Journal of Banking & Finance 72 (2016) S104–S118

Contents lists available at ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

Momentum and downside risk ☆

Byoung-Kyu Min [a,*], Tong Suk Kim [b]

[a] Discipline of Finance, Business School, The University of Sydney, Sydney, Australia
[b] College of Business, Korea Advanced Institute of Science and Technology (KAIST), Seoul, Republic of Korea

ARTICLE INFO

Article history:
Received 15 July 2014
Accepted 8 April 2016
Available online 23 April 2016

JEL classification:
G12
G14

Keywords:
Momentum
Economic state
Expected market risk premium

ABSTRACT

We examine whether time-variation in the profitability of momentum strategies is related to variation in macroeconomic conditions. We find reliable evidence that the momentum strategy exposes investors to greater downside risk. Momentum strategies deliver economically large and statistically reliable negative profits in bad economic states when the expected market risk premium is high, whereas positive profits in good economic states when the expected market risk premium is low. Our results are robust to alternative constructions of momentum portfolios, out-of-sample estimation of the expected market risk premium, and after controlling for the January effect, lagged market return, and investor sentiment.

1. Introduction

The pioneering work of Jegadeesh and Titman (1993) shows that the simple investing strategy of buying prior winners and selling prior losers generates significant profits both statistically and economically. Subsequent work has confirmed the robustness of this momentum effect.[1] There is substantial debate regarding the source of the profitability of momentum strategies.[2]

A recent and growing empirical literature on *time-series* analysis of momentum provides evidence that time-variation in momentum profits is not related to macroeconomic risk, but rather is consistent with theoretical predictions from behavioral models. Liew and Vassalou (2000) find that, whereas the Fama–French factors, HML and SMB, contain significant information about future GDP growth, momentum is not related to future economic growth. Griffin et al. (2003) provide international evidence that momentum profits are positive in both good and bad states, incompatible with the view that momentum is a reward for priced business cycle risk. Cooper et al. (2004) show that payoffs to momentum strategies are dependent on the lagged three-year market return, and they interpret their findings are consistent with behavioral models of momentum. Antoniou et al. (2013) study an intertemporal relation between

☆ We would like to thank Dong-Hyun Ahn, David Ardia, Ihsan Badshah, Joon Chae, Michel Dubois, Jangkoo Kang, Dongcheol Kim, Doseong Kim, Changjun Lee, Ben Marshall, Tai-Yong Roh, Rene Stulz, Lu Zhang, and two anonymous referees for many helpful and insightful comments. We also thank seminar participants at the Financial Management Association Annual Meeting in New York; 6th International Finance and Banking Society Conference in Lisbon; 5th Auckland Finance Meeting; the 4th Conference on Asia-Pacific Financial Markets in Seoul; the 15th Swiss Society for Financial Market Research Conference in Zurich; the 2009 Doctoral Consortium hosted by five Korean finance associations in Dogo; and the doctoral seminar at the Ohio State University. The paper received the outstanding paper award at the 4th International Conference on Asia-Pacific Financial Markets and the best paper award at the 2009 Doctoral Consortium hosted by Five Korean Finance Associations. The paper is based on Byoung-Kyu Min's second chapter of doctoral dissertation at the Korea Advanced Institute of Science and Technology. This article supersedes our previous work titled "When do momentum strategies lose money?" and "Momentum profits and macroeconomic states: is winner riskier than loser?" Any remaining errors are the authors' own responsibilities.
* Corresponding author. Tel.: +61 2 9036 6356; fax: +61 2 9351 6461.
E-mail addresses: byoungkyu.min@sydney.edu.au (B.-K. Min), tskim@business.kaist.ac.kr (T.S. Kim).

[1] Rouwenhorst (1998) documents that a momentum strategy works in international markets. Jegadeesh and Titman (2001) show that momentum profits persist even after the period covered by the 1993 study.

[2] Several behavioral and rational explanations for momentum have been suggested. Barberis et al. (1998),Daniel et al. (1998), and Hong and Stein (1999) each posit a different behavioral or cognitive bias as causing the momentum anomaly. Empirical studies supporting these behavioral explanations of momentum include Jegadeesh and Titman (2001), Jiang et al. (2005), Zhang (2006), Chui et al. (2010). Studies exploring risk-based explanations of momentum include Berk et al. (1999), Johnson (2002), Ahn et al. (2002), Sagi and Seasholes (2007),Liu and Zhang (2008), and Kim et al. (2014). Wang and Xu (2015) present evidences that challenge both behavioral and risk-based theories for momentum.

http://dx.doi.org/10.1016/j.jbankfin.2016.04.005
0378-4266/

momentum profits and investor sentiment and find that momentum profits arise mainly during periods of investor optimism.

We reexamine whether time-variation in the profitability of momentum strategies is related to variation in macroeconomic conditions. We adopt the approach taken by Lakonishok et al. (1994) to determine whether momentum strategies expose investors to greater downside risk. Lakonishok et al. (1994) argue that a strategy would be fundamentally risky if, first, there are at least some states of the world in which the strategy underperforms, and second, these periods of underperformance are, on average, "bad" states, in which the marginal utility of wealth is high, making the strategy unattractive to risk-averse investors.[3] To investigate time-variation in the profitability of momentum strategies, we first define bad times as periods during which the expected market risk premium has high values, and good times as periods during which the expected market risk premium has low values. Specifically, four economic states are classified by lowest to highest expected market risk premium values: "peak," "expansion," "recession," and "trough." We then estimate average momentum profits conditional on each economic state and examine whether the profitability of momentum strategies varies depending on the state of the economy.

Our main findings are easy to summarize. First, momentum strategies lose money when investors need most, exposing investors to greater downside risk. During the period from 1960 to 2011, the average momentum profit is an economically large and statistically reliable negative −2.23% per month (t-value = −2.90) in bad times when the expected market risk premium is highest. This result is robust to the benchmark risk adjustments and after controlling for the January effect. In the "trough" state, the CAPM-adjusted and Fama–French-adjusted profits are −2.08% (t-value = −2.74) and −2.06% (t-value = −2.81) per month, respectively. When excluding January, a momentum strategy still delivers a large negative profit of −1.72% per month (t-value = −2.28) when the economy is in the "trough" state.

Second, the payoffs to momentum strategies tend to positively covary with macroeconomic conditions. As shown in Fig. 1, the average momentum profits are 1.86%, 1.10%, 0.87%, and −2.23% in the "peak," "expansion," "recession," and "trough" states, respectively; as economic state becomes worse, average momentum profits show a monotonically decreasing pattern. As a result, the difference between momentum profits obtained in "non-trough" and "trough" periods is a huge and statistically significant 3.30% per month with a t-statistic of 4.10. Time-series regressions confirm a significant negative relation between momentum profits and the expected market risk premium. Moreover, we demonstrate that our evidence is robust to the out-of-sample estimation of the expected market risk premium in defining the economic states. We show that the classification of the state of the economy identified by the out-of-sample estimate of the market risk premium is essentially identical to that identified by the in-sample estimate.

The empirical finance literature has failed to provide evidence of distress risk in momentum strategies, because previous studies define economic states in terms of the *realized* market excess return or GDP growth. Most relevant to our work, Griffin et al. (2003) identify good states with high, and bad states with low, ex post realized market excess returns or GDP growth. Their results show that average momentum profits are positive during periods

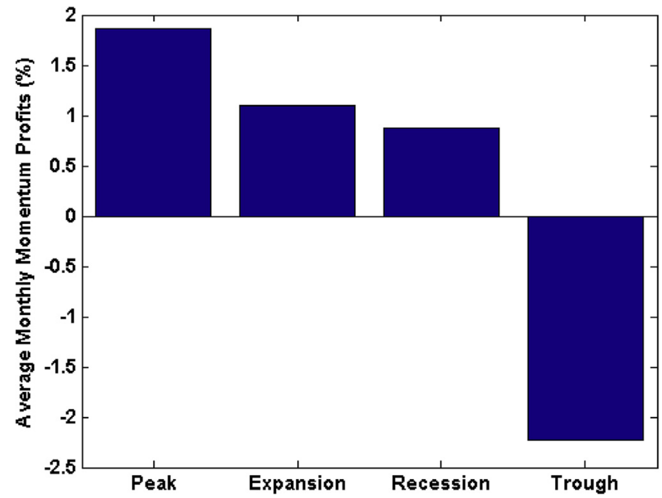

Fig. 1. Average momentum profits conditional on economic states. The figure shows the average monthly momentum profits conditional on the economic states. The economic states are classified based on the expected market risk premium, which is estimated as a following model: $R^e_{m,t} = \alpha + \beta \mathbf{Z}_{t-1} + e_{m,t}$, where $\mathbf{Z}_{t-1}$ is a vector representing conditioning variables that include the default spread, term spread, three-month T-bill rate, and CAY. State "peak" is defined as the lowest 10% periods of the expected risk premium; state "expansion" represents the remaining periods with the premium below its average; state "recession" represents the periods with the premium above its average except the 10% highest; and state "trough" represents the highest 10% periods of the expected market risk premium. The sample period is from January 1960 to December 2011.

of negative GDP growth, and even more strongly positive during periods of negative market excess returns than during periods of positive market excess returns in the U.S. Thus, Griffin, Ji, and Martin conclude that "there is no evidence that the profitability of momentum strategies is related to risk arising from macroeconomic states" (p. 2539).[4]

However, *ex-post* realized market excess return is a noisy measure for marginal utility or business cycles (Fama, 1981; Harvey, 1989; Stock and Watson, 1989, 1999). Further, the standard asset pricing theory predicts that investors demand an *ex-ante* risk premium for holding risky securities, and risk premium is countercyclical (Merton, 1973; Campbell and Cochrane, 1999). Many studies point out that realized returns are a noisy measure of expected returns or expected risk premium (Blume and Friend, 1973; Sharpe, 1964; Elton, 1999; Campello et al., 2008). Petkova and Zhang (2005) argue that the *expected* market risk premium, not the *ex-post* realized market excess return, should be used to measure the state of the economy. Following Petkova and Zhang (2005), we classify macroeconomic states based on the expected market risk premium and show that the basic inferences of Griffin et al. (2003) can be overturned with this reasonable change in measuring macroeconomic conditions.

Chordia and Shivakumar (2002) find that momentum profits are only reliably positive during NBER expansionary periods, with insignificant negative profits observed during NBER contractionary periods. The evidence presented in this paper, however, differs from Chordia and Shivakumar (2002) in several important ways. First, the explanatory power of the NBER classification of the business cycle for momentum payoffs seems to be driven by the January effect. We show that when controlling for the January effect, the relation between momentum profits and NBER contractionary periods disappears completely.[5] The finding of Chordia and

[3] The approach proposed by Lakonishok et al. (1994) has been used in several other studies. Using the approach of Lakonishok, Shleifer, and Vishny, Lettau and Ludvigson (2001b) argue that value stocks are riskier than growth stocks. Specifically, they show that periods in which the value portfolio underperforms the growth portfolio tend to coincide with bad states. Petkova and Zhang (2005) also discuss the approach of Lakonishok, Shleifer, and Vishny to explain why their conclusion regarding the relative risk of value and growth stocks differs from those of previous studies. Griffin et al. (2003) adopt the approach of Lakonishok, Shleifer, and Vishny to examine whether the momentum strategy is a risky investment.

[4] Liew and Vassalou (2000) also report larger positive mean momentum profits during periods of negative GDP growth than during periods of positive GDP growth.

[5] During the contractionary periods where January is excluded, average momentum profits are no longer negative.

Shivakumar (2002) that momentum profits are absent during NBER contractionary periods may thus be driven by the January effect. In contrast, as mentioned earlier, our evidence of distress risk in momentum strategies cannot be attributable to the January effect.

Second, whereas the NBER classification of the state of the economy is only available ex-post, our measure of the expected market risk premium can be obtained ex-ante from recursive out-of-sample forecasts.[6] This difference is particularly critical to investors looking to develop a real-time implementable trading strategy to enhancing profitability. For instance, investors can implement a conditional momentum strategy that reverses the momentum trading rule (i.e., buying loser stocks and selling winner stocks) when the market risk premium forecasted for the next period is especially high. Such a conditional strategy cannot be achieved using NBER identification of economic states, since investors do not know in real-time whether the next period will be contractionary. Finally, the explanatory power of the NBER contraction indicator becomes insignificant in the presence of our measure of economic states, whereas our measure remains statistically significant.

Cooper et al. (2004) show that momentum profits are significant only after "UP" market where the lagged three-year market return is positive. Cooper, Gutierrez, and Hameed interpret that if overconfidence is higher following market increases, then their findings are consistent with theoretical predictions from the behavioral models of Daniel et al. (1998) and Hong and Stein (1999). Stambaugh et al. (2012) and Antoniou et al. (2013) show that momentum profits are higher following periods of high sentiment, and that the sentiment index predicts positively the payoffs to momentum strategies. They interpret that sentiment-driven overpricing appears to be at least a partial explanation for the profitability of momentum strategies. We examine whether lagged three-year market return and investor sentiment can take away the explanatory power of the expected market risk premium. When we regress momentum profits on the expected market risk premium in the presence of either the lagged three-year market return or the investor sentiment index, the coefficient on the expected market risk premium is always significantly negative. Further, in the presence of the state variables suggested by the momentum literature, winner stocks continue to significantly underperform loser stocks in the "trough" state. These results indicate that the lagged three-year market return and the sentiment index do not capture the explanatory power of the expected market risk premium. Our interpretation that momentum strategies are fundamentally risky investments, combined with the robust explanatory power of the expected market risk premium, suggest that our findings are substantially distinct from those documented by Cooper et al. (2004), Stambaugh et al. (2012), and Antoniou et al. (2013).

The remainder of the paper is organized as follows. Section 2 describes the data, and discusses the empirical specification used in our analysis. Section 3 presents our main findings that momentum strategies expose investors to greater downside risk and that the profitability of momentum strategies vary depending on the state of the economy. Section 4 provides evidence on the robustness of the relation between momentum profits and the expected market risk premium. Section 5 presents our conclusions.

2. Data and empirical specification

2.1. Portfolio construction

Our main data source is the Center for Research in Security Prices (CRSP) monthly file. We use all common stocks (with CRSP share-code of 10 or 11) listed on NYSE and AMEX. The sample period is from January 1960 to December 2011.

We use two sets of momentum portfolios. The construction of the first set of portfolios follows Jegadeesh and Titman (1993). We rank NYSE and AMEX stocks into deciles based on their 6-month ranking period returns (months $t-7$ through $t-2$). To control for short-term return reversal and avoid microstructure bias, we skip one month between the end of the ranking period and the beginning of the holding period. Decile portfolios are formed by equally weighting all firms in the decile ranking. The momentum profit is the return of the top decile portfolio (the winners) less the return of the bottom decile portfolio (the losers). We form momentum portfolios every month and hold them for the subsequent 6-month period, from t through $t+5$. Thus, portfolios have overlapping holding period returns. We refer to this momentum portfolio construction as the JT momentum construction.

To evaluate the pervasiveness and robustness of our results, we also consider alternative way of constructing momentum portfolios. The construction of the second set of portfolios follows Fama and French (1996), and the data are obtained from the data library of Ken French.[7] The procedure is the same as for the JT momentum construction, except that the ranking period of the strategy is 11 months (from month $t-12$ to month $t-2$ with the skip-a-month) and the holding period is one month. This strategy is referred to as the FF momentum construction. Note that the JT momentum construction is an overlapping construction approach, while the FF momentum construction is a non-overlapping approach. Since the data are publicly available from French's web site, it allows one to easily replicate most of our results.

Table 1 reports the averages and corresponding t-statistics for the monthly excess returns (returns in excess of the monthly Treasury bill rate) on the momentum decile portfolios for each type of momentum portfolio construction (JT construction in Panel A, FF construction in Panel B) as well as the Winner-Minus-Loser (WML) portfolios. Two benchmark-adjusted returns, the CAPM and Fama–French (1993) risk-adjusted returns, are also reported.[8] The benchmark-adjusted returns are defined as returns net of what is attributable to exposures to risk factor(s). We estimate the benchmark-adjusted returns as the intercepts from the following regressions:

$$R_{i,t} = \alpha_i + \beta_1 MKT_t + \epsilon_t, \tag{1}$$

$$R_{i,t} = \alpha_i + \beta_1 MKT_t + \beta_2 SMB_t + \beta_3 HML_t + \epsilon_t, \tag{2}$$

where $R_{i,t}$ is the portfolio's excess return in month t, MKT_t is the market factor (CRSP value-weighted market excess return), SMB_t is the size factor (a return spread between small and big firms), and HML_t is the book-to-market factor (a return spread between stocks with high and low book-to-market ratios). The estimated intercepts in Eqs. (1) and (2) are the CAPM-adjusted alpha and the Fama–French-adjusted alpha, respectively.

During the entire sample period from January 1960 to December 2011, the average excess returns increase monotonically from the loser portfolio to the winner portfolio. The momentum payoff is sizable and reliably positive: the JT construction earns a significant return of 0.76% per month (t-value = 3.17) and the FF construction earns a comparable return of 0.99% per month

[6] Indeed, the NBER announces the turning points of the business cycle with a delay.

[7] Fama and French (1996) show that their momentum strategy is as strong as those constructed by Jegadeesh and Titman (1993) such that their three-factor model cannot explain the payoffs to this strategy.

[8] We examine whether linearity of the Fama–French model is important in our study. We consider alternative specification for the benchmark model, in which both the Fama–French factors and the square of these factors constitute risk factors. The risk-adjusted momentum profits by using this augmented Fama–French model does not affect our results.

Table 1
Descriptive statistics of momentum portfolios. The table reports the average monthly excess return, CAPM alphas, and Fama–French alphas of momentum portfolios, along with their t-statistic reported in parenthesis. Two sets of momentum portfolios are used. The first set of portfolio follows Jegadeesh and Titman (1993) and is reported in Panel A. All NYSE and AMEX stocks are ranked into deciles based on their 6-month ranking period returns (months $t-7$ through $t-2$ with the skip-a-month). Decile portfolios are formed by equally weighting all firms in the decile ranking. The Winner-Minus-Loser (WML) portfolio is the return difference between the top decile portfolio (Winner) and the bottom decile portfolio (Loser). The momentum portfolios are formed every month and held for the subsequent 6-month period, from t through $t+5$. The second set of portfolio follows Fama and French (1996) and is reported in Panel B. The procedure is the same as for the Jegadeesh and Titman (1993) momentum construction, except that the ranking period of the strategy is 11 months (from month $t-12$ to month $t-2$ with the skip-a-month) and the holding period is one month. The sample period is from January 1960 to December 2011.

	Loser	2	3	4	5	6	7	8	9	Winner	WML
Panel A: Jegadeesh and Titman (1993) momentum portfolios											
Mean return	0.35	0.53	0.70	0.73	0.79	0.80	0.85	0.89	0.97	1.11	0.76
(t-stat)	(0.96)	(1.94)	(2.89)	(3.25)	(3.68)	(3.90)	(4.14)	(4.22)	(4.33)	(4.23)	(3.17)
CAPM alpha	−0.28	0.00	0.21	0.26	0.33	0.36	0.40	0.43	0.48	0.57	0.85
(t-stat)	(−1.15)	(−0.03)	(1.60)	(2.30)	(3.24)	(3.77)	(4.29)	(4.43)	(4.54)	(4.02)	(3.76)
FF alpha	−0.78	−0.41	−0.17	−0.09	0.01	0.06	0.12	0.15	0.22	0.31	1.09
(t−stat)	(−3.99)	(−3.61)	(−1.89)	(−1.13)	(0.15)	(0.96)	(1.93)	(2.42)	(3.16)	(3.43)	(4.98)
Panel B: Fama and French (1996) momentum portfolios											
Mean return	0.36	0.53	0.63	0.66	0.77	0.81	0.89	0.98	1.14	1.35	0.99
(t-stat)	(0.99)	(2.06)	(2.76)	(3.18)	(3.84)	(4.14)	(4.59)	(4.88)	(5.26)	(4.99)	(3.98)
CAPM alpha	−0.26	0.03	0.17	0.22	0.34	0.39	0.47	0.55	0.68	0.80	1.06
(t-stat)	(−1.04)	(0.20)	(1.36)	(2.16)	(3.51)	(4.20)	(5.16)	(5.73)	(6.18)	(5.25)	(4.47)
FF alpha	−0.58	−0.28	−0.14	−0.06	0.06	0.13	0.23	0.33	0.48	0.69	1.27
(t-stat)	(−2.79)	(−2.46)	(−1.64)	(−0.89)	(1.10)	(2.33)	(4.30)	(6.25)	(7.14)	(7.37)	(5.21)

(t-value = 3.98). All benchmark-adjusted momentum profits are significant positive, confirming that the momentum is identified as an anomaly with respect to the CAPM and Fama–French models.

Fig. 2 plots cumulative gains from the momentum strategy, assuming a one-dollar investment that goes long winner stocks and short loser stocks, at the beginning of the sample in 1960. For the purpose of comparison, Fig. 2 also plots cumulative gains from a one-dollar investment that goes long the market portfolio and short the risk free asset. Fig. 2 shows that the dollar value of the momentum investment has significantly increased over time to achieve a terminal value in 2011 over $115. This amount of increase in terminal value is significant, given that the terminal value of a market strategy is only $8.25 in 2011. It is important, however, to note that the dollar value of the momentum strategy has fluctuated up and down over time. In fact, the cumulative gain reached the maximum value in 2001 over $400. This suggests that the terminal value of the momentum investment is not linearly increased as the investment horizon is longer.

2.2. Estimation of the expected market risk premium

In order to examine whether momentum profits are related to macroeconomic risk, we adopt the approach taken by Lakonishok et al. (1994). They argue that a strategy would be fundamentally risky if, first, there are at least some states of the world in which the strategy underperforms, and second, these periods of underperformance are, on average, "bad" states, in which the marginal utility of wealth is high, making the strategy unattractive to risk-averse investors.

In prior research, Liew and Vassalou (2000) and Griffin et al. (2003) investigate whether momentum strategies are risky. Their approaches are similar to those used by Lakonishok et al. (1994) to analyze value and growth strategies. For instance, Griffin, Ji, and Martin define economic states in terms of the realized market excess returns and GDP growth; they identify good states as periods with high ex post market excess returns or GDP growth, and bad states as those with low ex post market excess returns or GDP growth. Their results show that average momentum profits are positive during periods of negative GDP growth, and even more strongly positive during periods of negative market excess returns than during periods of positive market excess returns in the U.S. Therefore, Griffin, Ji, and Martin conclude that momentum strategies are not risky investments because they do not expose investors to greater downside risk.

However, *ex-post* realized market excess return is at best a very noisy measure for marginal utility or business cycles. It is well documented in the macroeconomic literature that the ex post market excess return does not have substantial predictive power for business cycles (Fama, 1981; Harvey, 1989; Stock and Watson, 1989, 1999).[9] Further, the standard asset pricing theory predicts that investors demand an *ex-ante* risk premium for holding risky securities, and that risk premium is countercyclical (Merton, 1973; Campbell and Cochrane, 1999). Many studies point out that realized returns are a noisy measure of expected returns or expected risk premium (Blume and Friend, 1973, Sharpe, 1964; Elton, 1999; Campello et al., 2008).[10] Petkova and Zhang (2005) argue that more precise measures for aggregate economic conditions are the default spread, the term spread, and the short-term interest rate, macroeconomic variables that are common instruments used to model the expected market risk premium.

It is therefore reasonable to expect that inferences made by Griffin et al. (2003) could lead them to the incorrect conclusion. We argue that it is necessary to reevaluate the riskiness of momentum strategies by using the expected market risk premium as a measure of the state of the economy.

The expected market risk premium is unobservable and thus must be estimated. To model this risk premium, we use macroeconomic variables that are known for their ability to predict market excess return and capture fluctuations in economic condition. These conditioning variables include the default spread (DEF), the term spread (TERM), the three-month T-bill rate (RF), and the variable CAY. The CAY is constructed by Lettau and Ludvigson (2001a) to capture movements in the consumption–aggregate wealth ratio. It is obtained as the error term from the cointegration relation

[9] Stock and Watson (2003) summarize it clearly, "Stock returns generally do not have substantial in-sample predictive content for future output, even in bivariate regressions with no lagged dependent variables (Fama, 1981 and Harvey, 1989), and any predictive content is reduced by including lagged output growth" (p. 797).

[10] Elton (1999) shows that realized returns can deviate significantly from expected returns. He also questions the common practice of using realized returns as a proxy for expected returns in asset pricing tests.

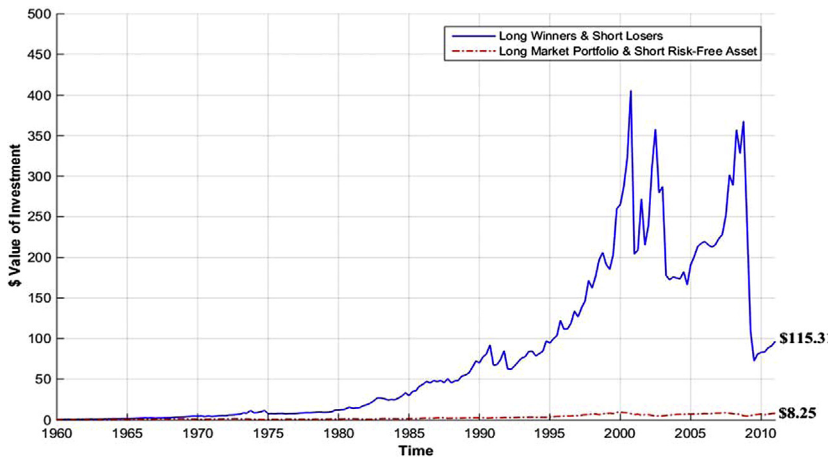

Fig. 2. Cumulative gains from the momentum strategy. The figure plots cumulative gains from the momentum strategy (FF construction), assuming a one-dollar investment that goes long winner stocks and short loser stocks, at the beginning of the sample in 1960. The figure also plots cumulative gains from a one-dollar investment that goes long the market portfolio and short the risk free asset.

among consumption, asset holdings, and labor income.[11] The motivation for using these variables comes from the time-series predictability literature.[12] The default spread is the yield spread between Moody's BAA and AAA corporate bonds. The term spread is the yield spread between ten-year government bonds and one-year government bonds. Data on bond yields are obtained from the Federal Reserve Bank of St. Louis. Since the CAY is quarterly in frequency, we use quarterly data for estimating the market risk premium.

Following Fama and French (1989) and Ferson and Harvey (1991), the expected market risk premium is estimated by regressing the (quarterly) market excess return from time $t-1$ to t, $R^e_{m,t}$, on the (quarterly) macroeconomic variables known at time $t-1$:

$$R^e_{m,t} = \eta_0 + \eta_1 DEF_{t-1} + \eta_2 TERM_{t-1} + \eta_3 RF_{t-1} + \eta_4 CAY_{t-1} + e_{m,t}. \quad (3)$$

Then, the expected market risk premium, $EMRP_t$, is the fitted value from Eq. (3) as follows:

$$EMRP_t = \hat{\eta}_0 + \hat{\eta}_1 DEF_{t-1} + \hat{\eta}_2 TERM_{t-1} + \hat{\eta}_3 RF_{t-1} + \hat{\eta}_4 CAY_{t-1}. \quad (4)$$

Table 2 presents the estimation results of Eq. (3). Panel A reports the regression coefficients, with their t-statistics in parentheses. If the market excess return is not predictable, all of the coefficients on the lagged conditioning variables should be statistically indistinguishable from zero. The χ^2 is the Wald statistic on the null hypothesis that the coefficients of the four conditioning variables are jointly zero. We see that the set of instrumental variables have reliable predictive power for the market excess return. The p-value of the χ^2 statistic is less than 5% and the CAY is statistically significant (t-value = 2.74). This result indicates that including the CAY is critical to reliably estimating the expected market risk premium, and is consistent with the finding of Lettau and Ludvigson (2001a) that the CAY has stronger forecasting power than other popular forecasting variable over short horizons.

Table 2
Estimation of the expected market risk premium. The table shows estimation results for the following regression using quarterly observations:

$$R^e_{m,t} = c_0 + c_1 DEF_{t-1} + c_2 TERM_{t-1} + c_3 RF_{t-1} + c_4 CAY_{t-1} + e_{m,t}.$$

$R^e_{m,t}$ is the market excess return. DEF_{t-1} is the default spread (DEF), defined as the yield spread between Moody's BAA and AAA corporate bonds. $TERM_{t-1}$ is the term spread, computed as the yield spread between ten-year government bonds and one-year government bonds. RF_{t-1} is the three-month T-bill rate. CAY_{t-1} is represents deviations from a common trend among consumption, asset wealth, and labor income created by Lettau and Ludvigson (2001a,b). Panel A reports the regression coefficients and their t-statistics in parentheses. The $\chi^2_{(4)}$ is the Wald statistic on the null hypothesis that the coefficients of the four conditioning variables are jointly zero. Panel B reports the average of the estimated market risk premium conditional on the economic states, and the number of quarters in each state. State "peak" is defined as the lowest 10% periods of the expected risk premium; state "expansion" represents the remaining periods with the premium below its average; state "recession" represents the periods with the premium above its average except the 10% highest; and state "trough" represents the highest 10% periods of the expected market risk premium. The sample period is from 1960:Q1 to 2011:Q4.

Constant	DEF	TERM	RF	CAY	$\chi^2_{(4)}$	p-value	Adj-R^2 (%)
Panel A: estimation of the expected market risk premium							
0.66	3.60	−0.39	−0.52	1.06	11.184	0.048	3.59
(0.36)	(1.33)	(−0.39)	(−1.13)	(2.74)			

	Peak	Expansion	Recession	Trough
Panel B: properties of the estimated market risk premium				
Average	−1.85	0.20	2.61	4.90
Number	60	258	246	60

Following Petkova and Zhang (2005), we classify economic states based on the expected market risk premium as follows: state "peak" includes the 10% of periods with the lowest expected risk premium; "expansion" state represents the remaining periods in which the premium is below its average; "recession" state represents the periods in which the premium is above its average but still below the 10% of periods with the highest premium; and "trough" state represents the 10% of periods with the highest expected market risk premium. This sorting procedure is consistent with the stock market return predictability literature, which shows that expected market risk premium is higher in bad times, and is correlated with business cycle (Fama and Schwert, 1977;

[11] Lettau and Ludvigson (2001a) propose a theoretical framework in which consumption, labor income, and asset holdings share a common stochastic trend (i.e., these three variables are cointegrated), and that stationary deviations from this common trend capture movements in the consumption–aggregate wealth ratio. They further show that these stationary deviations predict future market returns, since the consumption–aggregated wealth ratio should summarize expected future returns on the market portfolio.

[12] The three-month T-bill rate has been shown to be negatively related to future market returns, and can act as a proxy for expectations of future economic growth (Fama, 1981; Fama and Schwert, 1977). The default spread has been known to track long-term business conditions; it is higher during recessions and lower during expansions (Keim and Stambaugh, 1986; Fama and French, 1989). Fama and French (1989) show that term spread is closely related to short-term business cycles, identified by the NBER. Finally, Lettau and Ludvigson (2001a) show that the CAY is superior to other popular forecasting variables in predicting future stock market returns over short horizons.

Fama and French, 1989). This classification is also consistent with modern asset pricing theories, which feature the countercyclical price of risk (Campbell and Cochrane, 1999; Zhang, 2005). Panel B of Table 2 shows the average estimated market risk premium conditional on our definition of economic states. The averages of the market risk premium are −1.85%, 0.20%, 2.61%, and 4.90% per quarter for the "peak," "expansion," "recession," and "trough" states, respectively. The number of quarters classified as "peak," "expansion," "recession," and "trough" are 60, 258, 246, and 60, respectively. Fig. 3 plots a time-series of the estimated expected market risk premium, along with the contractionary period (marked as shaded region) defined by the NBER. Consistent with aforementioned theoretical and empirical studies, Fig. 3 demonstrates that our estimated expected market risk premium exhibits strong countercyclical variations over business cycles. For instance, the expected market risk premium becomes especially high during the recent financial crisis period.

3. Empirical results

3.1. Momentum profits and economic states

The primary purpose of this paper is to examine whether the periods in which momentum strategies yield negative profits are "bad" states where the marginal utility of consumption is high. In addition, we examine whether the profits to momentum trading strategies vary across good and bad times and whether any differences observed are significant.

We estimate average momentum profits conditional on the economic states defined in Section 2.2. To test whether average momentum profits are equal to zero in each state, we regress the time-series of momentum profits on four dummy variables for PEAK, EXPANSION, RECESSION, and TROUGH without intercept. To test whether the average profits in the "trough" state are different from those in other states ("peak," "expansion," and "recession"), we regress the time-series of momentum profits on TROUGH and NON-TROUGH dummies, with an intercept.[13] This approach, adopted in Cooper et al. (2004), helps preserve the full time-series of returns, and enables us to reliably estimate *t*-statistics adjusting serial correlation. Table 3 reports average momentum profits for each series (raw, CAPM-adjusted, and Fama–French-adjusted) conditional on the state of the economy. Panel A reports results for the JT momentum construction, while Panel B reports results for the FF construction.

The results in Table 3 are fairly clear. First, the winner portfolios significantly underperform the loser portfolios in the "trough" state. For the JT momentum construction in "trough" states when marginal utility of wealth is especially high, the averages of the raw, CAPM, and Fama–French momentum profits are large and statistically significantly negative at −2.23% (*t*-value = −2.90), −2.08% (*t*-value = −2.74), and −2.06% (*t*-value = −2.81) per month, respectively. The results for the FF construction are quantitatively similar to those for the JT construction. In "trough" states, the raw, CAPM, and FF momentum profits are −1.73%, −1.62%, and −1.63% per month, respectively, and are also statistically significant.[14]

Second, the payoffs to momentum strategies tend to positively covary with macroeconomic conditions. For instance, average raw monthly momentum profits for the JT construction are 1.86%, 1.10%, 0.87%, and −2.23% in "peak," "expansion," "recession," and "trough" states, respectively, showing a monotonically decreasing pattern as economic state becomes worse. As a result, the difference between "non-trough" and "trough" momentum profits is large and statistically significant at 3.30% per month with a *t*-statistic of 4.10. The results from the risk-adjusted profits and those from the FF momentum construction both indicate that payoffs to momentum trading strategies show a monotonically increasing pattern where payoffs increase as macroeconomic distress risk decreases. In fact, the difference between "non-trough" and "trough" momentum profits are statistically significant for all cases considered.[15]

Fig. 4 shows four scatter plots, each corresponding to a particular economic state, where the *x*-axis is the expected market risk premium and the *y*-axis denotes momentum profits.[16] During the "peak" state, most of WML portfolio returns reside in a positive range. In the "expansion" state, payoffs to momentum strategies overall shift down, but for the most part remain positive. The "recession" state shows that momentum profits are more biased toward negative values. Finally, during the "trough" state, about half of momentum profit observations are negative, and the volatility of the profits soars. Clearly, when momentum trading strategies lose money, they lose a significant amount of money. Momentum strategies can lose as much as 84% in a quarter.

In order to more thoroughly illustrate that momentum is related to economic distress risk, Fig. 5 plots a time-series of quarterly profits of the momentum strategy (JT construction) and the estimated market risk premium. Fig. 5 clearly shows that momentum earns large negative returns when the predicted market risk premium is highest. In particular, the periods in which momentum trading generates the four most strongly negative profits coincide with our estimated "trough" state. Four largest negative quarterly profits are −84%, −83%, −53%, and −45%, occurring in 2009:Q2, 1991:Q1, 2009:Q3, and 1975:Q1, respectively.[17]

Next, we examine whether our results hold after controlling for the January effect in momentum payoffs. A number of studies show that momentum profits are negative in January, and positive during non-January months (e.g., Jegadeesh and Titman, 1993; Grundy and Martin, 2001; George and Hwang, 2004).[18] Therefore, it is important to investigate whether significant negative momentum profits in the "trough" state can be attributable to this January effect.

Table 4 reports average momentum profits conditional on our economic states across two separate periods: January and non-January months. As in Table 3, Panel A reports results for the JT momentum construction, while Panel B reports results for the FF construction.[19] In January, momentum generates negative profits in all economic states, consistent with the literature. Our primary

[13] Specifically, the NON-TROUGH dummy takes a value of one for "peak," "expansion," and "recession" states, and zero for "trough" state.

[14] We examine robustness with alternative classifications of the "trough" state by using different threshold values. Specifically, we redefine the "trough" state as either the 15%, 7%, or 5% of periods with the highest expected market risk premium. We obtain similar results under these different classifications. Interestingly, we find stronger negative momentum profits in the "trough" state when this state is more finely sliced and classified. For instance, when the "trough" state is redefined as the 5% of periods with the highest expected market risk premium, the average raw monthly momentum profit is more strongly negative at −4.32% (*t*-value = −4.01). These results are available upon request.

[15] When we reclassify "non-trough" and "trough" states to "good" (peak and expansion) and "bad" (recession and trough) states, we find that the average momentum profits in the "bad" state are significantly lower than those in the "good" state, although the statistical significance becomes weaker.

[16] For brevity, we only report the results for the JT momentum construction. The results for the FF construction yield very similar results, and are available from the authors upon request.

[17] In our unreported results, we also plot the cumulative gains from the momentum strategy and the estimated market risk premium. Consistent with Fig. 5, the dollar value of the momentum strategy falls sharply when the expected market risk premium is highest.

[18] One possible explanation for the January effect in momentum profits, suggested by Grinblatt and Moskowitz (1999), is tax-loss selling of the loser stocks in December, leading the price of those stocks to rebound in January (thus resulting in negative momentum profits in January).

[19] Unless stated otherwise, we maintain this format in the following Tables.

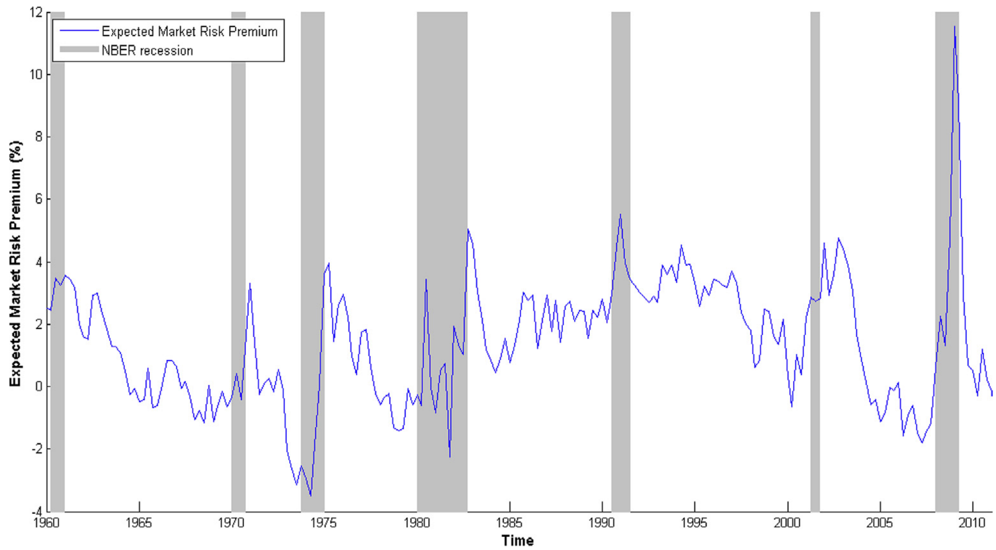

Fig. 3. Time-series of the expected market risk premium. The figure is a time-series plot of the quarterly expected market risk premium, which is estimated as a following model: $R^e_{m,t} = \alpha + \beta \boldsymbol{Z_{t-1}} + e_{m,t}$, where $\mathbf{Z_{t-1}}$ is a vector representing conditioning variables that include the default spread, term spread, three-month T-bill rate, and CAY. The shaded regions are the contractionary periods defined by the NBER. The sample period is from 1960:Q1 to 2011:Q4.

Table 3
Momentum profits and economic states. The table reports the average raw monthly momentum profits, CAPM alphas, and Fama–French alphas conditional on the economic states. The economic states are classified based on the expected market risk premium, which is estimated as a following model: $R^e_{m,t} = \alpha + \beta \boldsymbol{Z_{t-1}} + e_{m,t}$, where $\boldsymbol{Z_{t-1}}$ is a vector representing conditioning variables that include the default spread, term spread, three-month T-bill rate, and CAY. State "peak" is defined as the lowest 10% periods of the expected risk premium; state "expansion" represents the remaining periods with the premium below its average; state "recession" represents the periods with the premium above its average except the 10% highest; and state "trough" represents the highest 10% periods of the expected market risk premium. The difference of momentum profits between "non-trough" and "trough" is reported in the last column. Panel A reports the results for the Jegadeesh and Titman (1993) momentum construction, while Panel B reports the results for the Fama and French (1996) construction. The sample period is from January 1960 to December 2011.

	Peak	Expansion	Recession	Trough	Non-trough vs Trough
Panel A: Jegadeesh and Titman (1993) momentum construction					
Average profit	1.86	1.10	0.87	−2.23	3.30
(*t*-stat)	(2.43)	(2.97)	(2.30)	(−2.90)	(4.10)
CAPM alpha	1.64	1.11	1.08	−2.08	3.23
(*t*-stat)	(2.15)	(3.02)	(2.85)	(−2.74)	(4.05)
Fama–French alpha	1.81	1.43	1.36	−2.06	3.50
(*t*-stat)	(2.46)	(4.02)	(3.68)	(−2.81)	(4.53)
Panel B: Fama and French (1996) momentum construction					
Average profit	2.17	1.44	0.89	−1.73	3.01
(*t*-stat)	(2.74)	(3.77)	(2.27)	(−2.17)	(3.60)
CAPM alpha	2.01	1.45	1.05	−1.62	2.95
(*t*-stat)	(2.53)	(3.80)	(2.64)	(−2.05)	(3.55)
Fama–French alpha	2.18	1.73	1.30	−1.63	3.21
(*t*-stat)	(2.80)	(4.59)	(3.32)	(−2.10)	(3.93)

interest is the results for non-January months. The results for non-January months mirror the essential features drawn from the overall samples; that is, negative payoffs of momentum strategies are skewed toward the "trough" states in which investors require the highest risk premium. Specifically, during "trough" states excluding January, momentum strategies still deliver large negative profits: −1.72% (*t*-statistic of −2.28) and −1.12% (*t*-statistic of −1.43) per month for the JT and FF construction, respectively. These negative profits are still sizable in magnitude, although the statistical significance becomes weaker. Also, the difference between "non-trough" and "trough" momentum payoffs remains statistically significant for all cases considered. The results in Table 4 suggest that our finding that winner stocks underperform loser stocks in extremely bad economic states cannot be attributable to the January effect.

Chordia and Shivakumar (2002) find that momentum profits are only reliably positive during NBER expansionary periods, with insignificant negative profits observed during NBER contractionary periods. We examine whether results documented in Chordia and Shivakumar (2002) hold in our sample. The results, reported in Table 5, show that the average profits of momentum strategies during NBER expansionary periods are statistically positive for both JT and FF portfolio constructions, while momentum payoffs during NBER contractionary periods are negative and insignificant: −0.71% per month (*t*-statistic of −1.14) for the JT construction, and −0.15% per month (*t*-statistic of −0.23) for the FF construction. However, the dependency of momentum payoffs on NBER contractionary periods seems to be mainly driven by the January effect. To show this, we estimate the average profits of momentum strategies conditional on NBER expansionary and contractionary periods in January and non-January months. Surprisingly, when controlling for the January effect, the explanatory power of the NBER classification of the business cycle completely disappears. During the contractionary periods without January, average momentum payoffs are no longer negative for all cases considered. The WML portfolio return for the FF construction is even reliably positive at 1.08% per month (*t*-statistic of 1.72). These results raise the question of

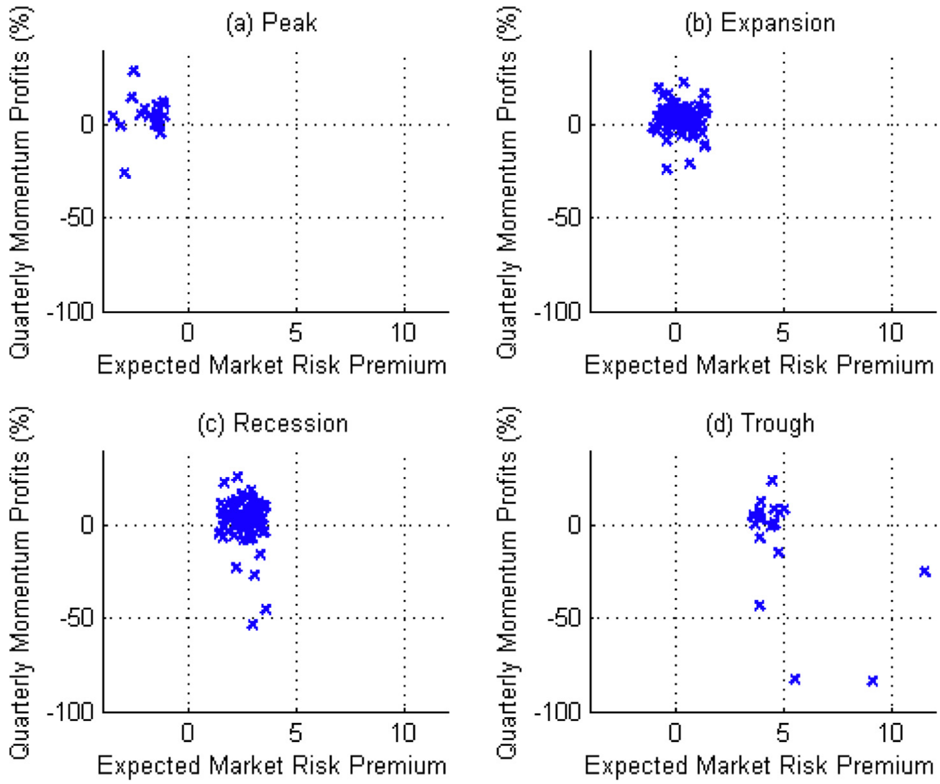

Fig. 4. Expected market risk premium & momentum profits. The figure shows scatter plots of quarterly momentum profits against the expected market risk premium across different economic states. The expected market risk premium is estimated as a following model: $R^e_{m,t} = \alpha + \beta \mathbf{Z_{t-1}} + e_{m,t}$, where $\mathbf{Z_{t-1}}$ is a vector representing conditioning variables that include the default spread, term spread, three-month T-bill rate, and CAY. State "peak" is defined as the lowest 10% periods of the expected risk premium; state "expansion" represents the remaining periods with the premium below its average; state "recession" represents the periods with the premium above its average except the 10% highest; and state "trough" represents the highest 10% periods of the expected market risk premium. The sample period is from 1960:Q1 to 2011:Q4.

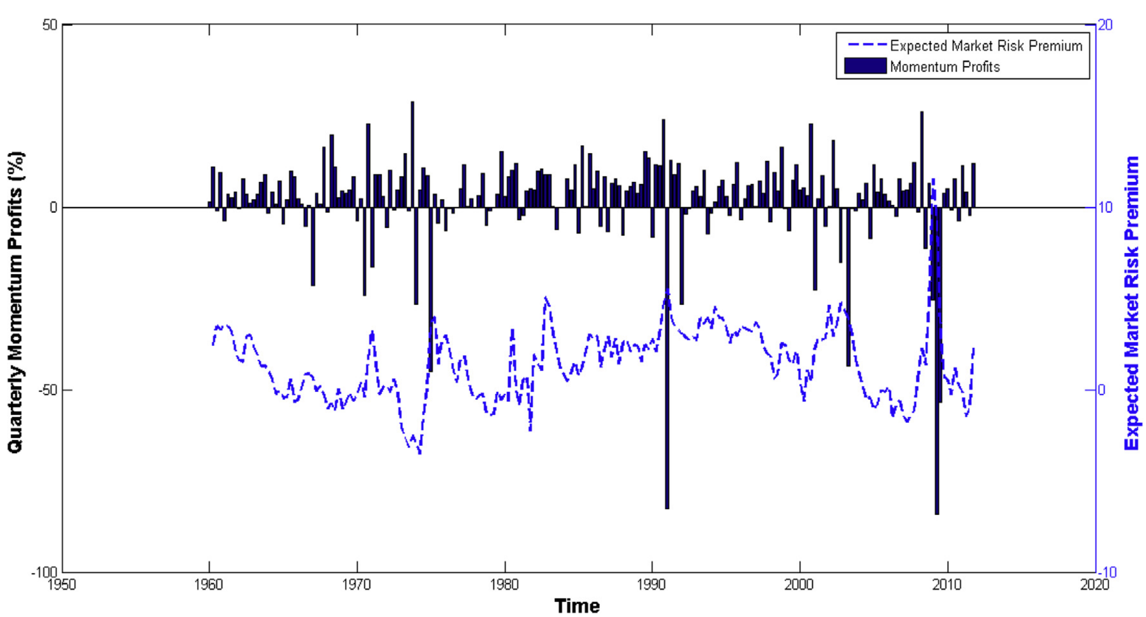

Fig. 5. Time-series of momentum profits with the expected market risk premium. The figure is time-series plots of quarterly momentum profits (bar graph) from the Jegadeesh and Titman (1993) momentum construction and the expected market risk premium (dashed line). The expected market risk premium is estimated as a following model: $R^e_{m,t} = \alpha + \beta \mathbf{Z_{t-1}} + e_{m,t}$, where $\mathbf{Z_{t-1}}$ is a vector representing conditioning variables that include the default spread, term spread, three-month T-bill rate, and CAY. The sample period is from 1960:Q1 to 2011:Q4.

Table 4
Momentum profits and economic states: January vs non-January months. The table reports the average raw monthly momentum profits, CAPM alphas, and Fama–French alphas conditional on the economic states across two separate periods, January and Non-January months. The economic states are classified based on the expected market risk premium, which is estimated as a following model: $R^e_{m,t} = \alpha + \beta \boldsymbol{Z_{t-1}} + e_{m,t}$, where $\boldsymbol{Z_{t-1}}$ is a vector representing conditioning variables that include the default spread, term spread, three-month T-bill rate, and CAY. State "peak" is defined as the lowest 10% periods of the expected risk premium; state "expansion" represents the remaining periods with the premium below its average; state "recession" represents the periods with the premium above its average except the 10% highest; and state "trough" represents the highest 10% periods of the expected market risk premium. The difference of momentum profits between "non-trough" and "trough" is reported in the last column. Panel A reports the results for the Jegadeesh and Titman (1993) momentum construction, while Panel B reports the results for the Fama and French (1996) construction. The sample period is from January 1960 to December 2011.

	Peak	Expansion	Recession	Trough	Non-trough vs trough
Panel A: Jegadeesh and Titman (1993) momentum construction					
January					
Average profit	−2.24	−4.43	−8.11	−6.73	0.82
(t-stat)	(−0.98)	(−3.38)	(−6.84)	(−2.97)	(0.34)
CAPM alpha	−2.28	−4.45	−7.72	−6.70	0.97
(t-stat)	(−1.01)	(−3.42)	(−6.53)	(−2.97)	(0.41)
Fama–French alpha	−1.07	−2.89	−6.46	−6.97	2.62
(t-stat)	(−0.48)	(−2.21)	(−5.45)	(−3.15)	(1.10)
Non-January					
Average profit	2.32	1.51	1.75	−1.72	3.42
(t-stat)	(3.07)	(4.21)	(4.72)	(−2.28)	(4.29)
CAPM alpha	2.10	1.52	1.92	−1.59	3.34
(t-stat)	(2.79)	(4.27)	(5.16)	(−2.11)	(4.22)
Fama–French alpha	2.10	1.66	2.02	−1.53	3.39
(t-stat)	(2.84)	(4.74)	(5.52)	(−2.08)	(4.37)
Panel B: Fama and French (1996) momentum construction					
January					
Average profit	−2.74	−4.35	−8.63	−7.23	1.04
(t-stat)	(−1.17)	(−3.22)	(−7.05)	(−3.08)	(0.42)
CAPM alpha	−2.77	−4.36	−8.36	−7.21	1.15
(t-stat)	(−1.19)	(−3.24)	(−6.82)	(−3.08)	(0.46)
Fama–French alpha	−1.86	−3.25	−7.42	−7.50	2.45
(t-stat)	(−0.80)	(−2.37)	(−5.97)	(−3.23)	(0.98)
Non-January					
Average profit	2.72	1.88	1.83	−1.12	3.06
(t-stat)	(3.48)	(5.07)	(4.76)	(−1.43)	(3.71)
CAPM alpha	2.57	1.89	1.94	−1.02	3.00
(t-stat)	(3.29)	(5.11)	(5.03)	(−1.31)	(3.65)
Fama–French alpha	2.59	2.00	2.03	−0.99	3.06
(t-stat)	(3.34)	(5.43)	(5.29)	(−1.28)	(3.76)

whether the finding of Chordia and Shivakumar (2002) that momentum profits are absent during NBER contractionary periods may be driven entirely by the January effect.[20]

We also examine whether our measure of "bad times" has more explanatory power for momentum profits than the NBER contraction indicator. We consider two dummy variables: (1) *TROUGH*, a dummy variable that takes a value of one during the "trough" state, and zero otherwise; and (2) *CONTRACTION* is a dummy variable that takes a value of one during NBER contractionary periods, and zero otherwise. We regress the momentum payoffs on both the *TROUGH* and *CONTRACTION* variables. The objective is to compare the relative ability of each variable to explain momentum profits. The results, presented in Table 6, show that *CONTRACTION* is not a significant variable for explaining momentum profits in the presence of our measure of bad economic states, *TROUGH*. The t-statistics of *CONTRACTION* range between −1.57 and −1.16. In contrast, *TROUGH* remains statistically significant, with corresponding t-statistics ranging between −2.48 and −2.18. Further, the magnitude of the coefficients on *TROUGH* is more than double those on *CONTRACTION*. These results suggest that our measure of "bad times," based on the expected market risk premium, is a more useful indicator of momentum profits than the NBER contraction indicator.

In sum, we provide evidence that the payoffs to momentum strategies are closely related to risk arising from macroeconomic states classified by the expected market risk premium. Winner stocks indeed significantly underperform loser stocks in the "trough" state, when the marginal value of wealth is highest. This shows that the momentum strategy exposes investors to greater downside risk. Thus, our results support the view that momentum strategies are fundamentally risky.

3.2. Regression analysis

In this section, we examine the relation between momentum profits and the expected market risk premium as a continuous measure of economic state, not just the discrete states as before. Even though informal, examining the profitability of momentum strategies conditional on economic states suggested by Lakonishok et al. (1994) is perhaps the simplest and the most intuitive way to study the relation between momentum strategies and macroeconomic risk. We supplement this informal test with a more formal test. If momentum strategies expose investors to greater systematic risk, then momentum profits should have a *negative* relation with expected market risk premium. To test this hypothesis, we regress momentum profits on the expected market risk premium as a continuous variable:

$$WML_t = b_0 + b_1 EMRP_t + \xi_t. \quad (5)$$

Since the estimated market risk premium is quarterly in frequency, we convert monthly holding period returns on momentum portfolios into quarterly holding period returns.

Note, however, that the expected market risk premium, $EMRP_t$, is a generated regressor from Eq. (3). The measurement error created by the generated regressor can affect our inferences. To correct for the additional uncertainty induced through the generated regressor, we estimate Eqs. (3) and (5) simultaneously using the Generalized Method of Moments (GMM) in one-step. We define $\boldsymbol{Z_{t-1}} \equiv [\iota \quad DEF_{t-1} \quad TERM_{t-1} \quad RF_{t-1} \quad CAY_{t-1}]$ to be the vector of conditioning variables including a constant term, where ι is a vector of ones. We define $\boldsymbol{\eta} \equiv [\eta_0 \quad \eta_1 \quad \eta_2 \quad \eta_3 \quad \eta_4]$ to be the vector of regression coefficients in Eq. (3). The moment conditions are orthogonality conditions associated with the regression models of (3) and (5):

$$E\left[\left(R^e_{m,t} - \boldsymbol{Z_{t-1}\eta}\right)\boldsymbol{Z'_{t-1}}\right] = 0, \quad (6)$$

$$E\left[(WML_t - b_0 - b_1 \boldsymbol{Z_{t-1}\eta})(\iota \quad \boldsymbol{Z_{t-1}\eta})'\right] = 0. \quad (7)$$

There are, in total, seven moment conditions and seven parameters to be estimated so that the system is exactly identified. Therefore, the estimated coefficients from the one-step GMM estimation are identical to those from the two-step simple regression models of Eqs. (3) and (5), but standard errors are adjusted for the fact that $EMRP_t$ is a generated regressor.

Table 7 reports results on whether returns on the momentum trading strategies are related to the expected market risk premium. Table 7 consists of two panels that differ in terms of the dependent

[20] We are not the first to show that the relation between the contractionary periods designated by the NBER and momentum profits is not robust. Griffin et al. (2003) report that the explanatory power of NBER contractionary periods also critically depends on whether a month is skipped between the ranking and holding period. To address this concern, we skip a month between the ranking and holding period for both momentum portfolio constructions.

Table 5
Momentum profits conditional on the NBER expansionary and contractionary periods. The table reports the average raw monthly momentum profits, CAPM alphas, and Fama–French alphas conditional on the NBER expansionary and contractionary periods. The column titled "January" reports the results for January, while the column titled "non-January" reports the results for non-January months. Panel A reports the results for the Jegadeesh and Titman (1993) momentum construction, and Panel B reports the results for the Fama and French (1996) construction. The sample period is from January 1960 to December 2011.

	Whole period		January		Non-January	
	Expansionary	Contractionary	Expansionary	Contractionary	Expansionary	Contractionary
Panel A: Jegadeesh and Titman (1993) momentum construction						
Average profit	1.02	−0.71	−4.70	−13.15	1.54	0.47
(t-stat)	(3.93)	(−1.14)	(−5.59)	(−6.66)	(6.07)	(0.77)
CAPM alpha	1.14	−0.78	−4.48	−13.18	1.63	0.39
(t-stat)	(4.40)	(−1.27)	(−5.37)	(−6.75)	(6.50)	(0.65)
Fama–French alpha	1.37	−0.49	−3.48	−11.62	1.73	0.47
(t-stat)	(5.43)	(−0.82)	(−4.12)	(−5.98)	(6.95)	(0.80)
Panel B: Fama and French (1996) momentum construction						
Average profit	1.19	−0.15	−5.06	−13.18	1.76	1.08
(t-stat)	(4.43)	(−0.23)	(−5.82)	(−6.47)	(6.73)	(1.72)
CAPM alpha	1.28	−0.21	−4.89	−13.21	1.83	1.02
(t-stat)	(4.76)	(−0.33)	(−5.65)	(−6.52)	(7.01)	(1.64)
Fama–French alpha	1.49	0.04	−4.18	−12.15	1.91	1.08
(t-stat)	(5.57)	(0.06)	(−4.72)	(−5.96)	(7.31)	(1.75)

Table 6
Momentum profits and bad states: trough from the expected market risk premium vs the NBER contraction. The table presents results from regressing momentum profits on *TROUGH*. and *CONTRACTION*. variables, where *TROUGH* is defined as a dummy variable that takes a value of one during the state "trough", and zero otherwise, and *CONTRACTION* is defined as a dummy variable that takes a value of one during the NBER contractionary periods, and zero otherwise. State "trough" represents the highest 10% periods of the expected market risk premium. In Panel A, the dependent variable is the WML portfolio return from the Jegadeesh and Titman (1993) momentum construction. In Panel B, the dependent variable is the WML portfolio return from the Fama and French (1996) momentum construction. Reported are the regression coefficients, the t-statistics (in parentheses), and the adjusted R-squares. The sample period is from 1960:Q1 to 2011:Q4.

	TROUGH	*CONTRACTION*	*MKT*	*SMB*	*HML*	Adj-R^2 (%)
Panel A: Jegadeesh and Titman (1993) momentum construction						
Average profit	−3.09	−1.41				3.01
(t-stat)	(−2.18)	(−1.41)				
CAPM alpha	−2.99	−1.61	−0.20			5.01
(t-stat)	(−2.20)	(−1.58)	(−2.12)			
FF alpha	−3.27	−1.52	−0.18	−0.45	−0.43	12.10
(t-stat)	(−2.28)	(−1.57)	(−1.87)	(−3.24)	(−2.32)	
Panel B: Fama and French (1996) momentum construction						
Average profit	−2.85	−1.05				2.08
(t-stat)	(−2.24)	(−1.16)				
CAPM alpha	−2.77	−1.20	−0.15			3.12
(t-stat)	(−2.28)	(−1.32)	(−2.07)			
FF alpha	−3.04	−1.14	−0.15	−0.34	−0.39	7.51
(t-stat)	(−2.48)	(−1.36)	(−1.92)	(−2.39)	(−2.45)	

variable of the regressions. In Panel A, the dependent variable is the WML portfolio return from the JT momentum construction. In Panel B, the dependent variable is the WML portfolio return from the FF construction. The t-statistics in parentheses are those obtained from the simple regression model of (5), whereas those in square brackets are the ones obtained from the one-step GMM estimation. The results of Section 3.1 are confirmed here using a regression analysis. We find that the market risk premium contains critical information about the raw and risk-adjusted momentum profits. The coefficient on the market risk premium is significantly negative in our specifications. For the simple regression models, t-statistics range between −2.45 and −2.05. When the standard error is obtained from the one-step GMM estimation, statistical significances become weaker, but the coefficient on the market risk premium is still significant at the 10% level. These results confirm our finding that momentum is low (high) when investors require a high (low) risk premium. The adjusted R-squared values are in the 8–24% range across different specifications.

Table 7
Regressions of momentum profits on the expected market risk premium. The table reports results from regressing momentum profits on the expected market risk premium. $EMRP_t$ is the expected market risk premium, MKT_t is the market factor (CRSP value-weighted market excess return), SMB_t is the size factor (a return spread between small and big firms), and HML_t is the book-to-market factor (a return spread between stocks with high and low book-to-market ratios). In Panel A, the dependent variable is the WML portfolio return from the Jegadeesh and Titman (1993) momentum construction. In Panel B, the dependent variable is the WML portfolio return from the Fama and French (1996) momentum construction. Reported are the regression coefficients, the t-statistics, and the adjusted R-squares. The t-statistics in parentheses are from standard errors obtained from the simple regression model. The t-statistics in square brackets are calculated using standard errors obtained from the one-step GMM estimation. The sample period is from 1960:Q1 to 2011:Q4.

	EMRP	*MKT*	*SMB*	*HML*	Adj-R^2(%)
Panel A: Jegadeesh and Titman (1993) momentum construction					
Average profit	−1.96				8.42
(t-stat)	(−2.24)				
[t-stat]	[−1.94]				
CAPM alpha	−1.71	−0.24			10.35
(t-stat)	(−2.05)	(−1.96)			
[t-stat]	[−1.76]	[−1.92]			
FF alpha	−1.86	−0.10	−0.84	−0.48	23.64
(t-stat)	(−2.11)	(−0.76)	(−4.16)	(−2.42)	
[t-stat]	[−1.79]	[−0.72]	[−4.39]	[−2.32]	
Panel B: Fama and French (1996) momentum construction					
Average profit	−1.93				8.77
(t-stat)	(−2.45)				
[t-stat]	[−1.88]				
CAPM alpha	−1.68	−0.25			11.06
(t-stat)	(−2.21)	(−1.99)			
[t-stat]	[−1.65]	[−1.99]			
FF alpha	−1.82	−0.12	−0.79	−0.47	24.07
(t-stat)	(−2.41)	(−0.88)	(−4.86)	(−2.29)	
[t-stat]	[−1.67]	[−0.83]	[−4.65]	[−2.18]	

The market risk premium has large explanatory power for momentum profits in economic terms. Consider the JT constructed momentum raw profit. The regression coefficient of the market risk premium is −1.96. To measure the economic significance, note that the standard deviation of the estimated market risk premium is 2.03. Thus, a one-standard-deviation increase in the expected market risk premium is associated with a 3.98% decrease in momentum profits during a quarter, a roughly −16% annual decrease.

In sum, results from the regression analysis reported in Table 7 deliver the same message as the comparison of returns conditional on the economic states in Table 3. The data support the view that momentum is driven by macroeconomic risk.

3.3. Out-of-sample estimation of the expected market risk premium

One possible concern about the findings presented above is the potential for "look-ahead" bias due to the fact that the expected market risk premium is estimated using the full sample. In this section, we address this concern by performing out-of-sample estimation where the parameters in Eq. (3) are reestimated every period, using only data available up to time $t-1$. The out-of-sample analysis complements the previous evidence on the robustness of the relation between the expected market risk premium and momentum profits.

The recursive out-of-sample forecasts of the market risk premium is formed as follows. The initial coefficient estimates are obtained over the twenty-year period from 1960:Q1 to 1979:Q4. The first out-of-sample quarter is 1980:Q1. The quarterly observation of 1980:Q1 is added to the initial period. Eq. (3) is reestimated, and an out-of-sample forecast for 1980:Q2 is obtained. This process is repeated until the end of the sample, 2011:Q4. By implementing this approach, the predicted market risk premium at time t is obtained using the estimated coefficients from the most recent in-sample regression (i.e., from 1960:Q1 to time $t-1$) and the realizations of the lagged instrumental variables at time t.

To understand how the out-of-sample estimate of the market risk premium compares to the in-sample estimate, Fig. 6 plots the time-series of the out-of-sample estimate (solid line) and in-sample estimate (dashed line) over the period from 1980:Q1 to 2011:Q4. The plot reveals two interesting facts. First, we see that the magnitude of the fluctuation in the out-of-sample estimate is larger than that in the in-sample estimate. This should not be a surprise, since the recursively estimated coefficients tend to show larger variations than the coefficients estimated using the full sample. Second and more importantly, the out-of-sample and in-sample estimates of the market risk premium strongly comove: the correlation between the two is 0.83. Of greater interest is the fact that the periods in which the out-of-sample estimate of the risk premium is especially high are essentially identical to those identified by the in-sample estimate. This suggests that classifying economic states based on the out-of-sample estimate is unlikely to identify different states from those identified by the in-sample estimate.

To assess the robustness of out-of-sample estimation of the market risk premium, we conduct the same exercise as in Section 3.1. That is, we redefine the economic states using the out-of-sample estimate of the expected market risk premium, and then estimate the averages of raw, CAPM-adjusted, and Fama–French-adjusted profits conditional on each state. Table 8 presents the results. As can be seen, the results confirm our main finding that momentum profits are negative and statistically significant when investors require the highest risk premium. In "trough" states, momentum strategies yield significant negative monthly profits of -2.39% and -1.83% for JT and FF portfolio constructions, respectively. Similar results are obtained for the benchmark risk-adjusted profits. Further, differences between "non-trough" and "trough" momentum profits are again large and statistically significant for all cases considered. These findings suggest that our evidence is robust to the out-of-sample estimation of the expected market risk premium for defining the economic states.

The out-of-sample estimation of the market risk premium has an important implication for traders looking to develop a trading strategy that can enhance momentum profitability. When the next period of the expected market risk premium estimated using information observable at time $t-1$ is especially high, our analysis suggests that a high chance of the momentum strategy losing money in the next period. Therefore, there is a clear way to modify the momentum strategy to enhance profitability. A trader can develop a conditional momentum strategy that reverses the momentum trading rule (i.e., buying loser stocks and selling winner stocks) when the next period is expected to be a "trough" state. If loser stocks indeed outperform winner stocks in the next period, the conditional momentum strategy can turn losses into profits, generating enhanced profitability. When the next period of the expected market risk premium is not forecast to be high, a trader can maintain the original momentum trading rule (i.e., buying winner stocks and selling loser stocks). Note that our proposed strategy is conditional on economic conditions, and a real-time implementable strategy.[21]

4. Additional results

This section presents evidence on the robustness of the relation between momentum profits and the expected market risk premium. Specifically, we examine whether lagged market return or investor sentiment can take away the explanatory power of the expected market risk premium.

4.1. Market state

Cooper et al. (2004) find that the profits to momentum strategies depend on the lagged (medium-term) market return. They show that momentum profits are significant only after "UP" market where the lagged three-year market return is positive. We explore whether our previous results, reported in Table 9, remain robust after controlling for the lagged market return. We estimate the following models:

$$WML_t = \delta_0 + \delta_1 LAGMKT_{t-1} + \delta_2 EMRP_t + \epsilon_t, \tag{8}$$

$$WML_t = \delta_0 + \delta_1 LAGMKT_{t-1} + \delta_2 TROUGH_t + \epsilon_t, \tag{9}$$

where *LAGMKT* is the lagged three-year market return of the value-weighted index including dividends.[22] Including the *TROUGH* dummy variable in Eq. (9) is an attempt to capture any difference in the momentum profits in the "trough" state.

Our results, reported in Table 9, confirm that *LAGMKT* has explanatory power. When used alone, the coefficient on *LAGMKT* is positive and statistically significant, indicating that momentum profits tend to be high when the lagged three-year market return becomes high. When both *LAGMKT* and *EMRP* are included in regressions, the coefficients on both variables are statistically significant at the 10% level or better across all specifications, indicating that each variable has independent power in explaining momentum profits. Specifically, when we use the JT momentum construction (Panel A), the coefficient on *EMRP* is equal to -1.92 (t-statistic = -2.12). For the benchmark-adjusted profit using the Fama–French model, the coefficient is -1.72 (t-statistic = -1.88). These coefficients are very similar in magnitude to those reported in Table 7, suggesting that even the magnitude of the economic

[21] The proposed trading strategy is based on the *time-series* relation between momentum profits and economic conditions, measured by the expected market risk premium. On the other hand, prior studies document the *cross-sectional* relation between momentum profits and firm characteristics. One can propose other simple trading rules by combining the cross-sectional and time-series aspects of the momentum effect. For instance, the momentum strategy conditional on both firm size and the expected market risk premium could be one of such modified strategies. That is, a trader consider small stocks, rather than the whole stock universe, in forming dynamic momentum strategy; a trading rule is either to buy or sell small stocks winners and small stocks losers, depending on the forecasted market risk premium.

[22] We also use the GMM to estimate Eqs. (3) and (8) simultaneously to correct for the additional uncertainty created by the generated regressor.

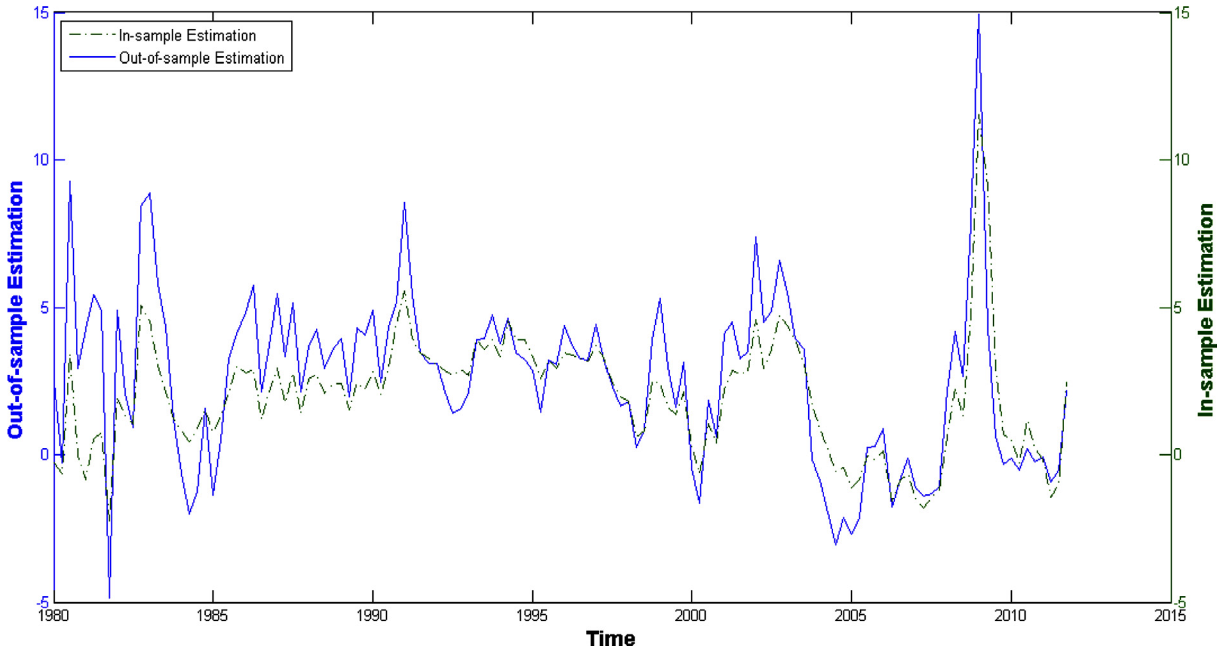

Fig. 6. Out-of-sample and in-sample estimates of the expected market risk premium. The figure is time-series plots of the out-of-sample estimate of the expected market risk premium (solid line) and in-sample estimate of the expected market risk premium (dashed line). The sample period is from 1960:Q1 to 2011:Q4.

impact for the market risk premium is unchanged in the presence of *LAGMKT*.[23] Next, when *EMRP* is replaced by the *TROUGH* dummy variable, we still find that momentum payoffs are significantly lower during "trough" states, even after controlling for the lagged three-year market return.[24]

In sum, Table 9 shows that the explanatory power of the expected market risk premium in momentum profits goes beyond that of the lagged market return. Further, the winner portfolio continues to significantly underperform the loser portfolio in "trough" states in the presence of the lagged market return. We conclude that our findings are substantially distinct from those documented by Cooper et al. (2004).

Cooper et al. (2004) interpret that if overconfidence is higher following market increases, then their findings are consistent with theoretical predictions from the behavioral models of Daniel et al. (1998) and Hong and Stein (1999). However, the more recent study of Sagi and Seasholes (2007) presents a rational asset pricing model that can also reproduce the evidence in Cooper et al. (2004) It should therefore be emphasized that the dependency of momentum profits on the lagged market return no longer discriminates between behavioral and rational explanations for momentum profits. In contrast, our evidence that momentum strategies deliver significant negative returns when investors require the highest risk premium suggests a more straightforward interpretation that momentum strategies expose investors to greater downside risk.

4.2. Investor sentiment

Stambaugh et al. (2012) and Antoniou et al. (2013) show that momentum profits are higher following periods of high sentiment, and that the sentiment index predicts positively the payoffs to momentum strategies.[25] In particular, Stambaugh et al. (2012) interpret that sentiment-driven overpricing appears to be at least a partial explanation for the profitability of momentum strategies. We investigate whether the relation between the expected market

Table 8

Momentum profits and economic states based on the out-of-sample estimate of the expected market risk premium. The table reports the average raw monthly momentum profits, CAPM alphas, and Fama–French alphas conditional on the economic states based on the out-of-sample estimate of the expected market risk premium. The recursive out-of-sample forecasts of the market risk premium is as follows. The initial coefficient estimates are obtained over the twenty-year period from 1960:Q1 to 1979:Q4 from the following model: $R^e_{m,t} = \alpha + \beta \mathbf{Z_{t-1}} + e_{m,t}$, where $\mathbf{Z_{t-1}}$ is a vector representing conditioning variables that include the default spread, term spread, three-month T-bill rate, and CAY. The first out-of-sample quarter is 1980:Q1. Subsequently, the quarterly observation of 1980:Q1 is added to the initial period. The regression model is re-estimated, and an out-of-sample forecast for 1980: Q2 is obtained. This process is repeated until the end of the sample, 2011:Q4. By implementing this approach, the predicted market risk premium at time t is obtained using the estimated coefficients from the most recent in-sample regression (i.e., from 1960:Q1 to time $t-1$) and the realizations of the lagged instrumental variables at time t. Then, the economic states are re-defined using the out-of-sample estimate of the expected market risk premium as in Table 3. Panel A reports the results for the Jegadeesh and Titman (1993) momentum construction, while Panel B reports the results for the Fama and French (1996) construction. The sample period is from January 1960 to December 2011.

	Peak	Expansion	Recession	Trough	Non-trough vs trough
Panel A: Jegadeesh and Titman (1993) momentum construction					
Average profit	2.11	1.24	1.10	−2.39	3.63
(t-stat)	(1.59)	(2.24)	(2.18)	(−2.78)	(3.90)
CAPM alpha	2.11	1.21	1.35	−2.28	3.62
(t-stat)	(1.61)	(2.21)	(2.66)	(−2.67)	(3.93)
Fama–French alpha	1.79	1.59	1.55	−2.25	3.84
(t-stat)	(1.40)	(2.92)	(3.10)	(−2.70)	(4.24)
Panel B: Fama and French (1996) momentum construction					
Average profit	2.83	1.41	1.07	−1.83	3.17
(t-stat)	(2.04)	(2.43)	(2.03)	(−2.03)	(3.26)
CAPM alpha	2.82	1.39	1.23	−1.76	3.17
(t-stat)	(2.04)	(2.41)	(2.29)	(−1.96)	(3.26)
Fama–French alpha	2.64	1.69	1.39	−1.78	3.39
(t-stat)	(1.92)	(2.91)	(2.59)	(−2.00)	(3.50)

[23] We find that the correlation between our market risk premium measure and the lagged three-year (realized) market return is only −0.03.

[24] We repeat our analysis by defining *LAGMKT* as lagged two-year and one-year returns. The results are qualitatively the same.

[25] Stambaugh et al. (2012) study the role of investor sentiment in 11 financial market anomalies, including momentum, while Antoniou et al. (2013) focus exclusively on momentum.

Table 9
Regressions of momentum profits on lagged market return and the expected market risk premium. The table presents results from regressing momentum profits on lagged market return and the expected market risk premium. *LAGMKT* is the lagged three-year market return of the value-weighted index including dividends. $EMRP_t$ is the expected market risk premium. *TROUGH* is a dummy variable that takes a value of one during the state "trough", and zero otherwise. In Panel A, the dependent variable is the WML portfolio return from the Jegadeesh and Titman (1993) momentum construction. In Panel B, the dependent variable is the WML portfolio return from the Fama and French (1996) momentum construction. Reported are the regression coefficients, the *t*-statistics, and the adjusted *R*-squares. The *t*-statistics in parentheses are from standard errors obtained from the simple regression model. The *t*-statistics in square brackets are calculated using standard errors obtained from the one-step GMM estimation. The sample period is from 1960:Q1 to 2011:Q4.

	LAGMKT	*EMRP*	*TROUGH*	*MKT*	*SMB*	*HML*	Adj-R^2 (%)
Panel A: Jegadeesh and Titman (1993) momentum construction							
Average profit	9.65						5.22
(*t*-stat)	(2.53)						
Average profit	9.33	−1.92					13.33
(*t*-stat)	(3.07)	(−2.51)					
[*t*-stat]	[2.89]	[−2.12]					
Average profit	7.81		−9.88				9.39
(*t*-stat)	(2.47)		(−1.95)				
FF alpha	9.68	−1.72		−0.21	−0.76	−0.46	28.64
(*t*-stat)	(3.01)	(−2.29)		(−1.47)	(−3.72)	(−2.51)	
[*t*-stat]	[2.96]	[−1.88]		[−1.55]	[−4.08]	[−2.42]	
FF alpha	8.58		−10.00	−0.29	−0.73	−0.49	26.79
(*t*-stat)	(2.55)		(−1.98)	(−1.77)	(−3.66)	(−2.64)	
Panel B: Fama and French (1996) momentum construction							
Average profit	8.66						4.43
(*t*-stat)	(2.30)						
Average profit	8.35	−1.89					12.91
(*t*-stat)	(2.48)	(−2.60)					
[*t*-stat]	[2.34]	[−2.04]					
Average profit	7.07		−8.55				7.68
(*t*-stat)	(2.15)		(−1.60)				
FF alpha	8.78	−1.69		−0.22	−0.72	−0.45	28.43
(*t*-stat)	(2.76)	(−2.52)		(−1.56)	(−4.54)	(−2.37)	
[*t*-stat]	[2.46]	[−1.75]		[−1.55]	[−4.46]	[−2.24]	
FF alpha	7.95		−8.63	−0.30	−0.69	−0.47	25.39
(*t*-stat)	(2.58)		(−1.83)	(−1.95)	(−4.39)	(−2.25)	

risk premium and momentum profits remains unchanged when controlling for the sentiment measure.

Following Stambaugh et al. (2012) and Antoniou et al. (2013), we use the investor sentiment measure of Baker and Wurgler (2006).[26] Baker and Wurgler construct their composite sentiment index by taking the first principal component of the following six proxies: the closed-end fund discount, the number and the first-day returns of IPO's, NYSE turnover, the equity share in total new issues, and the dividend premium.[27] To remove a potential link to economic fundamentals, Baker and Wurgler regress raw sentiment measures on a set of macroeconomic variables including growth in industrial production, real growth in durable consumption, non-durable consumption, services consumption, growth in employment, and a NBER contraction indicator. Using this orthogonalized index measure, *SENT*, we run the following regressions:[28]

$$WML_t = \gamma_0 + \gamma_1 SENT_{t-1} + \gamma_2 EMRP_t + \zeta_t, \tag{10}$$

$$WML_t = \gamma_0 + \gamma_1 SENT_{t-1} + \gamma_2 TROUGH_t + \zeta_t. \tag{11}$$

In this way we examine whether the sentiment measure can take away the explanatory power of either the expected market risk premium or our measure of the bad state (i.e., the "trough" state defined in Section 2.2). The results are similar when using the raw sentiment index, and are thus omitted. Since the Baker and Wurgler index data are available from July 1965 to December 2010, our regression is restricted to this sample period.

Panel A of Table 10 reports the results for the JT momentum construction. Similar results are obtained for the FF construction. We confirm that sentiment affects momentum profits. We find a significant positive relation between the lagged sentiment index and the returns on the WML portfolio, consistent with previous findings that momentum payoffs tend to be higher when sentiment is high. The results also show that the expected market risk premium continues to have a significant negative relation with momentum profits even after controlling for the sentiment effect. For all cases considered, the coefficient on *EMRP* is negative and significant at the 10% level or better. Further, the coefficient on the *TROUGH* dummy remains statistically significant in the presence of *SENT*, suggesting that the finding that momentum strategies deliver significantly lower returns when the expected risk premium is especially high is not materially related to investor sentiment. In contrast, the predictive power of the sentiment index depends on the benchmark adjustment. For the raw profits without benchmark adjustment, the explanatory power of sentiment remains unchanged when controlling for the expected market risk premium. After adjusting for benchmark exposure, however, we see that the predictive power of investor sentiment becomes weaker in the presence of either *EMRP* or the *TROUGH* variable, with *t*-statistics ranging from 1.04 to 1.55.

We examine the robustness of our results to using an alternative measure of sentiment. The University of Michigan Consumer Sentiment Index has been widely used in investor sentiment studies (e.g., Lemmon and Portniaquina, 2006; Bergman and Roychowdhury, 2008). Whereas the Baker and Wurgler index is based on stock market indicators, the Michigan Consumer Sentiment Index is a survey-based measure. The monthly survey is mailed to a random set of 500 households and solicits their views about the economy. We re-estimate the regression models of Eqs. (10) and (11) using the Michigan sentiment index, and present the

[26] Antoniou et al. (2013) use the Consumer Confidence index published by the Conference Board for their main analysis. They show that their results are virtually unchanged when using the Baker Wurgler sentiment index as a robustness analysis.
[27] The principal component analysis eliminates idiosyncratic noise in the six measures, picking up their common movement.
[28] We also use the GMM to estimate Eqs. (3) and (10) simultaneously to correct for the additional uncertainty created by the generated regressor.

Table 10
Regressions of momentum profits on investor sentiment and the expected market risk premium. The table presents results from regressing momentum profits (from the Jegadeesh and Titman (1993) momentum construction) on investor sentiment and the expected market risk premium. *SENT* is the investor sentiment measure. *EMRP*. is the expected market risk premium. *TROUGH* is a dummy variable that takes a value of one during the state "trough", and zero otherwise. In Panel A, the Baker and Wurgler (2006) index is used as a proxy for sentiment. In Panel B, the University of Michigan Consumer Sentiment Index is used as a proxy for sentiment. Reported are the regression coefficients, the *t*-statistics, and the adjusted *R*-squares. The *t*-statistics in parentheses are from standard errors obtained from the simple regression model. The *t*-statistics in square brackets are calculated using standard errors obtained from the one-step GMM estimation.

	SENT	*EMRP*	*TROUGH*	*MKT*	*SMB*	*HML*	Adj-R^2 (%)
Panel A: Baker and Wurgler sentiment index (July 1965 – December 2010)							
Average profit	1.71						0.90
(*t*-stat)	(2.30)						
Average profit	2.09	−2.23					10.60
(*t*-stat)	(2.37)	(−2.40)					
[*t*-stat]	[2.01]	[-1.99]					
Average profit	1.64		−12.69				7.65
(*t*-stat)	(2.18)		(−2.13)				
FF alpha	1.40	−2.10		−0.15	−0.81	−0.54	25.49
(*t*-stat)	(1.45)	(−2.18)		(−1.05)	(−3.76)	(−2.55)	
[*t*-stat]	[1.47]	[−1.78]		[−0.97]	[−4.00]	[−2.39]	
FF alpha	0.93		−12.81	−0.24	−0.77	−0.57	24.17
(*t*-stat)	(1.12)		(−2.03)	(−1.48)	(−3.65)	(−2.63)	
Panel B: University of Michigan Consumer Sentiment Index (January 1960 – December 2011)							
Average profit	0.28						6.32
(*t*-stat)	(2.18)						
Average profit	0.26	−1.82					13.77
(*t*-stat)	(2.60)	(−2.58)					
[*t*-stat]	[2.33]	[−1.92]					
Average profit	0.23		−10.03				10.59
(*t*-stat)	(2.19)		(−2.13)				
FF alpha	0.21	−1.77		−0.11	−0.75	−0.51	27.16
(*t*-stat)	(2.24)	(−2.42)		(−0.89)	(−3.90)	(−2.63)	
[*t*-stat]	[2.57]	[−1.68]		[−1.08]	[−4.17]	[−2.41]	
FF alpha	0.18		−10.10	−0.19	−0.72	−0.51	24.78
(*t*-stat)	(1.85)		(−2.06)	(−1.33)	(−3.67)	(−2.69)	

results in Panel B of Table 10. When the Michigan index is used as an alternative proxy for sentiment, the results are similar to those obtained using the Baker and Wurgler index.

The results in Table 10 point to the conclusion that investor sentiment is not linked to our market risk premium measure, and the predictive power of the sentiment index does not capture that of the expected risk premium. Overall, the expected market risk premium contains information about the profitability of momentum strategies over and above the information contained in the sentiment index.

5. Conclusion

We study the profitability of momentum strategies during good and bad economic states. The main findings are twofold. First, we find that winner stocks significantly underperform loser stocks when the marginal value of wealth is highest, showing that the momentum strategy exposes investors to greater downside risk. Second, the payoffs to momentum strategies tend to positively covary with macroeconomic conditions. When we regress momentum profits on the expected market risk premium, the coefficient on the expected market risk premium is always negative and statistically significant. Overall, our results support the view that momentum strategies are fundamentally risky investments.

The large negative momentum profit observed in extremely bad economic states is particularly noteworthy. Even though previous studies (e.g., Chordia and Shivakumar, 2002; Cooper et al., 2004) show that momentum profits are procyclical, the procyclical nature alone (i.e., the lower, but not necessarily significantly negative, profits in bad times) is not sufficient evidence that momentum strategies are risky investments. As Cooper et al. (2004) interpret, procyclical payoffs could be also consistent with theoretical predictions from the behavioral models. In contrast, we provide direct evidence that momentum strategies deliver *significant* negative profits in bad times, demonstrating that momentum strategies expose investors to downside risk.

Behavioral studies have concluded that momentum strategies cannot be risky investments. Barberis and Thaler (2003) summarize the related literature: "Stocks are risky if they fail to pay out at times of high marginal utility – in 'bad' times – and instead pay out when marginal utility is low – in 'good' times. The problem is that…, there is little evidence that the portfolios with anomalously high average returns do poorly in bad times, whatever plausible measure of bad times is used" (p. 1091–1092). Our findings suggest that when we identify "bad times" according to the expected market risk premium, as opposed to ex-post realized market excess return as used in previous studies, we do find evidence of distress risk for momentum strategies.

References

Ahn, D.H., Conrad, J., Dittmar, R.F., 2002. Risk adjustment and trading strategies. Rev. Financ. Stud. 16, 459–485.
Antoniou, C., Doukas, J.A., Subrahmanyam, A., 2013. Cognitive dissonance, sentiment, and momentum. J. Financ. Quant. Anal. 48, 245–275.
Baker, M., Wurgler, J., 2006. Investor sentiment and the cross-section of stock returns. J. Finance 61, 1645–1680.
Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. J. Financ. Econ. 49, 307–343.
Barberis, N., Thaler, R., 2003. A survey of behavioral finance. In: Constantinides, George, Harris, Milt, Stulz, Rene (Eds.), Handbook of the Economics of Finance. North-Holland.
Bergman, N., Roychowdhury, S., 2008. Investor sentiment and corporate disclosure. J. Acc. Res. 46, 1057–1083.
Berk, J.B., Green, R.C., Naik, V., 1999. Optimal investment, growth options, and security returns. J. Finance 54, 1553–1608.
Blume, M.E., Friend, I., 1973. A new look at the capital asset pricing model. J. Finance 28, 19–33.
Campbell, J.Y., Cochrane, J.H., 1999. By force of habit: a consumption-based explanation of aggregate stock market behavior. J. Polit. Econ. 107, 205–251.
Campello, M., Chen, L., Zhang, L., 2008. Expected returns, yield spreads, and asset pricing tests. Rev. Financ. Stud. 21, 1297–1338.
Chordia, T., Shivakumar, L., 2002. Momentum, business cycle and time-varying expected returns. J. Finance 57, 985–1019.

Chui, A.C.W., Titman, S., Wei, K.C.J., 2010. Individualism and momentum around the world. J. Finance 65, 361–392.
Cooper, M.J., Gutierrez, R.C., Hameed, A., 2004. Market states and momentum. J. Finance 59, 1345–1365.
Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. J. Finance 53, 1839–1885.
Elton, E.J., 1999. Expected return, realized return, and asset pricing tests. J. Finance 54, 1199–1220.
Fama, E.F., 1981. Stock returns, real activity, inflation, and money. Am. Econ. Rev. 71, 545–565.
Fama, E.F., French, K.R., 1989. Business conditions and expected returns on stocks and bonds. J. Financ. Econ. 25, 23–49.
Fama, E.F., French, K.R., 1996. Multifactor explanations of asset pricing anomalies. J. Finance 51, 55–84.
Fama, E.F., Schwert, G.W., 1977. Asset returns and inflation. J. Financ. Econ. 5, 115–146.
Ferson, W., Harvey, C.R., 1991. The variation of economic risk premiums. J. Polit. Econ. 99, 285–315.
George, T.J., Hwang, C., 2004. The 52-week high and momentum investing. J. Finance 59, 2145–2176.
Griffin, J.M., Ji, S., Martin, J.S., 2003. Momentum investing and business cycle risk: evidence from pole to pole. J. Finance 58, 2515–2547.
Grinblatt, M., Moskowitz, T., 1999. The Cross Section of Expected Returns and Its Relation to Past Returns: New Evidence. University of California, Los Angeles, Working paper.
Grundy, B.D., Martin, J.S., 2001. Understanding the nature of risks and the sources of rewards to momentum investing. Rev. Financ. Stud. 14, 29–78.
Harvey, C.R., 1989. Forecasts of economic growth from the bond and stock markets. Financ. Anal. J. 45, 38–45.
Hong, H., Stein, J., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. J. Finance 54, 2143–2184.
Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. J. Finance 48, 65–91.
Jegadeesh, N., Titman, S., 2001. Profitability of momentum strategies: an evaluation of alternative explanations. J. Finance 56, 699–720.
Jiang, G., Lee, C.M.C., Zhang, G.Y., 2005. Information uncertainty and expected stock returns. Rev. Acc. Stud. 10, 185–221.
Johnson, T.C., 2002. Rational momentum effects. J. Finance 57, 585–607.
Keim, D.B., Stambaugh, R.F., 1986. Predicting returns in the stock and bond markets. J. Financ. Econ. 17, 357–390.
Kim, D., Roh, T.-Y., Min, B.-K., Byun, S.-J., 2014. Time-varying expected momentum profits. J. Bank. Financ. 49, 191–215.
Lakonishok, J., Shleifer, A., Vishny, R., 1994. Contrarian investment, extrapolation, and risk. J. Finance 49, 1541–1578.
Lemmon, M., Portniaquina, E., 2006. Consumer confidence and asset prices: some empirical evidence. Rev. Financ. Stud. 19, 1499–1529.
Lettau, M., Ludvigson, S., 2001a. Consumption, aggregate wealth, and expected stock returns. J. Finance 56, 815–849.
Lettau, M., Ludvigson, S., 2001b. Resurrecting the (C)CAPM: a cross-sectional test when risk premia are time-varying. J. Politic. Econ. 109, 1238–1287.
Liu, L.X., Zhang, L., 2008. Momentum profits, factor pricing, and macroeconomic risk. Rev. Financ. Stud. 21, 2417–2448.
Liew, J., Vassalou, M., 2000. Can book-to-market, size and momentum be risk factors that predict economic growth? J. Financ. Econ. 57, 221–245.
Merton, R., 1973. An intertemporal capital asset-pricing model. Econometrica 41, 867–887.
Petkova, R., Zhang, L., 2005. Is value riskier than growth? J. Financ. Econ. 78, 187–202.
Rouwenhorst, K.G., 1998. International momentum strategies. J. Finance 53, 267–284.
Sagi, J.S., Seasholes, M.S., 2007. Firm-specific attributes and the cross section of momentum. J. Financ. Econ. 84, 389–434.
Sharpe, W.F., 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. J. Finance 19, 425–442.
Stambaugh, R.F., Yu, J., Yuan, Y., 2012. The short of it: investor sentiment and anomalies. J. Financ. Econ. 104, 288–302.
Stock, J.H., Watson, M.W., 1989. New indexes of coincident and leading economic indicators. In: NBER Macroeconomics Annual, pp. 352–394.
Stock, J.H., Watson, M.W., 1999. Business cycle fluctuations in U.S. macroeconomic time series. In: Taylor, J.B., Woodford, M. (Eds.), Handbook of Macroeconomics, vol. 1, pp. 3–64.
Stock, J.H., Watson, M.W., 2003. Forecasting output and inflation: the role of asset prices. J. Econ. Lit. 41, 788–829.
Wang, K.Q., Xu, J., 2015. Market volatility and momentum. J. Empir. Financ. 30, 79–91.
Zhang, L., 2005. The value premium. J. Finance 60, 67–103.
Zhang, X.F., 2006. Information uncertainty and stock returns. J. Finance 61, 105–136.