum payoff. The regressors are market volatility measures. Vol denotes the lagged 12-month (month t-12 to month t-1) market volatility, which is estimated as the standard deviation of daily market returns in the most recent 12-month period. Vol+ (Vol−) is equal to Vol if the lagged three-year (month t-36 to month t-1) market return is positive (negative) and otherwise equal to 0. In this table and the subsequent ones, the volatility measures Vol, Vol+, and Vol− are all in percentage terms (i.e., all being multiplied by 100). Reported are the regression coefficients, the robust t-statistics (in parentheses), and the adjusted R-squares. All regressions in Tables 2 through 9 are of the form:

$$y_t = a + b' x_{t-1} + \varepsilon_t,$$

where x_{t-1} is the vector of predictors, which is measured at the end of month t-1. In these regressions, unless it is pointed out otherwise, the dependent variable is the payoff to the momentum strategy described in Table 1. That is, $y_t \equiv \text{MOM}_t$ which is the month t momentum payoff or the winner-loser month t return difference. While all the regressions in Tables 2 through 9 include an intercept, it is not reported for brevity.

Vol	Vol+	Vol−	Adj-R^2	Vol	Vol+	Vol−	Adj-R^2
August 1929 - July 2009				August 1929 - March 1956			
−2.50			0.022	−1.81			0.005
(−3.60)				(−2.44)			
	−0.71	−2.92	0.036		−0.05	−2.20	0.016
	(−1.66)	(−4.48)			(−0.08)	(−3.62)	
April 1956 - November 1982				December 1982 - July 2009			
−2.47			0.006	−3.74			0.049
(−2.04)				(−2.31)			
	−2.10	−2.47	0.003		−1.06	−4.29	0.079
	(−1.18)	(−2.29)			(−1.48)	(−4.71)	

Table 3: Market State and a Robustness Check

This table reports predictive regressions in which the dependent variable is the momentum payoff. In Panel A, market state, denoted as MKT, is the lagged three-year market return. MKT is measured in the annual term (i.e., the monthly average multiplied by 12) throughout this and the subsequent tables. Construction of Vol, Vol+, and Vol− is the same as in Table 2. In Panel B, the regressor MKT is the same as in Panel A, but the volatility measures are different. Vol denotes the lagged six-month market volatility, which is estimated as the standard deviation of daily market returns in the most recent six-month period. Vol+ (Vol−) is equal to Vol if the lagged six-month market return is positive (negative) and otherwise equal to 0. In Panel C, MKT is replaced with the lagged six-month market return, and the other variables are the same as in Panel B. Reported are the regression coefficients, the robust t-statistics (in parentheses), and the adjusted R-squares.

	MKT	Vol	Vol+	Vol−	Adj-R^2
A.	7.95	−1.64			0.029
	(2.38)	(−2.38)			
	1.78		−0.71	−2.68	0.035
	(0.33)		(−1.64)	(−2.34)	
B.	7.92	−1.59			0.030
	(2.28)	(−2.10)			
	7.03		−0.90	−1.84	0.032
	(2.13)		(−1.15)	(−2.61)	
C.	0.42	−2.27			0.022
	(0.42)	(−3.56)			
	−3.85		−0.78	−3.53	0.032
	(−2.83)		(−1.14)	(−3.93)	

Table 4: Macroeconomic Variables

Monthly observations from April 1953 to June 2009 are obtained, from the CITIBASE database, for the dividend yield of the CRSP value-weighted index (DIV), the yield spread between Baa-rated bonds and Aaa-rated bonds (DEF), the yield spread between ten-year Treasury bonds and three-month Treasury bills (TERM), and the yield on a T-bill with three months to maturity (YLD). The other regressors MKT, Vol, Vol+, and Vol− are the same as in Panel A of Table 3. In this table, the dependent variable in Panel A is the momentum payoff described in Table 1. In Panel B, the dependent variable is the Fama-French momentum factor (MomFF), which is constructed using six value-weighted portfolios formed on size and past returns. The portfolios (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). The momentum factor is the average return 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). In Panel C, the dependent variable is the payoff to a momentum strategy with larger-cap stocks, which is the return difference between the portfolios Big High and Big Low. The data on all the momentum payoffs in the three panels are available at the web site of French. Reported are the regression coefficients, the robust t-statistics (in parentheses), and the adjusted R-squares.

	DIV	DEF	TERM	YLD	MKT	Vol	Vol+	Vol−	Adj-R^2
A.	−0.24	−1.86	0.49	0.38	3.68	−2.09			0.056
	(−1.02)	(−2.14)	(2.06)	(3.69)	(1.99)	(−2.44)			
	−0.21	−1.52	0.43	0.32			−1.38	−2.91	0.060
	(−0.96)	(−1.80)	(1.93)	(3.05)			(−2.02)	(−3.18)	
B.	−0.14	−0.77	0.25	0.15	1.98	−1.41			0.029
	(−0.91)	(−1.54)	(1.57)	(2.07)	(1.14)	(−2.60)			
	−0.12	−0.51	0.21	0.10			−0.88	−1.95	0.034
	(−0.79)	(−1.01)	(1.35)	(1.35)			(−2.06)	(−3.13)	
C.	−0.10	−0.37	0.11	0.02	1.06	−1.70			0.016
	(−0.64)	(−0.77)	(0.66)	(0.29)	(0.51)	(−3.46)			
	−0.06	−0.06	0.06	−0.04			−1.10	−2.20	0.022
	(−0.43)	(−0.12)	(0.39)	(−0.49)			(−2.37)	(−3.93)	

Table 5: Asymmetric Predictability

The dependent variable of regressions in Panel A1 (A2) is the monthly return difference between the loser (winner) portfolio and the market index. In either of the panels, the regressors MKT, Vol, Vol+ and Vol− are the same as in Panel A of Table 3. Observations on these regressors are from July 1929 to June 2009 for Panels A1 and A2. In Panel B1 (B2), the dependent variable is the difference between the loser (winner) portfolio's return and the corresponding the Fama-French three factor model (FF3F) benchmark. See Section 2.2.3 for details on the FF3F adjustment. In Panels C1, C2, D1, and D2, the macroeconomic variables DIV, DEF, TERM, and YLD, defined in Table 4, are included in the regressions. The data on the macroeconomic variables is from April 1953 to June 2009. Other than these, Panels C1, C2, D1, and D2 are the same as Panels A1, A2, B1, and B2, respectively. Reported are the regression coefficients, the robust t-statistics (in parentheses), and the adjusted R-squares.

MKT	Vol	Vol+	Vol−	Adj-R^2	MKT	Vol	Vol+	Vol−	Adj-R^2
A1. Loser (Relative to the market)					A2. Winner (Relative to the market)				
−9.50	1.47			0.031	−1.55	−0.17			−0.002
(−2.77)	(2.29)				(−0.98)	(−0.41)			
		0.70	2.93	0.035			−0.01	0.01	−0.003
		(1.15)	(5.79)				(−0.03)	(0.02)	
B1. Loser (Adjusted by FF3F)					B2. Winner (Adjusted by FF3F)				
−3.63	1.11			0.021	0.07	−0.64			0.009
(−2.56)	(1.87)				(0.06)	(−2.45)			
		0.30	1.79	0.033			−0.49	−0.69	0.010
		(0.86)	(2.66)				(−1.93)	(−3.14)	

Table 5 (Continued)

DIV	DEF	TERM	YLD	MKT	Vol	Vol+	Vol−	Adj-R^2
C1. 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	2.63	0.053
(1.16)	(1.84)	(−1.72)	(−2.92)			(1.73)	(2.73)	
C2. 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)	
D1. 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	2.12	0.057
(−0.10)	(1.78)	(−2.34)	(−3.36)			(0.82)	(3.42)	
D2. 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)	

Table 6: Return Dispersion

This table reports predictive regressions in which the dependent variable is the momentum payoff. Monthly returns on the 100 size and book-to-market portfolios are obtained from the data library at the Ken French's web site. The measure RD_{1-3} is the three-month moving average of the cross-sectional standard deviation of the 100 portfolio returns. This stock return dispersion measure is available for the whole 1929-2009 sample period. The regressors MKT, Vol, Vol+ and Vol− are the same as in Table 5. Reported are the regression coefficients, the robust t-statistics (in parentheses), and the adjusted R-squares.

RD_{1-3}	MKT	Vol	Vol+	Vol−	Adj-R^2
−0.11					0.004
(−2.21)					
0.02	8.03	−1.76			0.028
(0.35)	(2.29)	(−2.07)			
0.04			−0.91	−3.19	0.035
(0.76)			(−1.88)	(−3.84)	

Table 7: VIX

This table reports predictive regressions in which the dependent variable is the momentum payoff. VIX is the Chicago Board Options Exchange (CBOE) Volatility Index. The data on VIX is obtained from the web site of CBOE, which is available from January 1990 to June 2009. The regressors MKT, Vol, Vol+ and Vol− are the same as in Table 5. Reported are the regression coefficients, the robust t-statistics (in parentheses), and the adjusted R-squares.

VIX	MKT	Vol	Vol+	Vol−	Adj-R^2
−0.08					−0.002
(−1.05)					
	8.45	−3.49			0.060
	(2.18)	(−2.39)			
			−1.06	−4.29	0.079
			(−1.03)	(−4.42)	
0.18	6.80	−5.78			0.071
(2.77)	(1.72)	(−3.13)			
0.16			−3.33	−6.26	0.088
(2.42)			(−1.94)	(−4.96)	

Table 8: Baker-Wurgler Index

Monthly observations of the Baker-Wurgler sentiment index are obtained from the web site of Jeffrey Wurgler (http://www.stein.nyu.edu/~jwurgler). The data is from January 1966 to December 2005. This index, denoted by $\text{Sent}^{\perp}$, is based on six sentiment proxies, and it is orthogonalized to a set of macroeconomic indicators. For details of the index construction, see Baker and Wurgler (2006). The other regressors MKT, Vol, Vol+ and Vol− are the same as in Table 7. In Panel A, the dependent variable is the momentum payoff, as defined in Table 1. The momentum portfolios are equally-weighted. In Panel B, the dependent variable is the momentum payoff based on the identical sorting procedure, but the winner and loser portfolios are value-weighted. Reported are the regression coefficients, the robust t-statistics (in parentheses), and the adjusted R-squares.

	$\text{Sent}^{\perp}$	MKT	Vol	Vol+	Vol−	Adj-R^2
A.	0.38	3.59	−1.68			0.009
	(2.22)	(1.65)	(−2.43)			
	0.39			−1.33	−2.33	0.009
	(2.38)			(−1.92)	(−3.29)	
B.	0.02	3.81	−1.96			0.005
	(0.12)	(1.28)	(−2.51)			
	0.03			−1.61	−2.65	0.006
	(0.17)			(−1.87)	(−3.88)	

Table 9: Black-Scholes-Merton Probabilities of Bankruptcy

The approach of Hillegeist et al. (2004), which is based on the Black-Scholes-Merton option-pricing model, is used to estimate default probabilities of firms (denoted as BSM probs). The average of the BSM probs across all stocks is denoted by Avg. The difference in the average BSM probs between the loser and winner portfolios is denoted by Diff. Like the volatility measures, Avg and Diff in this and next tables are in percentage terms (i.e., multiplied by 100). Vol denotes the lagged 12-month market volatility, which is estimated as the standard deviation of daily market returns in the most recent 12-month period. 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 equal to Vol, Avg, and Diff, respectively, if the lagged three-year market return is negative and otherwise equal to 0. The dependent variable in the predictive regressions is the momentum payoff. Reported are the regression coefficients, the robust t-statistics (in parentheses), and the adjusted R-squares. The sample period is from January 1971 to June 2008.

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)	

Table 10: Predictive Power of BSM Probabilities in Down Markets

The dependent variable in the predictive regressions in this table is the momentum payoff. The regressors MKT and Vol are the lagged three-year market return and the lagged 12-month market volatility, respectively, which are the same as in previous tables such as Table 8. Definitions of Avg and Diff are the same as in Table 9. In the sample period from January 1971 to June 2008, down markets are defined as the months when the lagged six-month market return is negative. The months other than down markets are excluded. The regressions are run over the time series of the remaining months. Since only the down market months are included for this table, the notations are simplified. We omit the "−" sign after the variables (e.g., using Vol to stand for Vol−). Reported are the regression coefficients, the robust t-statistics (in parentheses), and the adjusted R-squares.

A. Single-predictor regressions					B. Multiple-predictor regressions				
MKT	Vol	Avg	Diff	Adj-R^2	MKT	Vol	Avg	Diff	Adj-R^2
7.15				−0.003	5.84	0.14	−0.34		−0.012
(1.75)					(1.14)	(0.09)	(−2.55)		
	−2.58			−0.006	6.50	1.46		−0.34	0.015
	(−3.25)				(1.37)	(0.97)		(−3.83)	
		−0.41		−0.003	5.52		0.33	−0.40	0.017
		(−3.98)			(1.50)		(1.67)	(−3.23)	
			−0.32	0.023	6.22	0.73	0.28	−0.41	0.009
			(−3.93)		(1.25)	(0.40)	(1.05)	(−3.38)	

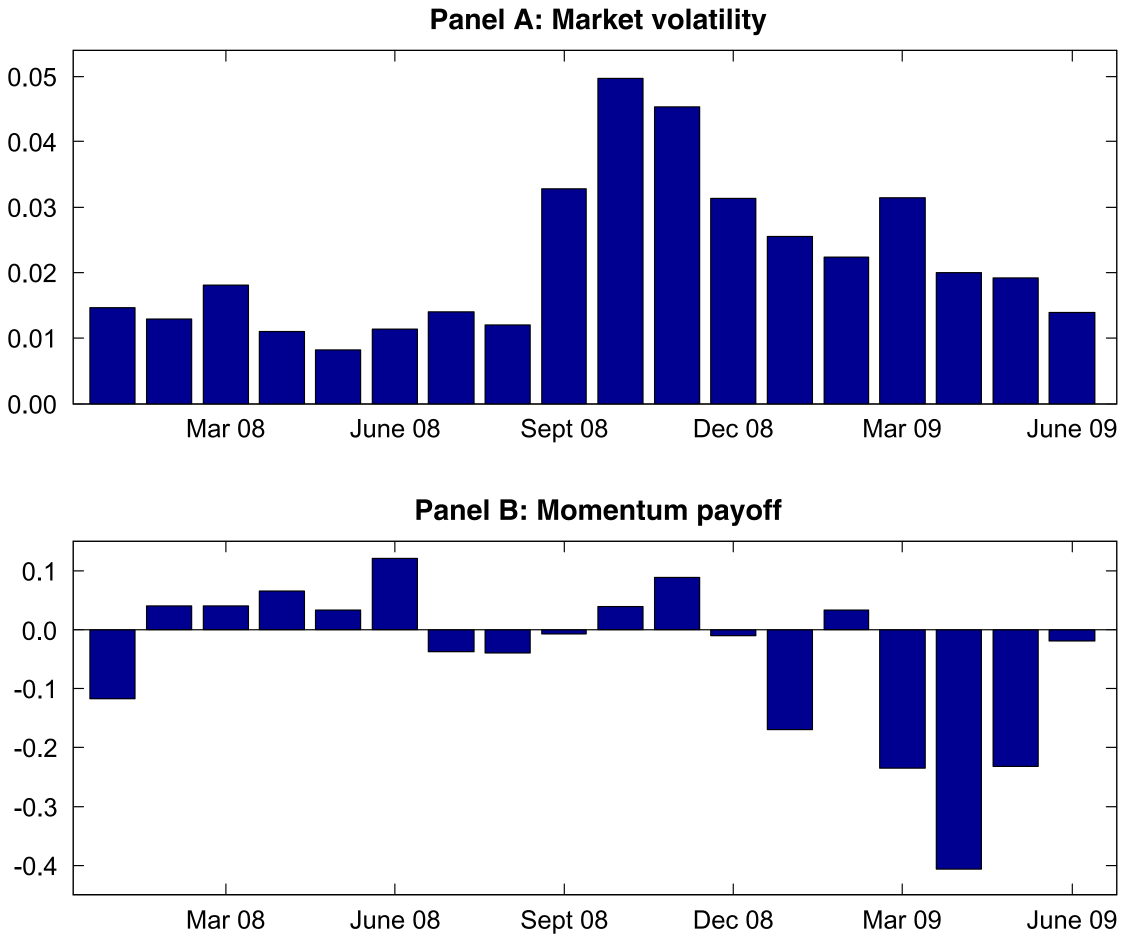

Figure 1. Market volatility and momentum payoff in the 2008-2009 episode

In Panel A, market volatility is computed as the standard deviation of daily market returns in the month. Panel B plots the payoff to a momentum strategy. The data for the strategy is obtained from the Ken French data library. Stocks are sorted into deciles using returns over the ranking period from month t-12 to month t-2, where month t is the holding period. The momentum payoff is the month t return difference between the equal-weighted portfolios of the winner and loser deciles.

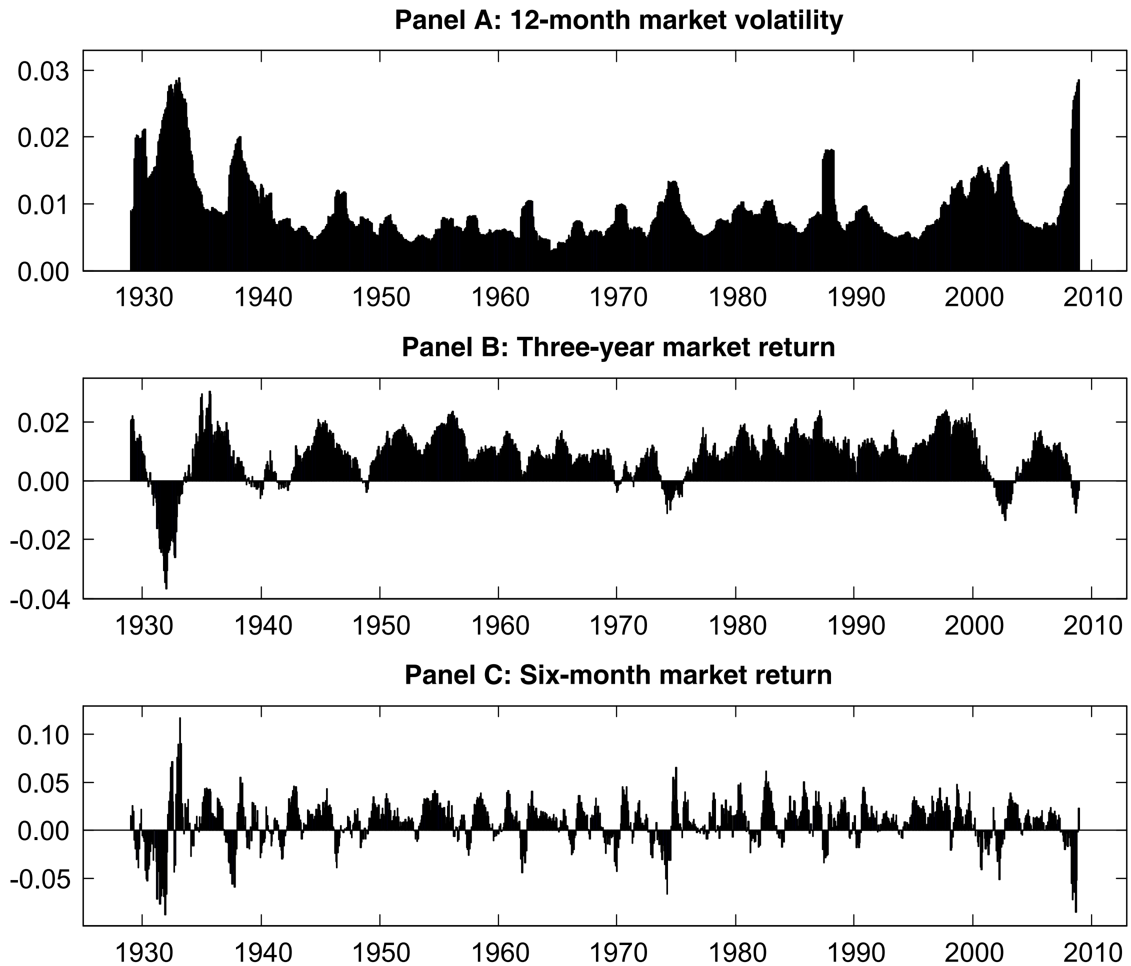

Figure 2. Market volatility and market state

In Panel A, market volatility is measured by the lagged 12-month realized volatility, which is estimated as the standard deviation of daily market returns in the 12-month period. 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, measured in terms of the monthly average.

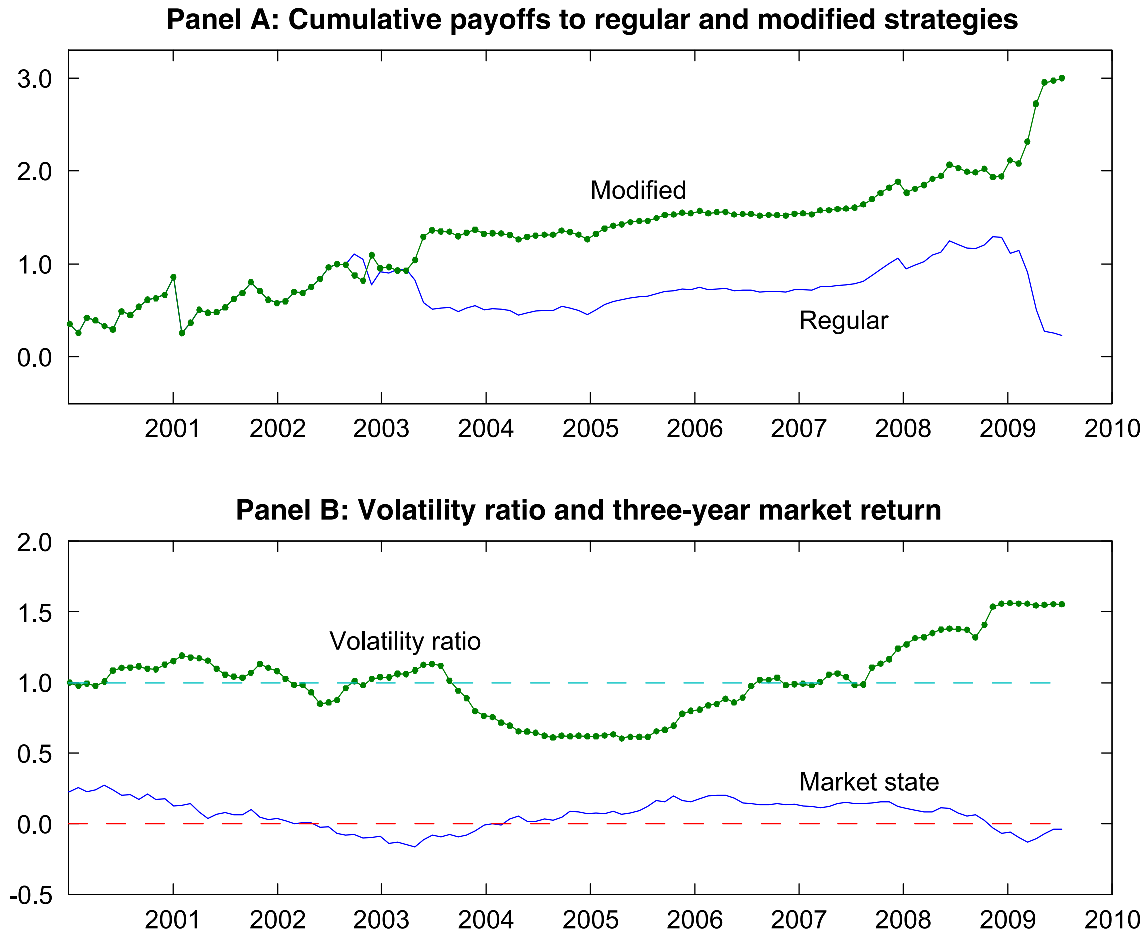

Figure 3. Recent performance of the modified strategy

In Panel A, the cumulative payoffs to the modified strategy and the regular momentum strategy are presented by the dotted and undotted curves respectively. In Panel B, the dotted curve depicts volatility ratio, which is the ratio of the lagged 12-month market volatility to the lagged 36-month market volatility. The lagged 12-month (36-month) market volatility is the standard deviation of daily market returns in the 12-month (36-month) period. The undotted curve represents the lagged three-year market return, which is measured in the annual term (i.e., the monthly average multiplied by 12) in this figure. The two horizontal dashed lines are provided to distinguish periods of high (low) volatility and positive (negative) market states.