Time-Varying Momentum Payoffs and Illiquidity*

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Abstract

This paper shows that the profitability of the momentum trading strategy strongly varies with the state of market illiquidity, consistent with behavioral models of investor's expectations. Periods of high market illiquidity are followed by low, often massively negative, momentum payoffs. The predictive power of market illiquidity uniformly exceeds that of competing state variables, including market states, market volatility, and investor sentiment, and is robust in both in- and out-of-sample experiments as well as among large cap firms. Market illiquidity also captures the cross section dispersion in momentum payoffs implemented among high versus low volatility stocks. Focusing on the most recent decade, while momentum profitability is nonexistent unconditionally, it regains significance in periods of low market illiquidity, and moreover, market illiquidity similarly affects the profitability of the earnings momentum trading strategy.

1. Introduction

Unconditionally, the momentum strategy of buying past winner stocks and selling past loser stocks, as documented by Jegadeesh and Titman (1993), generates a significant 1.18 percent return per month over the 1928 through 2011 sample period. Conditionally, however, momentum payoffs could be low, often massively negative, depending on the realizations of market-wide state variables. For example, Cooper, Gutierrez, and Hameed (2004) show that the momentum strategy is unprofitable following periods of declines in aggregate market valuations, or DOWN market return states. In addition, Wang and Xu (2010) document that lower momentum payoffs follow high market volatility, and Daniel and Moskowitz (2012) show that crashes in momentum payoffs, as the one documented in 2009, follow DOWN and high market volatility states.[1]

This paper shows that momentum payoffs crucially depend on the state of market illiquidity, and in particular, illiquid market states are followed by diminishing momentum payoffs. Conceptually, the momentum-illiquidity relation is implied by integrating the behavioral models of Daniel, Hirshleifer, and Subrahmanyam (1998) and Baker and Stein (2004). In the former, investors overreact to private information due to overconfidence, which together with self-attribution bias in their reaction to subsequent public information, invokes return continuations. The model suggests that momentum is weaker (stronger) in periods of lower (higher) aggregate investor overconfidence. Baker and Stein (2004) establish the overconfidence-illiquidity relation. In their model, overconfident investors underreact to information in order flow and lower the price impact of trades. With short-sale constraints, overconfident investors keep out of the market since they are active only when their valuations exceed those of rational investors. In periods of excessive pessimism, overconfident investors avoid holding and trading stocks, and increase market illiquidity. An alternative explanation for the momentum-illiquidity relation is that (overconfident) traders are trend chasers and they stay out of the market when the cost of trading is high. So, if trend chasers trade in the market when the cost of trading is low, they contribute to price momentum but not when the cost of trading (or

[1] The momentum strategy records huge losses of 79 percent in August 1932 and 46 percent in April 2009 (see Daniel and Moskowitz (2012)).

illiquidity) is high.[2] Both of the above views imply that the level of market illiquidity provides an indicator of the relative prominence of overconfident investors and hence, predicts momentum payoffs.[3]

Indeed, the overall evidence here indicates that momentum payoffs are strongly and negatively related to illiquid market states. The momentum-illiquidity relation is both statistically significant and economically meaningful. To illustrate, in time series predictive regressions, a one standard deviation increase in market illiquidity reduces the momentum profits by 0.87% per month while the overall sample average of the momentum payoff is 1.18%. The strong predictive power of market illiquidity remains robust in the presence of DOWN market states and market volatility. In fact, these state variables display diminishing, often nonexistent, explanatory power when market illiquidity is accounted for.

Using cross sectional regressions based on individual securities reinforces the illiquidity momentum relation. In particular, while there is significant momentum in the cross-sectional regression of stock returns on its own past returns, the individual stock price momentum is the weakest following illiquid market states. Moreover, controlling for the effect of the market state variables, and in particular market illiquidity, significantly diminishes the ability of past returns to forecast trends in future stock prices. Specifically, we run a two-stage analysis. The first step considers the regression of stock returns on past state variables to remove the component in stock returns which is forecasted by market illiquidity, DOWN market state, and market volatility. In the second stage, the unexpected part of individual stock returns is regressed on its own past returns. Indeed, stock level momentum is considerably reduced and even completely disappears in some specifications (all of which account for market illiquidity).

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[2] We thank Yakov Amihud for this insight.

[3] Cooper, Gutierrez and Hameed (2004) relate market UP and DOWN states to investor overconfidence, but, they do not examine the liquidity-momentum relation. Momentum payoffs are also consistent with other behavioral biases. Grinblatt and Han (2005) and Frazzini (2006) provide evidence that the momentum phenomenon is related to the disposition effect where investors hang on losers but realize gains. Hong and Stein (1999) and Hong, Lim and Stein (2000) link price momentum to slow diffusion of information across heterogeneous investor groups due to communication frictions. We leave the exploration of the relation, if any, between market illiquidity and these behavioral biases for future work. For example, if the propensity of disposition traders (who are not trading on information) to stay out of the market is higher after large unrealized losses, it can also generate a positive relation between market liquidity and momentum .

We also examine the effect of market illiquidity on momentum interactions with firm level volatility and size. For instance, Jiang, Lee, and Zhang (2005) and Zhang (2006) show that high return volatility stocks earn significantly higher momentum profits than low volatility stocks. We find that high aggregate illiquidity predicts low momentum profits in both the high and low volatility stocks, beyond the influence of DOWN and market volatility states. More importantly, the differences in the profits across the two groups of stocks are related to the larger reaction of high volatility stocks to market illiquidity, but not to the other state variables.

The analysis is then extended to the most recent decade wherein price momentum yields insignificant profits. Strikingly, momentum profitability does resurface upon conditioning on the market states, particularly the state of market illiquidity. Moreover, over the past decade there is an almost identical predictive effect of the lagged market state variables on the profitability of the earnings momentum strategy. Specifically, earnings momentum payoffs are significantly lower following periods of low market liquidity, or a decline in market valuations, or higher market volatility. Examining all three market state variables jointly, aggregate market illiquidity uniformly outperforms.

Next, we account for the recent evidence that momentum payoffs depend on inter-temporal variation in investor sentiment (see Stambaugh, Yu, and, Yuan (2012) and Antoniou, Doukas, and Subrahmanyam (2013)). Our results show that the predictive effect of illiquidity on momentum payoffs is robust even in the presence of investor sentiment, as measured by the Baker and Wurgler (2006, 2007) suggested sentiment index. When the equity market is illiquid, momentum is unprofitable in all sentiment states, including the most optimistic sentiment state. Moreover, negative momentum payoffs are recorded during optimistic sentiment states when the market is illiquid, indicating that the market illiquidity state is not subsumed by the sentiment measure

Finally, we show that the cross-sectional difference in the level of stock liquidity, along with time varying aggregate illiquidity, is an important determinant of the time variation in momentum payoffs. Specifically, WML goes long on winners (less illiquid stocks) and short on losers (more illiquid stocks). The illiquid loser stocks are associated with higher future returns, consistent with the positive cross-sectional relation between illiquidity level and stock returns (Amihud and Mendelson (1986), and Amihud (2002)), weakening the momentum effect. During normal periods, price continuations attributable to overconfident investors dominate the cross-sectional liquidity effects, hence, generating a positive momentum payoff. However, when markets are illiquid, we observe two reinforcing effects. First, the prominence of overconfidence investors diminishes. Second, the gap between the illiquidity of the loser and winner portfolios considerably widens, causing the loser portfolio to earn a higher return during the holding period to compensate for higher illiquidity. This joint effect brings about large negative momentum payoffs – or momentum crash. Our findings on the effect of illiquidity level on momentum payoffs adds to the important studies on the liquidity risk (beta) exposure of the momentum portfolio in Pastor and Stambaugh (2003), Sadka (2006) and Assness, Moskowitz and Pedersen (2013). While there is a general positive correlation between liquidity risk and illiquidity level as documented in Archarya and Pedersen (2005), the correlation turns negative in the winner and loser portfolios.

The paper is organized as follows. Section 2 presents a description of the characteristics of the momentum portfolios. In Section 3, we present evidence on the effect of market illiquidity and other state variables on momentum payoffs constructed from portfolio and individual security returns. The findings from out of sample tests are provided in Section 4. Further analysis of the illiquidity effects, and several robustness checks are presented in Section 5, followed by some concluding remarks in Section 6.

2. Data Description

The sample consists of all common stocks listed on NYSE, AMEX, and NASDAQ obtained from the Center for Research in Security Prices (CRSP), with a share code of 10 or 11. The sample spans the January 1926 through December 2011 period. Our portfolio formation method closely follows the approach in Daniel and Moskowitz (2012). Specifically, at the beginning of each month t, all common stocks are sorted into deciles based on their lagged eleven-month returns. Stock returns over the portfolio formation months, $t-12$ to $t-2$, are used to sort stocks into ten portfolios. The top (bottom) ten percent of stocks constitute the winner (loser) portfolios. The breakpoints for these portfolios are based on returns of those stocks listed on NYSE only, so that the extreme portfolios are not dominated by the more volatile NASDAQ firms. The holding period returns for each stock is obtained after skipping month $t-1$, to avoid the short-term reversals reported in the literature (see Jegadeesh (1990), for example). Finally, the portfolio holding period return in month t is the value-weighted average of stocks in each decile. Similar to Daniel and Moskowitz (2012), we require the stock to have valid share price and number of shares outstanding at the formation date, and at least eight valid monthly returns over the eleven-month formation period. In addition, the data on analyst (consensus) earnings forecasts are obtained from I/B/E/S while the actual earnings and announcement dates are gathered from COMPUSTAT.

We first provide some summary statistics on the portfolios used in evaluating the momentum strategy. Panel A of Table 1 presents characteristics of these ten portfolios over the full sample period. The mean return in month t is increasing in past year returns and the winner portfolio outperforms the loser portfolio to generate a full-sample average winner-minus-loser (*WML*) portfolio return of 1.18 percent. Consistent with the existing literature, these profits are not due to exposure to common risk factors. For one, the unconditional CAPM market beta of the loser portfolio (the short side of the momentum strategy) is in fact significantly larger than the beta for the winner portfolio by about 0.5. Consequently, the CAPM risk-adjusted *WML* increases to 1.50 percent per month. Moreover, the *WML* returns are higher after adjusting for the Fama-French common risk factors – market (excess return on the value-weighted CRSP market index over the one month T-bill rate), size (small minus big return premium (SMB)), and value (high book-to-market minus low book-to-market return premium (HML)) – these factors are obtained from Kenneth French.[4] The Fama-French three-factor risk-adjusted return for the *WML* portfolio is highly significant at 1.73 percent per month.

Table 1 also presents other characteristics of the portfolios. Several of these characteristics, including the Sharpe ratio and skewness of the portfolio returns, are similar to those reported in

[4] We thank Kenneth French for making the common factor returns available at this website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. Incidentally, the construction of our ten momentum portfolio is also similar to the ones reported in his website.

Daniel and Moskowitz (2012). For instance, the momentum profit (WML) is highly negatively skewed (skewness = −6.25), suggesting that momentum strategies come with occasional large crashes. Also reported are the cross-sectional differences in illiquidity across these portfolios. We employ the Amihud (2002) measure of stock illiquidity, $ILLIQ_{i,t}$, defined as $\left[\sum_{d=1}^{n}\left|R_{i,d}\right|/\left(P_{i,d}\times N_{i,d}\right)\right]/n$, where n is the number of trading days in each month t, $\left|R_{i,d}\right|$ is the absolute value of return of stock i on day d, $P_{i,d}$ is the daily closing price of stock i, and $N_{i,d}$ is the number of shares of stock i traded during day d. The greater the change in stock price for a given trading volume, the higher would be the value of the Amihud illiquidity measure.

We find striking cross-sectional differences in the (value-weighted) average illiquidity of these portfolios. The loser and winner decile portfolios (deciles 1 and 10) contain among the most illiquid stocks. The liquidity of the stocks in the long and short side of the momentum strategy is lower than that of the intermediate portfolios. In particular, the loser portfolio is the most illiquid, with an average $ILLIQ$ of 8.4, compared to $ILLIQ$ of between 0.8 and 1.2 for the intermediate four portfolios. The $ILLIQ$ value of the winner portfolio is also higher at 2.2. The larger average illiquidity among the loser and winner portfolios indicates that the performance on the momentum strategy is potentially linked to the overall illiquidity at the market level.

In Panel B of Table 1, we compute measures of aggregate market liquidity and examine their time-series correlation with the WML returns. The level of market illiquidity in month $t-1$, $MKTILLIQ_{t-1}$, is defined as the value-weighted average of each stock's monthly Amihud illiquidity. Here, we restrict the sample to all NYSE/AMEX stocks as the reporting mechanism for trading volume differs between NYSE/AMEX and NASDAQ stock exchanges (Atkins and Dyl (1997)).[5] $MKTILLIQ_{t-1}$ is significantly negatively correlated with WML_t returns, with a correlation of −0.26, suggesting that momentum payoffs are low following periods of low aggregate liquidity. In unreported results, we consider an alternative measure that captures the innovations in aggregate

[5] Our measure of $MKTILLIQ$ serves as a proxy for aggregate market illiquidity, rather than illiquidity of a specific stocks exchange. This is corroborated by the strong correlation between $MKTILLIQ$ and the aggregate illiquidity constructed using only NASDAQ stocks (the correlation is 0.78).

market illiquidity, $INNOV\_MKTILLIQ_{t-1}$. It is obtained as the percentage change in $MKTILLIQ_{t-1}$ compared to the average of $MKTILLIQ$ over the previous two years ($t-24$ to $t-2$). Our results hold using this alternative market illiquidity measure. For example, we obtain a significant correlation of −0.12 between $INNOV\_MKTILLIQ_{t-1}$ and WML_t.

We also report the correlation between WML and two other aggregate variables that have been shown to predict the time variation in momentum payoffs. First, Cooper, Gutierrez, and Hameed (2004) show that the performance of the market index over the previous two years predicts momentum payoffs, with profits confined to positive market return states. We compute the cumulative returns on the value-weighted market portfolio over the past 24 months (i.e., months $t-24$ to $t-1$), and denote the negative market returns by a dummy variable ($DOWN_{t-1}$) that takes the value of one only if a negative cumulative two-year return is recorded in month $t-1$. Consistent with Cooper, Gutierrez, and Hameed (2004), we find that $DOWN$ market states are associated with lower momentum profits. The correlation between the two variables is −0.13.

Wang and Xu (2010) document that, in addition to $DOWN$ market states, the aggregate market volatility significantly predicts momentum profits. Specifically, they find that the momentum strategy pays off poorly following periods of high market volatility. We use the standard deviation of daily value-weighted CRSP market index returns over the month $t-1$ as our measure of aggregate market volatility, $MKTVOL_{t-1}$. Indeed, the evidence suggests a significant negative correlation between $MKTVOL_{t-1}$ and WML_t (−0.12), confirming the findings in Wang and Xu (2010).

Moreover, Panel B also shows that all three aggregate market level variables ($MKTILLIQ$, $DOWN$, and $MKTVOL$) are reasonably correlated, with correlations ranging from 0.33 to 0.42. This is not surprising since one could expect aggregate market illiquidity to be higher during bad market conditions, such as during economic recessions and volatile periods (see e.g., Næs, Skjeltorp and Ødegaard (2011)). While the univariate correlation between WML_t and $MKTILLIQ_{t-1}$ is supportive of a significant role for aggregate liquidity in explaining the time variation in momentum profits, it is also important to evaluate the relative predictive power of the three dimensions of market conditions.

Indeed, we will show in our analysis that the market illiquidity appears to be the strongest predictor of momentum profitability using in- and out-of-sample experiments.

In Panel C of Table 1, we report the autocorrelation coefficient of the three state variables. Indeed, the three variables are strongly persistent, although the autocorrelation is far smaller than 1.0. (For perspective, the aggregate dividend yield, the term spread, and the default spread display an autocorrelation coefficient of about 0.99). Such autocorrelation could result in a small sample bias in predictive regressions (see, e.g., Stambaugh (1999)). Our results are robust to augmentation of the regression estimates for serial correlations in the explanatory variables prescribed in Amihud and Hurvich (2004) and Amihud, Hurvich, and Wang (2009).

3. Time Variation in Momentum Payoffs

3.1 Price Momentum in Portfolio Returns

In this section, we examine the predictive role of market illiquidity in explaining the inter-temporal variation in momentum payoffs, controlling for market volatility and market states. Our examination is based on the following time-series regression specification:

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t. \tag{1}$$

More precisely, we consider all eight combinations of the predictive variable, starting from the IID model which drops all predictors and retains the intercept only, ending with the all-inclusive model, which retains all predictors. In all these regressions, the independent variable WML_t is the value-weighted return on the winner minus loser momentum deciles, formed based on the stock returns from month $t-12$ to $t-2$, as explained earlier.

The aggregate market illiquidity, $MKTILLIQ_{t-1}$, refers to the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms in month $t-1$. $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the previous twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise. $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return in month $t-1$. Indeed, Næs, Skjeltorp, and Ødegaard (2011) show that stock market liquidity is pro-cyclical and worsens considerably during bad economic states. This suggests that $DOWN$ and $MKTVOL$ state variables could capture market liquidity effects. Thus, controlling for the two competing variables is essential.

Next, the vector F stands for the Fama-French three factors, including the market factor, the size factor, and the book-to-market factor. In turn, the set of regressions gauges the ability of the three state variables, i.e., the market illiquidity, the market volatility, and DOWN market states, to predict the risk-adjusted returns on the momentum portfolio. We also run these predictive regressions excluding the Fama-French risk factors and obtain similar results (which are not reported to conserve space).

The estimates of the eight regression specifications are reported in Panel A of Table 2. The evidence coming up from Table 2 uniformly suggests a negative effect of aggregate market illiquidity on momentum profits. The slope coefficients of the market illiquidity measure are negative across the board, ranging from −0.253 [t-value = −2.41] for the all-inclusive specification (Model 8) to −0.35 [t-value = −4.28] for the illiquidity-only predictive model (Model 2). Indeed, the momentum payoff considerably drops during illiquid periods, which suggests that momentum could potentially crash following illiquid market states.

Consistent with Cooper, Gutierrez, and Hameed (2004) and Wang and Xu (2010), we also find that momentum payoffs are lower in $DOWN$ market states and when market volatility ($MKTVOL$) is high. For instance, focusing on the predictive model that retains only $DOWN$ ($MKTVOL$), the slope coefficient is −2.405 (−1.592) recording t-value of −3.44 (−3.23). Nevertheless, the marginal effect of illiquidity on momentum payoffs is over and beyond the effects of market and volatility states. Observe from Panel A of Table 2 that the inclusion of $MKTILLIQ$ weakens the predictive influence of $DOWN$ and $MKTVOL$ on WML (Model 8).

To illustrate, consider Model 8 which is an all-inclusive specification. While market illiquidity is statistically significant at all conventional levels, market volatility is insignificant and the market states variable is significant only at the 5% level. Further, a one standard deviation increase in market illiquidity reduces the momentum profits by 0.87% per month, which is economically significant compared to the average monthly momentum profits 1.18%.[6] Indeed, the main evidence coming up from Table 2 confirms the important predictive role of market illiquidity on a stand-alone basis as well as on a joint basis − joint with market volatility and market states.[7]

We consider the same eight regression specifications using separately the winner and loser payoffs as the dependent variables. In particular, we regress excess returns on the (value-weighted) loser and winner portfolios separately on the same subsets of predictive variables. Here, the risk-free rate is proxied by the monthly return on the one-month U.S. Treasury Bill, available in CRSP. As previously, we control for risk exposures of the winner and loser portfolios using the Fama-French risk factors so that the predictive regressions are not influenced by the predictability in these risk components. The results for the loser and winner portfolio returns are presented in Panels B and C of Table 2, respectively.

The evidence here is mutually consistent with that reported for the WML spread portfolio. The reported figures exhibit significant influence of $MTKILLIQ$ on the returns to both the loser and winner portfolios. Focusing on loser (winner) stocks, the market illiquidity effect is positive (negative) and significant across all specifications. To illustrate, the coefficient on $MKTLIIQ$ for loser stocks ranges between 0.133 and 0.199, while the corresponding figures for winner stocks are −0.120 and −0.151, all of which are significant. That is, the continuation in the loser and winner portfolios declines significantly following periods of high market illiquidity, with a stronger effect on past losers. Again, the effect of $MKTILLIQ$ is not being challenged by the variation in either $DOWN$ or $MKTVOL$. In fact, the predictive power of market states and market volatility weakens considerably, often disappears, in the presence of market illiquidity. For instance, focusing on the all-inclusive specification for winner stocks (Panel C, Model 8), both $DOWN$ and $MKTVOL$ are insignificant.

Indeed, we show that the predictive effect of market illiquidity on momentum profits is robust. It remains significant after adjusting for the previously documented effects of down market and market volatility (Cooper, Gutierrez, and Hameed, 2004; Wang and Xu, 2010; Daniel and Moskowitz, 2012).

[6] For instance, the economic impact for $MKTILLIQ$ is quantified as $-0.253\% \times 3.454 = -0.87\%$, where -0.253% is the regression parameter of $MKTILLIQ$ on monthly momentum profits and 3.454 is the standard deviation of $MKTILLIQ$.
[7] When we repeat the regression analysis with $INNOV\_MKTILLIQ$, we find that market illiquidity continues to be significant at conventional levels.

More importantly, including aggregate market illiquidity weakens, often eliminates, the explanatory power of these alternative market state and volatility variables in time-series predictive regressions. Perhaps this dominance is not surprising as recent work shows that periods of negative market states as well as high market volatility periods are associated with market illiquidity. Hameed, Kang, and Viswanathan (2010), for one, provide strong evidence that negative market returns and high market volatility are related to stock illiquidity. Such relation is also consistent with equilibrium models that predict liquidity dry-ups as a response to increased demand for liquidity or withdrawal of liquidity provision following periods of large decline in market valuations or increases in market volatility.[8] The asymmetric effect of market return on liquidity is consistent with the notion that DOWN market return states generate low momentum payoffs due to changes in aggregate liquidity. The empirical evidence on the volatility-illiquidity interaction is also documented by Chordia, Sarkar, and Subrahmanyam (2005). Moreover, Næs, Skjeltorp and Ødegaard (2011) show that stock market liquidity is pro-cyclical and worsens considerably during bad economic states, which suggests that market illiquidity could cause momentum payoffs to vary over the business cycle.

3.2 Price Momentum in Individual Securities

Past work shows that there is significant gain as the testing ground shifts from portfolios to individual securities. Lo and MacKinlay (1990) argue that to avoid the data snooping bias it is preferable to implement asset pricing tests using individual securities rather than portfolios. Litzenberger and Ramaswamy (1979) argue that valuable firm-specific information is lost with the aggregation to portfolios. Avramov and Chordia (2006) use returns on individual securities in a conditional beta asset-pricing setup to show new insights on the validity of various pricing models to account for market anomalies. For example, they find that the impact of momentum on the cross-section of individual stock returns are influenced by business cycle related variation in security risk and especially asset mispricing.

[8] These theoretical models include the collateral-based models in Garleanu and Pedersen (2007), Brunnermeier and Pedersen (2009); co-ordination failure models in Morris and Shin (2004) and limits to arbitrage based models in Kyle and Xiong (2001).

Motivated by these papers, we now turn to the cross-section of individual stock returns to examine the impact of aggregate market illiquidity and the other state variables on momentum. In particular, we consider both cross-sectional and time series regressions.

We run two monthly cross-sectional regression specifications at the firm level. In both regressions the dependent variable is the future one month return. In the first regression, the explanatory variable is return on past eleven months, $R_{i,t-12:t-2}$, as well as the lagged Amihud stock level illiquidity measure, $ILLIQ_{i,t-1}$. The second regression is similar except that we account for both past returns as well as past negative returns, which allows us to examine if firm level momentum is different for loser stocks.

That is, the two monthly cross-sectional specifications take the form:

$$R_{i,t} = \alpha_0 + \beta_{0t}\, R_{i,t-12:t-2} + \gamma_t\, ILLIQ_{i,t-1} + e_{i,t} \quad (2)$$

$$R_{i,t} = \alpha_0 + \beta_{0t}\, R_{i,t-12:t-2} + \beta_{Nt}\, R^{-}_{i,t-12:t-2} + \gamma_t\, ILLIQ_{i,t-1} + e_{i,t} \quad (2')$$

The variable $R_{i,t}$ in Equation (2) is the return of stock i in month t, $R_{i,t-12:t-2}$ is the cumulative stock return in the formation period from months $t-12$ to $t-2$ and $R^{-}_{i,t-12:t-2}$ in Equation (2') is the cumulative return in the formation period if the return is negative and is zero otherwise. In the first regression specification in Equation (2), we simply regress stock returns on its own past returns and past stock illiquidity, $ILLIQ_{i,t-1}$ to obtain the stock momentum coefficient in month t, β_{0t}. The regression is estimated each month so that the coefficient β_{0t} measures the security level momentum in month t for stock returns. In Equation (2'), the coefficient β_{Nt} measures the additional marginal momentum effect among stocks that have declined in value during the formation period.

The second stage entails time series regressions. Here, the dependent variable is the estimated monthly momentum betas which come from the monthly cross-sectional regressions above. The explanatory variables are the market illiquidity, DOWN market states, and market volatility. Specifically, we regress the monthly firm level return momentum estimate, β_{0t} or β_{Nt}, obtained from the cross-sectional regression of future one-month return on the cumulative past own (or negative) stock returns.

In particular, the following time series regressions are estimated:

$$\beta_{0t} = \alpha_0 + \gamma_1 MKTILLIQ_{t-1} + \gamma_2 DOWN_{t-1} + \gamma_3 MKTVOL_{t-1} + e_t. \quad (3)$$

$$\beta_{Nt} = \alpha_0 + \gamma_1 MKTILLIQ_{t-1} + \gamma_2 DOWN_{t-1} + \gamma_3 MKTVOL_{t-1} + e_t. \quad (3')$$

The time-series averages of the first cross-section regression coefficients as well as the Newey-West adjusted t-statistics are reported in Panel A of Table 3. To make sure that the trading volume-related Amihud (2002) illiquidity is comparable across stocks and to use stocks traded over the full sample period from 1928 to 2011, we restrict our sample to stocks traded on NYSE/AMEX.

The results provide individual security level evidence of a strong continuation in stock returns in the cross-section, i.e., β_{0t} is positive and highly significant in both regressions. Notice also that the continuation in past losers is stronger. The additional predictive variable, the negative past returns, is highly significant recording a slope coefficient equal to 0.015. Notice also that illiquid stocks earn higher future returns than more liquid stocks, similar to Amihud (2002). Indeed, the slope coefficient of the illiquidity control variable averages to 0.015 in the first specification and 0.018 in the second, both of which are statistically and economically significant at all conventional levels. The overall evidence is consistent with the notion that the major profitability of individual stock momentum trading strategies emerges from the short side of the trade, and, moreover, that stock level illiquidity considerably impacts future stock returns even in the presence of past returns.

Next, we move to the time series specifications. In Panel B of Table 3, we estimate time series regressions of the momentum coefficient β_{0t} on various collections of the three state variables, as in Equation (3). The results display a strong negative correlation between aggregate market illiquidity and momentum in stock return for all models considered. When the state variables $DOWN$ and $MKTILLIQ$ enter individually (Model 2 and Model 3) they significantly predict lower momentum in the following month. However, the predictive effect of $MKTVOL$ on momentum in individual securities is only significant at the 10% level.

Strikingly, the predictive ability of the $DOWN$ market state vanishes in the presence of market illiquidity (Model 4). The estimated slope coefficient is −0.521 and its t-value is −0.39. Similarly, the effect of $MKTVOL$ on momentum disappears controlling for $MKTILLIQ$ (Model 5). Here, the estimated slope coefficient is 0.469 and its t-value is 0.46. In all specifications, the level of market illiquidity displays a robust negative effect on momentum in individual securities.

In Panel C of Table 3, we use the individual stock momentum following negative past stock returns (β_{Nt}) as the dependent variable, as in Equation (3'). Again, we reach a similar conclusion: while stock level momentum is stronger following negative returns, this momentum effect weakens during illiquid market conditions. In particular, the $MKTILLIQ$ records negative and strongly significant slope coefficients across the board, while both $DOWN$ and $MKTVOL$ are significant on a stand-alone basis but not in the presence of $MKTILLIQ$. In untabulated analysis, we control for the effect of individual stock volatility on stock returns in equation (2) and (2'). While lagged stock volatility is negatively related to future stock returns, controlling for stock level volatility does not affect the main findings in Table 3.

The similarity in the effect of $MKTILLIQ$ on momentum in portfolio returns (Table 2) and individual stock returns (Table 3) lends credence to the proposition that momentum strategies demands liquidity and the payoffs become weak or are likely to crash when the aggregate market is illiquid. Although $DOWN$ market return states and high $MKTVOL$ period are also indicative of low market liquidity, the Amihud measure of aggregate market illiquidity appears to display a strong residual effect. Moreover, in the presence of the market illiquidity measure, the predictive power of market states and market volatility is attenuated and often even disappears.

3.3 Individual Security Momentum and Variation with State Variables

The above-documented findings indicate that stock level momentum payoffs are robustly related to the state of market illiquidity. We now turn to a follow-up question of whether the stock exposures to these state variables drive the documented price momentum.

Our analysis here is based on a two-pass regression method, with using monthly individual stock returns as the dependent variable. In the first stage, we run the following time-series regressions for each firm to remove the expected stock returns forecasted by past market state variables and contemporaneous asset pricing factors,

$$R_{i,t}^{e} = \alpha_i + \beta_{i1} MKTILLIQ_{t-1} + \beta_{i2} DOWN_{t-1} + \beta_{i3} MKTVOL_{t-1} + c'F_t + e_{i,t} \tag{4}$$

where $R_{i,t}^{e}$ is the excess return of stock i in month t, $MKTILLIQ_{t-1}$, $DOWN_{t-1}$, $MKTVOL_{t-1}$ refer to the aggregate state variables used to describe the market illiquidity, down market return dummy, and market volatility. The vector F stacks Fama-French three factors (market, size, and book-to-market). Equation (4) produces the unexpected part of individual stock returns, $R_{i,t}^{*} = \alpha_i + e_{i,t}$.

In the second stage, we run cross-sectional regression of $R_{i,t}^{*}$ on its own past return $R_{i,t-12:t-2}$, to gauge the extent to which the state variables account for stock level momentum. Specifically, we estimate the following monthly cross-sectional regressions,

$$R_{i,t}^{*} = \alpha_0 + \beta_1 R_{i,t-12:t-2} + u_{i,t}, \tag{5}$$

Panel A of Table 4 presents the cross-sectional average of first-stage results in Equation (4). In Model 1, we employ the three factor Fama-French model for risk adjustment. Controlling for the factor-risk exposure, Model 2 shows that high aggregate market illiquidity ($MKTILLIQ$) predicts a higher stock return, consistent with the notion that stocks have significant exposure to aggregate illiquidity. On the other hand, $DOWN$ and $MKTVOL$ states, on their own, do not carry significant loadings on individual future stock returns (Models 3 and 4). When we include all three state variables in Model 8, $MKTILLIQ$ continues to significantly predict higher average stock returns. The partial effect of $DOWN$ markets is positive, albeit weakly significant. The effect of $MKTVOL$, on the other hand, is significant but negative. Unlike the positive returns following illiquid periods, high market volatility is associated with lower future stock returns. The latter finding is consistent with the anomaly reported in Ang, Hodrick, Xing, and Zhang (2006) that high idiosyncratic stock volatility predicts low future stock returns.

Panel B presents the second-stage results in Equation (5), after augmenting the stock returns with the Fama-French return spreads as risk controls. Interestingly, accounting for the predictability of individual stock returns using the aggregate state variables lowers the stock level momentum. For example, the individual stock momentum beta reduces from 0.006 to 0.003 in the presence of $MKTILLIQ$ in Model 2. The individual stock momentum becomes insignificant controlling for the predictive effect of multiple state variables, as shown in Models 6 and 8, both of which retain market illiquidity.

Indeed, we reinforce our main findings that price momentum is driven by aggregate illiquidity, as well as the market volatility and DOWN market states. The results indicate that not only do market state variables, and market illiquidity in particular, predict stock returns, but that the proper adjustment for market states substantially eliminates the time series momentum in individual stock returns.

The overall results suggest that aggregate market illiquidity is related to the momentum payoff in both time-series and cross-sectional analysis, for both value-weighted portfolios and individual stocks. Momentum strategy payoffs are significantly reduced following an illiquid market state. Furthermore, the market illiquidity provides additional explanatory power to the previously documented effects of down market and market volatility, and a proper control for market illiquidity helps to forecast and avoid the huge loss realized during momentum crash.

4. Predicting Momentum Profits: Out of Sample Tests

An informative way to demonstrate the importance of market states is to examine their forecasting abilities on momentum profitability in an out-of-sample test. This allows us to examine how the market states help to predict the negative momentum payoffs, especially to avoid the huge losses in momentum crashes in real time. Table 5 presents the summary statistics of the mean, standard deviation, and the mean squared error (MSE) of the forecast errors based on time-series estimation of out-of-sample forecasts. More precisely, we attempt to predict, out-of-sample, the component of momentum payoff which is not captured by the risk factors. The forecast of momentum profits ($\widehat{WML}_t$) in each month t is obtained as follows:

$$\widehat{WML}_t = \hat{\alpha}_0 + \hat{\beta}_{1t-1}MKTILLIQ_{t-1} + \hat{\beta}_{2t-1}DOWN_{t-1} + \hat{\beta}_{3t-1}MKTVOL_{t-1} + \hat{c}_{t-1}{}'F_t \quad (6)$$

where $\widehat{WML}_t$ is based on the lagged values of the three market state proxies (market illiquidity ($MKTILLIQ$), down market dummy ($DOWN$), and market volatility ($MKTVOL$)). The ex-ante slope coefficients corresponding to the three market state variables and the common factors are computed based on the regression in Equation (1) using information available up to month $t-1$. The predicted WML is adjusted for risk factor realizations in month t. The slope coefficients of the predictive variables in Equation (6) are estimated using the full history of the return data up to month $t-1$, with a minimum of five years.[9] The results are presented in Table 5. We follow the same sequence of model specifications as those in Table 2. In Panel A, the forecast error is the difference between realized momentum profit and the forecasted one. In Panel B, we define the (predicted) negative momentum profit dummy to take the value of one if the (predicted) momentum profit is negative and zero otherwise, and the forecast error is the difference between the realized and predicted dummy variable.

Our out-of-sample analysis, based on the recursive approach in Panel A of Table 5, shows that the aggregate market illiquidity (Model 2), and market illiquidity joint with down market dummy (Model 5) has the biggest effect in reducing the mean squared forecast error (MSE) compared with the baseline model (Model 1). This is followed by Models 6 and 8 in generating a lower MSE, where we add market volatility. More specifically, the no-predictability model (Model 1) generates a mean squared error of 47.502. Accounting for market illiquidity (Model 2) reduces the MSE to 46.382.

While this reduction could be perceived to be modest, the economic implications are indeed highly significant. For one, Cooper, Gutierrez, and Hameed (2004) show the considerable impact of market states on momentum using a metric based on investment payoffs. In terms of MSE, the market states model (Model 3) generates MSE smaller than the no predictability model, consistent with Cooper et al, but higher than the MSE attributable to the illiquidity model. Similarly, Daniel and Moskowitz (2012) advocate the joint impact of market states and market volatility. Indeed, the model retaining these two predictors (Model 7) generates MSE of 47.171, smaller than that of the no predictability model – consistent with Daniel and Moskowitz, but still higher than that of the illiquidity model.

Similarly, $MKTILLIQ$ shows up as a state variable in the models with lower out-of-sample MSE in predicting a negative momentum payoff, across all specifications in Panel B of Table 5. Specifically, the four models with lowest MSE are again Models 2, 5, 6 and 8 where $MKTILLIQ$ is

[9] We also consider a fixed five year rolling window and obtain qualitatively similar results.

accounted for in the predictions of negative momentum payoffs. Overall, the out-of-sample evidence supports our contention that illiquid market states has a significant effect in predicting momentum payoffs, in general, as well as negative momentum payoffs in particular.

5. Further Analysis and Robustness Checks

5.1 Momentum-Volatility Interactions and Market States

The return to the momentum trading strategy has been shown to vary across firms grouped by specific firm characteristics. Jiang, Lee and Zhang (2005) and Zhang (2006) report that momentum effects are more pronounced among firms with high return volatility and other characteristics that are correlated with information uncertainty about the value of the firm.[10] A natural question that arises is whether the market state variables could explain the differential drift in stock prices across the sub-group of firms.

Since we are able to obtain reliable stock return volatility measures for each firm for our full sample period from 1928 to 2011 but not the other firm characteristics, we focus on portfolios of stocks sorted by stock volatility. Specifically, at the beginning of each month t, we sort stocks in our loser/winner momentum deciles (defined by their returns in months $t-12$ to $t-2$), into five sub-groups depending on the volatility of the stock's weekly returns in excess of the market returns measured over the previous rolling 52 weeks, $\sigma_{i,t-1}$. Here, both return momentum cutoffs and volatility portfolio breakpoints are based on those obtained from NYSE firms only. Following Zhang (2006), we apply a $5 price filter each month.

Table 6 presents the results. We estimate time series regressions similar to that outlined in Equation (1), except that the *WML* payoff is assessed differently. In Panel A (B), *WML* is the momentum profits among the highest (lowest) volatility stocks. In Panel C, the dependent variable is the momentum payoff differential between the high and low volatility stocks. In Panel A of Table 6, the risk-adjusted momentum payoff for the high volatility stocks is significant at 1.98 percent per month (Model 1). In Model 2, we find that the momentum payoffs are significantly lower following

[10] Zhang (2006) also consider other firm characteristics that proxy for information uncertainty including firm size, firm age, analyst coverage, dispersion in analyst forecasts, and cash flow volatility. Avramov, Chordia, Jostova, and Philipov (2007) find that momentum profits are limited to a subset of firms with low credit ratings.

months of high aggregate illiquidity ($MKTILLIQ$), or decline in total market valuations as well as high market volatility (Models 3 to 4). Considering two or more state variables in multivariate settings, the effect of $MKTILLIQ$ dominates across the board. For example, in Model 8, only $MKTILLIQ$ significantly predicts lower momentum payoffs when all three predictive variables are included.

We obtain similar results for the low volatility stocks in Panel B. Again, the risk-adjusted momentum payoff of 1.34 percent is significant after adjusting for the common factors in Model 1. Here, the market return state variable also seems to be a robust predictor while market volatility becomes an insignificant predictor in all specifications where either market illiquidity or market return states or both are accounted for.

In unreported results (available upon request), we find that the momentum payoffs decreases monotonically across the volatility groups. For the low volatility stocks, both $MKTILLIQ$ and $DOWN$ significantly predict the momentum returns, although the level of momentum profits and the sensitivity of the profits to state variables are smaller for the low volatility stocks.

Next, we regress the difference in momentum payoffs between the high and low volatility stocks on the explanatory variables considering all the eight specifications. Results are reported in Panel C of Table 6. This regression enables us to examine whether the performance of the high and low volatility momentum portfolios are associated with the differential exposure to the market state and common factors. As shown in Model 1 of Panel C, the additional momentum profits of 0.64 percent attributable to the high volatility stocks is significant. Moreover, the high volatility stocks have significantly bigger exposure to the $MKTILLIQ$ variable. This is evident when $MKTILLIQ$ enters significantly either individually or along with the other state variables. In fact, in multiple regressions, $MKTILLIQ$ is the only significant variable – although only at the 10% level while both market return states and market volatility carry no information about the return differential between momentum strategies across high versus low volatility stocks. Interestingly, the common factor loadings for the two groups of stocks are not different from each other. These results reinforce the significant effect of the state of aggregate market illiquidity in explaining the cross-sectional variation in momentum payoffs.

5.2 Momentum in Large Firms

The evidence of momentum in stock prices is pervasive and significant profits are present in stocks sorted by firm size. For example, Fama and French (2008) find that the momentum strategy yields significant returns in big, small, as well as micro-cap stocks, although small and micro-cap stocks are more likely to dominate portfolios sorted by extreme (winner/loser) returns. They argue that it is important to show that the phenomenon is systemic and is not concentrated in a group of small, illiquid stocks that make up a small portion of total market capitalization.

In this sub-section, we examine whether the time variation in expected momentum payoffs among the sample of large firms is captured by market illiquidity. Following Fama and French (2008), the sample here consists of firms with market capitalization above the median NYSE firms each month. We also filter out firms with stock price below $5 each month.

The estimates of Equation (1) for the subset of large firms for the full sample period are presented in Table 7. Consistent with prior evidence, we continue to find significant (risk-adjusted) momentum profits of 1.57 percent in Model 1. More importantly, the state of market illiquidity, $MKTILLIQ$, predicts significantly lower returns to the momentum strategy applied to big firms. The slope coefficient ranges between −0.25 (t-value = −2.37) for Model 8 and −0.315 (t-value = −3.45) for Model 2. In addition, the other state variables, $DOWN$ and $MKTVOL$, also forecast lower profits, while the predictive power of $MKTVOL$ disappears in multiple regressions and DOWN is significant only at the 10% level. In sum, $MKTILLIQ$ stands out as the strongest predictor also in the sub-sample of large firms in all specifications, emphasizing our main contention that the systemic effect of the state of market illiquidity is robust.

5.3 Recent Sub-Sample and Earnings Momentum

While most of the research papers on the profitability of momentum strategies employ data before 2000, Chordia, Subrahmanyam and Tong (2013) show that price and earnings momentum payoffs are insignificant in the post-decimalization period, starting in 2001. In this sub-section, we examine whether the documented predictive effect of market states holds in the most recent decade, which includes episodes of crashes in the momentum payoffs (Daniel and Moskowitz (2012)), In addition to price momentum, we analyze earnings momentum using the 8 models studied earlier. Indeed, several studies document the prevalence of profits generated by a trading strategy that capitalizes on continuation in stock prices following the release of unexpected earnings, or earnings momentum. A zero-investment strategy of buying stocks with extreme positive earnings surprise and selling short stocks with extreme negative earnings surprise generates significant positive profits, consistent with Ball and Brown (1968), Bernard and Thomas (1989), Chan, Jegadeesh, and Lakonishok (1996), and Chordia and Shivakumar (2006). Chordia and Shivakumar (2006), for one, argue that price momentum is subsumed by the systematic component in earnings momentum.

We follow Chan, Jegadeesh, and Lakonishok (1996) for our measures of earnings surprise, namely changes in analysts' earnings forecasts, standardized unexpected earnings, and cumulative abnormal returns around earnings announcements. The earnings momentum strategy is similar to the price momentum strategy except for ranking by earnings news. Specifically, at the beginning of each month t, all common stocks are sorted into deciles based on their lagged earnings news at $t-2$. The top (bottom) ten percent of stocks in terms of earnings surprise constitute the winner (loser) portfolio. The earnings momentum portfolio consists of a long position in the winner decile portfolio (extreme positive earnings surprise stocks) and a short position in loser decile portfolio (extreme negative earnings surprise stocks). The strategy's holding period return in month t is the value-weighted average of returns on stocks in the extreme deciles.

Our first measure of earnings surprise, which is based on the changes in analysts' forecasts of earnings (*REV*), is defined as

$$REV_{it} = \sum_{j=0}^{6} \frac{f_{it-j} - f_{it-j-1}}{P_{it-j-1}} \tag{7}$$

where f_{it-j} is the mean (consensus) estimate of firm i's earnings in month $t-j$ for the current fiscal year, and P_{it-j-1} is the stock price in the previous month (see also Givoly and Lakonishok (1979) and Stickel (1991)). The earnings surprise measure, REV_{it}, provides an up-to-date measure at the monthly frequency since analyst forecasts are available on a monthly basis and it has the advantage of not requiring estimates of expected earnings.

An alternative measure of earnings surprise is the standardized unexpected earnings (*SUE*), defined as

$$SUE_{it} = \frac{e_{iq} - e_{iq-4}}{\sigma_{it}} \tag{8}$$

where e_{iq} is the most recent quarterly earnings per share for stock i announced as of month t, e_{iq-4} is the earnings per share announced four quarters ago, and σ_{it} is the standard deviation of unexpected earnings $(e_{iq} - e_{iq-4})$ over the previous eight quarters. While SUE_{it} is commonly used in the literature (see also Bernard and Thomas (1989), Foster, Olsen and Shevlin (1984) and Chordia and Shivakumar (2006)), this earnings surprise measure is not updated for stock i month t if the firm did not announce its earnings.

Finally, we also compute earnings surprise using the cumulative abnormal stock return (*CAR*) around the earnings announcement dates, where the stock i's return is in excess of the return on the market portfolio. Specifically, CAR_{it} for stock i in month t is computed from day −2 to day +1, with day 0 defined by the earnings announcement date in month t,

$$CAR_{it} = \sum_{d=-2}^{+1}(r_{id} - r_{md}) \tag{9}$$

where r_{id} is the return on stock i in day d, and r_{md} is the return on the CRSP equally weighted market portfolio. When measuring earnings surprise with SUE_{it} or CAR_{it}, we retain the same earnings surprise figures between reporting months.

Following Chordia, Subrahmanyam and Tong (2013), we start our sub-sample period from decimalization of trading in April 2001 and extend to the end of 2011. We begin with the presentation of estimates of the regression Equation (1) for the price momentum portfolio during the recent sample period. As shown in Panel A of Table 8, the risk-adjusted price momentum profit is insignificant at 0.24 percent in the 2001−2011 period (Model 1).[11] Figure 1 plots the payoffs to the price momentum and the value of the state variables. The figure suggests that the lack of profitability of price momentum in the recent decade is possibly related to periodic episodes of market illiquidity, since low momentum payoff months seem to coincide with periods of high lagged market illiquidity. In support of this assertion, controlling for the significant negative effect of $MKTILLIQ$ on WML in Model 2 in Panel A (Table 8), there is significant momentum payoffs as indicated by the regression intercept.

[11] The raw price momentum returns in 2001−2011 are lower and insignificant at 0.18 percent per month.

Additionally, in Model 3 we find that $DOWN$ market months are followed by huge negative momentum payoffs, leaving a significant 1.58 percent momentum profit in other months. We obtain similar evidence that months following high market volatility are associated with significantly lower momentum profits. However, the predictive power of $DOWN$ and $MKTVOL$ disappears in the presence of $MKTILLIQ$. Indeed, models 5 to 8 in Panel A comport well with the cumulative results we have presented thus far: the state of market illiquidity dominantly governs the (lack of) profitability of price momentum strategies.

Panels B to D in Table 8 lay out the results based on earnings momentum. In Panel B, the momentum portfolios use earnings surprise based on the revision in analyst forecasts of earnings (*REV*). As shown by estimate of Model 1 in Panel B of Table 8, we obtain a significant earnings momentum profit of 1.12 percent per month, after adjusting for the three Fama-French risk factors. Unlike the disappearance of price momentum, we obtain significant earnings momentum even in the most recent years. Nevertheless, the earnings momentum profits plotted in Figure 1 displays a high correlation with the lagged market illiquidity, similar to the payoffs from the price momentum strategy. This observation is confirmed in the regressions of earnings momentum profits on each of the state variables.

Earnings momentum profitability is significantly lower following illiquid aggregate market ($MKTILLIQ$) states (Model 2) and $DOWN$ markets (Model 3). Market volatility, $MKTVOL$, on the other hand, does not appear to have any significant predictive effects on earnings momentum on its own (Model 4). More importantly, $MKTILLIQ$ is the only state variable that retains its significance in the presence of two or more state variables, across all specifications in Models 5, 6 and 8.

When earnings surprise at the firm level is measured by changes in its standardized unexpected earnings (SUE), we find that only $MKTILLIQ$ enters significantly when the regression in Equation (1) is estimated with only one predictive variable (Model 2). As displayed in Panel C of Table 8 (Models 3 and 4), $DOWN$ and $MKTVOL$ are insignificant predictors of earnings momentum. When all the state variables are considered together, only the state of market illiquidity is able to significantly capture a drop in earnings momentum in the following month (see Model 8).

Finally, in Panel D of Table 8 the earnings surprise is constructed using the abnormal stock price reactions in the announcement month t (*CAR*). Interestingly, the average risk-adjusted earnings momentum profit using stocks sorted on CAR is not positive in the last decade, yielding an insignificant −0.17 percent per month (see Model 1). Controlling for the negative effect of $DOWN$ market states on momentum, the payoff to the earnings momentum regains a significant positive value of 0.5 percent following a rise in aggregate market valuations (Model 3). In addition, $MKTILLIQ$ (Model 2) and $MKTVOL$ (Model 4) also significantly predict future earnings momentum profits when they are the only single state variable in the regression specification. However, in an all-inclusive specification (Model 8) MKTILLIQ stands out as the only significant predictor.

In summary, the analysis of earnings momentum in the recent decade comports well with the cumulative evidence we have presented in this paper: the state of market illiquidity is a dominant predictor of the (lack of) profitability of price and earnings momentum strategies.

5.4 Does Investor Sentiment Explain Our Results?

Investor sentiment has been shown to affect the returns associated with a broad set of market anomalies. For example, Stambaugh, Yuan, and Yu (2012) show that various cross sectional anomalies, including price momentum, are profitable during periods of high investor sentiment. In particular, profitability of these long-short strategies stem from the short-leg of the strategies, reflecting binding short-sale constraints following high sentiment. Antoniou, Doukas, and Subrahmanyam (2013) also report that momentum strategies are not profitable when investor sentiment is pessimistic. In this sub-section, we consider if the predictive effect of illiquidity on momentum payoffs are subsumed by variation in investor sentiment.

We start our analysis by first documenting the momentum payoffs across states of investor sentiment. Similar to Stambaugh, Yu, and Yuan (2012), we adopt the investor sentiment index developed by Baker and Wurgler (2006, 2007).[12] We divide the sample period from 2001 to 2010 into three equal sub-periods of High, Medium and Low sentiment states depending on the level of the investor sentiment index in month $t-1$. For each state, we compute the Fama-French three-factor

[12] We thank Jeffry Wurgler for making publicly available their index of investor sentiment.

risk-adjusted returns to the loser and winner momentum deciles, and the momentum payoffs to the WML portfolio in month t. As shown in Table 9, we find significant positive WML payoff of 2.69 percent per month only in High sentiment states (Model 3). The momentum strategy fails to be profitable when investor sentiment is pessimistic, confirming the results presented in the above cited papers.

Next, we consider the role of the state of market illiquidity, in addition to investor sentiment. To do this, we first sort all the months in our sample into three equal sub-samples based on the level of aggregate market illiquidity in month $t-1$, $MKTILLIQ_{t-1}$. The tercile belonging to lowest (highest) $MKTILLIQ_{t-1}$ corresponds to the most liquid (illiquid) period. Within each of the three $MKTILLIQ_{t-1}$ terciles, we further sort the observations into High, Medium and Low sentiment in month $t-1$, to generate nine sub-periods. The payoffs to the winner, loser and WML portfolios in month t in each of the sub-periods are also reported in Table 9. Here, we find a strong influence on market illiquidity states on the momentum payoffs. When the equity market is illiquid, we do not observe any profits to the *WML* portfolio in all sentiment states, including the most optimistic sentiment state. Moreover, we obtain negative *WML* payoffs when sentiment is High but the market is illiquid. Interestingly, we find all the momentum profits are concentrated in the sub-period when $MKTILLIQ_{t-1}$ is moderate, indicating a non-linear effect of market illiquidity on price momentum.

The results based on the two-way sorting of sample months may be affected by the correlation between the state of investor sentiment and market illiquidity. We turn to the time series regression in Equation (1) as an alternative framework. We estimate the regression equation with investor sentiment as a state variable singly and in conjunction with other state variables. We consider two alternative definitions of the sentiment variable. The first is the level of sentiment index obtained from Baker and Wurgler (2006, 2007). The second is a low sentiment dummy variable that takes a value of one only if the sentiment index value belongs to the bottom tercile over the sample period, 2001−2011.

The results presented in Table 10 show that sentiment has a positive effect on momentum profits while low sentiment periods have low momentum payoffs. The exception is in Model 1 in Table 10, where sentiment has an insignificant coefficient, similar to the regression results presented in

Stambaugh, Yu, and Yuan (2012). The key result in Table 10 is that $MKTILLIQ$ is highly significant in all specifications and at conventional levels whereas DOWN and MKTVOL are insignificant in the joint specification and the two sentiment variables are insignificant at the 5% level.

5.5 Cross-Sectional Differences in Illiquidity and Momentum

The evidence so far indicates that momentum strategy is not profitable following bad market conditions, in particular when the aggregate market is illiquid. Furthermore, the decline in momentum profits is driven by the outperformance of the loser portfolio. While loser stocks are generally more illiquid than winner stocks (as shown in Table 1), we raise the question of whether the differential performance of winners and losers depend on their relative illiquidity. When loser stocks become relatively more illiquid than winner stocks, the losers are expected to earn higher future returns to compensate for the difference in illiquidity. Since the momentum strategy goes long on winners (less illiquid stocks) and short on losers (more illiquid stocks), the strategy essentially carries a negative illiquidity premium. Consequently, the momentum strategy is likely to generate low payoffs in times when the cross-sectional difference in illiquidity between the loser and winner portfolio is large. Moreover, we expect the cross-sectional differences in illiquidity to matter most when the aggregate market is highly illiquid.

To investigate if the cross-sectional differences in illiquidity affect the momentum payoffs, we introduce the notion of an illiquidity gap, defined as follows:

$$ILLIQGAP_{t-1} = ILLIQ_{WINNER,t-1} - ILLIQ_{LOSER,t-1} \tag{10}$$

where $ILLIQ_{WINNER,t-1}$ ($ILLIQ_{LOSER,t-1}$) is the value-weighted average of the stock level Amihud (2002) illiquidity measure of all stocks in the winner (loser) decile in month $t-1$. The level of $ILLIQGAP_{t-1}$ is mostly negative since the loser portfolio is unconditionally more illiquid than the winner portfolio. We assess if momentum payoffs are significantly lower following periods when the loser portfolio is relatively more illiquid than winners, implying a positive predictive relation between

$ILLIQGAP_{t-1}$ and WML_t. Specifically, we estimate the regression Equation (1), adding $ILLIQGAP_{t-1}$ as one of the explanatory variables.

Our analysis of the effect of illiquidity level differs from the important work in Pastor and Stambaugh (2003), Sadka (2007) and Assness, Moskowitz and Pedersen (2013) that examines the liquidity risk (beta) exposure of the momentum strategies. Their investigations show that the momentum portfolio has significant exposure to variations in systematic liquidity factor, which in turn explains some, albeit small, portion of the profits. To show the incremental impact of cross-sectional differences in illiquidity level on the returns on the winner and loser portfolios, our regressions explicitly control for the influence of the Pastor-Stambaugh liquidity factor (obtained from CRSP database).

As reported in Table 11, Model 2, $ILLIQGAP_{t-1}$ predicts significantly lower momentum profits when the loser portfolio is more illiquid than the winner portfolio. Model 3 in Table 11 shows that the predictive effect of $ILLIQGAP_{t-1}$ is incremental to the prediction that illiquid market states produce lower momentum payoffs. Moreover, these findings are unaffected by the inclusion of other state variables as well as the Pastor-Stambaugh liquidity factor. While there is a positive liquidity beta associated with the WML portfolio, the liquidity factor does not load significantly in our sample. [13] In unreported results, controlling for the effect of investor sentiment (see Table 10) does not change our estimated coefficients. We also consider the interaction of $MKTILLIQ_{t-1}$ and $ILLIQGAP_{t-1}$. The interaction effect of these two variables is highly significant as depicted in Model 6 of Table 11. The latter findings emphasize that the gap in the liquidity between losers and winner has the biggest effect of expected momentum profits when the aggregate market is most illiquid. When we interact $ILLIQGAP_{t-1}$ with excess return on the market portfolio, $RMRF_t$, we obtain a significant positive coefficient. While the momentum strategy carries a negative (unconditional) market beta, the strategy's exposure to market risk increases when $ILLIQGAP_{t-1}$ is large, consistent with the sharp increase in market beta of the loser portfolios during market crashes documented in Daniel and Moskowitz (2012).

[13] While there is a positive relation between liquidity betas and illiquidity level in portfolios sorted by illiquidity levels (see, e.g. Acharya and Pedersen (2005)), we find the liquidity betas of the loser and winner portfolios are negatively associated with the level of stock illiquidity. Details are available upon request.

Our findings in Table 11 highlights the relation between price momentum and illiquidity. In normal periods, the market is populated with overconfident investors, giving rise to positive momentum payoffs. The illiquidity premium attributable to the loser portfolio, which is generally more illiquid than the winner portfolio, attenuates but does not eliminate the positive momentum payoffs attributable to investor overconfidence. In illiquid periods, however, there are two reinforcing effects. First, the prominence of overconfident investors diminishes, which lowers the momentum in stock prices. Second, the illiquidity gap between the losers and winners widens, and the corresponding higher returns associated with illiquidity leads to momentum crashes.

6. Conclusion

This paper implements comprehensive in- and out of sample experiments to show that payoffs to momentum strategies are predicted by the state of market illiquidity. Periods of high market illiquidity are followed by low momentum payoffs. In the presence of market illiquidity, the power of the competing state variables, down market states and market volatility, in predicting momentum is attenuated and often even disappears altogether. Examining the profitability of momentum on the basis of individual securities delivers complementary evidence. The momentum illiquidity relation is consistent with behavioral models based on investor overconfidence in Daniel, Hirshleifer, and Subrahmanyam (1998) and Baker and Stein (2004).

When momentum payoff is interacted with stock volatility, we find that high volatility stocks earn higher profits than low volatility stocks and the differences in profits between the two groups are related to the bigger exposure of high volatility stocks to lagged market illiquidity, but not the other two state variables. Our evidence of lower profits to the momentum portfolio strategy following market illiquidity holds when the sample is restricted to only large firms, indicating that our findings are not limited to illiquid stocks that make up a small fraction of the equity market value.

Examining momentum profitability in the recent years reveals several intriguing findings. While the price momentum strategy is no longer profitable in the recent decade, significant profitability is regained upon conditioning on the state of the market. For instance, the momentum profits increase from an insignificant 0.24 percent unconditionally, to 1.58 percent following declines in aggregate market valuations. Considering the predictive effect of the collection of all three state variables, market illiquidity subsumes all the predictive power of the other variables.

We also analyze payoffs to the earnings momentum strategies, based on revision in earnings forecasts by analysts, standardized earnings surprises, and abnormal returns around earnings announcements. Again, we attain analogous findings: the drift in stock prices following the release of earnings information is weaker when the market is illiquid. While momentum payoffs are lower when investor sentiment is pessimistic, we find that market illiquidity continues to strongly predict momentum profits. We also obtain significant predictive effect of cross-sectional differences in illiquidity of the loser and winner stocks on momentum payoffs. Here, a large positive gap in the illiquidity of loser and winner stocks predicts an incremental decrease in the momentum payoffs as loser (illiquid) stocks earn a higher future returns. The effect of this illiquidity gap is strongest when the market is also illiquid.

Our overall evidence suggests that market illiquidity predicts time variation in momentum payoffs and conditioning on the state of market illiquidity could make investors avoid periods of momentum crash and reconsider momentum when its future payoffs are statistically significant and economically large.

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Table 1: Descriptive Statistics for Momentum Portfolios and Market States

Panel A presents characteristics of the monthly momentum portfolio in our sample during the period from 1928 to 2011. At the beginning of each month t, all common stocks listed on NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged eleven-month returns (formation period is from $t-12$ to $t-2$, skipping month $t-1$). The portfolio breakpoints are based on NYSE firms only. We report the average monthly value-weighted holding period (month t) returns of each decile portfolio, as well as the momentum profits (WML, winner minus loser deciles). The returns are further adjusted by CAPM and Fama-French three-factor model to obtain CAPM and 3-Factor Alphas. We also report the CAPM beta, return autocorrelation (AR(1)), standard deviation of return, Sharpe ratio, information ratio, skewness, and Amihud illiquidity (ILLIQ). Sharpe ratio (Information ratio) is computed as the average monthly excess portfolio return (CAPM alpha) divided by its standard deviation (portfolio tracking error) over the entire sample period. For all portfolios except WML, skewness refers to the realized skewness of the monthly log returns to the portfolios. For WML, skewness refers to the realized skewness of $\log(1+r_{WML}+r_f)$, following Daniel and Moskowitz (2012). Panel B reports the correlation of WML and market state variables, including the aggregate market illiquidity (MKTILLIQ), DOWN market dummy (for negative market returns over the previous 2 years), and market return volatility(MKTVOL).Panel C reports the autocorrelation of WML and market state variables. Newey-West adjusted t-statistics are reported in parentheses, and the numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Characteristics of Momentum Decile Portfolios

	1 (Loser)	2	3	4	5	6	7	8	9	10 (Winner)	WML
Raw Return (in %)	0.291	0.698***	0.701***	0.833***	0.821***	0.909***	0.987***	1.102***	1.168***	1.470***	1.179***
	(0.95)	(2.89)	(3.17)	(3.94)	(4.58)	(4.82)	(5.39)	(5.94)	(5.88)	(6.67)	(4.84)
CAPM Alpha (in %)	-0.926***	-0.388***	-0.290***	-0.113	-0.084	0.006	0.118*	0.254***	0.299***	0.572***	1.497***
	(-6.26)	(-3.73)	(-3.15)	(-1.45)	(-1.26)	(0.12)	(1.96)	(5.05)	(4.49)	(5.67)	(8.17)
CAPM Beta	1.550***	1.332***	1.171***	1.097***	1.027***	1.024***	0.966***	0.931***	0.966***	1.015***	-0.535***
	(16.77)	(14.23)	(15.14)	(19.12)	(19.71)	(26.99)	(39.99)	(38.10)	(24.76)	(11.67)	(-3.05)
3-Factor Alpha (in %)	-1.105***	-0.524***	-0.386***	-0.186***	-0.145**	-0.039	0.110*	0.259***	0.317***	0.624***	1.730***
	(-8.71)	(-5.09)	(-4.08)	(-2.58)	(-2.45)	(-0.83)	(1.90)	(5.13)	(4.37)	(6.65)	(9.29)
AR(1)	0.165	0.148	0.124	0.123	0.104	0.107	0.058	0.091	0.055	0.068	0.085
Std.Dev.(Raw Return)	9.883	8.217	7.098	6.502	6.021	5.879	5.584	5.423	5.735	6.562	7.952
Sharpe Ratio	0.000	0.049	0.057	0.083	0.087	0.104	0.124	0.149	0.152	0.179	0.148
Information Ratio	-0.183	-0.103	-0.096	-0.046	-0.039	0.003	0.066	0.138	0.136	0.164	0.203
Skewness	0.143	-0.018	-0.086	0.214	-0.106	-0.265	-0.580	-0.529	-0.760	-0.905	-6.252
ILLIQ	8.387	3.625	1.864	1.163	1.180	1.038	0.827	0.586	0.781	2.170	***

Table 1—Continued

Panel B: Correlation among Market States				
	WML	MKTILLIQ	DOWN	MKTVOL
WML	1.000			
MKTILLIQ	-0.258	1.000		
DOWN	-0.129	0.327	1.000	
MKTVOL	-0.122	0.396	0.422	1.000

Panel C: Autocorrelation of Market States				
	WML	MKTILLIQ	DOWN	MKTVOL
AR(1)	0.085	0.894***	0.875***	0.719***
	(1.01)	(22.05)	(28.80)	(14.82)

Table 2: Momentum Profits and Market States

Panel A presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles in month t, $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). Panels B and C report similar regression parameters, where the dependent variable is the excess value-weighted portfolio return in loser and winner deciles, respectively. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Momentum Profit (WML) Regressed on Lagged Market State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.730***	2.049***	2.169***	3.123***	2.284***	2.826***	3.035***	2.789***
	(9.29)	(9.57)	(10.50)	(6.86)	(11.44)	(6.49)	(6.97)	(6.62)
MKTILLIQ		-0.350***			-0.290***	-0.280***		-0.253**
		(-4.28)			(-3.05)	(-2.82)		(-2.41)
DOWN			-2.405***		-1.584**		-1.656***	-1.240*
			(-3.44)		(-1.96)		(-2.94)	(-1.87)
MKTVOL				-1.592***		-0.961*	-1.146**	-0.688
				(-3.23)		(-1.65)	(-2.55)	(-1.38)
RMRF	-0.387***	-0.373***	-0.393***	-0.391***	-0.380***	-0.378***	-0.394***	-0.382***
	(-3.42)	(-3.27)	(-3.37)	(-3.40)	(-3.27)	(-3.27)	(-3.38)	(-3.28)
SMB	-0.247*	-0.213	-0.224*	-0.231*	-0.204	-0.210	-0.219	-0.204
	(-1.80)	(-1.56)	(-1.67)	(-1.68)	(-1.52)	(-1.54)	(-1.62)	(-1.51)
HML	-0.665***	-0.599***	-0.659***	-0.667***	-0.606***	-0.613***	-0.662***	-0.615***
	(-3.57)	(-3.68)	(-3.62)	(-3.66)	(-3.68)	(-3.71)	(-3.67)	(-3.70)
Adj-Rsq	0.232	0.254	0.246	0.247	0.259	0.259	0.252	0.261
Obs	1,008	1,008	1,008	1,008	1,008	1,008	1,008	1,008

Table 2—Continued

Panel B: Excess Loser Portfolio Return Regressed on Lagged Market State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-1.105***	-1.287***	-1.402***	-1.939***	-1.462***	-1.775***	-1.875***	-1.746***
	(-8.71)	(-8.98)	(-9.99)	(-6.26)	(-10.56)	(-5.68)	(-6.35)	(-5.81)
MKTILLIQ		0.199***			0.154**	0.154**		0.133*
		(4.08)			(2.51)	(2.45)		(1.93)
DOWN			1.621***		1.186**		1.211***	0.993**
			(3.14)		(1.99)		(2.76)	(1.98)
MKTVOL				0.952***		0.605	0.626*	0.386
				(2.64)		(1.41)	(1.93)	(1.06)
RMRF	1.390***	1.383***	1.395***	1.393***	1.388***	1.386***	1.395***	1.389***
	(20.22)	(20.02)	(19.48)	(19.69)	(19.51)	(19.58)	(19.38)	(19.36)
SMB	0.514***	0.495***	0.498***	0.504***	0.487***	0.493***	0.496***	0.487***
	(6.07)	(5.73)	(5.92)	(5.88)	(5.71)	(5.70)	(5.84)	(5.69)
HML	0.373***	0.335***	0.369***	0.374***	0.341***	0.344***	0.371***	0.346***
	(3.02)	(3.05)	(3.05)	(3.07)	(3.04)	(3.06)	(3.07)	(3.05)
Adj-Rsq	0.783	0.787	0.787	0.786	0.789	0.788	0.788	0.790
Obs	1,008	1,008	1,008	1,008	1,008	1,008	1,008	1,008
Panel C: Excess Winner Portfolio Return Regressed on Lagged Market State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.624***	0.763***	0.768***	1.184***	0.822***	1.051***	1.160***	1.043***
	(6.65)	(7.39)	(7.11)	(5.90)	(7.89)	(6.05)	(5.89)	(6.06)
MKTILLIQ		-0.151***			-0.136***	-0.125***		-0.120**
		(-3.27)			(-2.87)	(-2.61)		(-2.48)
DOWN			-0.784***		-0.398		-0.445*	-0.247
			(-2.78)		(-1.31)		(-1.68)	(-0.85)
MKTVOL				-0.639***		-0.356*	-0.520**	-0.302
				(-3.19)		(-1.75)	(-2.53)	(-1.53)
RMRF	1.004***	1.010***	1.002***	1.002***	1.008***	1.008***	1.001***	1.007***
	(19.56)	(19.39)	(19.17)	(19.55)	(19.32)	(19.43)	(19.39)	(19.41)
SMB	0.267***	0.281***	0.274***	0.273***	0.284***	0.283***	0.276***	0.284***
	(4.05)	(4.49)	(4.29)	(4.25)	(4.56)	(4.51)	(4.34)	(4.55)
HML	-0.292***	-0.264***	-0.290***	-0.293***	-0.265***	-0.269***	-0.292***	-0.269***
	(-4.04)	(-4.17)	(-4.10)	(-4.17)	(-4.18)	(-4.22)	(-4.17)	(-4.21)
Adj-Rsq	0.757	0.763	0.759	0.761	0.764	0.764	0.761	0.764
Obs	1,008	1,008	1,008	1,008	1,008	1,008	1,008	1,008

Table 3: Individual Stock Momentum and Market States

Panel A presents the estimates of the following monthly Fama-MacBeth regressions,

$$R_{i,t} = \alpha_0 + \beta_{0t} R_{i,t-12:t-2} + \beta_{Nt} R^{-}_{i,t-12:t-2} + \gamma_t ILLIQ_{i,t-1} + e_{i,t},$$

where $R_{i,t}$ is the return of stock i in month t, $R_{i,t-12:t-2}$ is the accumulated stock return between month $t-12$ and $t-2$, $R^{-}_{i,t-12:t-2}$ is obtained by multiplying $R_{i,t-12:t-2}$ by a dummy variable that takes a value of 1 if $R_{i,t-12:t-2}$ is negative and zero otherwise, and $ILLIQ_{i,t-1}$ is the Amihud (2002) illiquidity. In Panel B (Panel C), the estimated monthly β_{0t} (β_{Nt}) coefficients from Panel A are regressed on the time-series of lagged state variables: $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return:

$$\beta_{0t} = \alpha_0 + \gamma_1 MKTILLIQ_{t-1} + \gamma_2 DOWN_{t-1} + \gamma_3 MKTVOL_{t-1} + e_t,$$
$$\beta_{Nt} = \alpha_0 + \gamma_1 MKTILLIQ_{t-1} + \gamma_2 DOWN_{t-1} + \gamma_3 MKTVOL_{t-1} + e_t,$$

The sample consists of all common stocks listed on NYSE and AMEX over the period 1928−2011. The Newey-West adjusted t-statistics are in parenthesis and numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Stock Return Regressed on Lagged Stock Return

	Model 1	Model 2
Intercept	0.942***	1.036***
	(4.01)	(4.86)
$Ret_{t-12:t-2}$	0.007***	0.010***
	(2.98)	(3.69)
$Ret_{t-12:t-2}^{-}$		0.015**
		(2.16)
ILLIQ	0.015**	0.018***
	(2.33)	(2.90)
Adj-Rsq	0.030	0.039
Obs	1,551,030	1,551,030

Panel B: β_{0t} Regressed on Lagged State Variables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	1.431***	1.176***	1.738***	1.507***	1.053*	1.628***	1.026*
	(4.94)	(10.67)	(3.80)	(9.20)	(1.82)	(3.96)	(1.85)
MKTILLIQ	-0.007***			-0.007***	-0.007***		-0.007***
	(-3.81)			(-3.17)	(-3.26)		(-2.96)
DOWN		-2.465**		-0.521		-2.071***	-0.857
		(-2.56)		(-0.39)		(-2.94)	(-0.85)
MKTVOL			-1.161*		0.469	-0.599	0.660
			(-1.71)		(0.46)	(-1.13)	(0.78)
Adj-Rsq	0.110	0.018	0.010	0.110	0.111	0.020	0.113
Obs	1,008	1,008	1,008	1,008	1,008	1,008	1,008

Panel C: β_{Nt} Regressed on Lagged State Variables

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	3.596***	2.871***	3.689***	3.847***	1.590	3.316***	1.481
	(5.44)	(6.58)	(2.79)	(7.81)	(1.28)	(2.76)	(1.22)
MKTILLIQ	-0.020***			-0.020***	-0.022***		-0.021***
	(-4.78)			(-4.02)	(-4.41)		(-3.99)
DOWN		-7.448***		-1.715		-7.061***	-3.365*
		(-3.12)		(-0.64)		(-3.72)	(-1.65)
MKTVOL			-2.504		2.494	-0.590	3.243*
			(-1.32)		(1.21)	(-0.38)	(1.83)
Adj-Rsq	0.120	0.020	0.006	0.120	0.124	0.021	0.127
Obs	1,008	1,008	1,008	1,008	1,008	1,008	1,008

Table 4: Individual Stock Momentum and Variation with Market States

Panel A presents the cross-sectional average coefficients obtained from the following time-series regressions for each firm i,

$$R_{i,t}^{e} = \alpha_i + \beta_{i1} MKTILLIQ_{t-1} + \beta_{i2} DOWN_{t-1} + \beta_{i3} MKTVOL_{t-1} + c'F_t + e_{i,t},$$

where $R_{i,t}^{e}$ is the excess return of stock i in month t, $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return. The vector F stacks Fama-French three factors, including market factor (RMRF), size factor (SMB) and book-to-market factor (HML). Panel B presents the results of the following monthly Fama-MacBeth regressions,

$$R_{i,t}^{*} = \alpha_0 + \beta_1 R_{i,t-12:t-2} + u_{i,t},$$

where $R_{i,t}^{*} = \alpha_i + e_{i,t}$, both come from the time-series regressions in Panel A over the entire sample period, $R_{i,t-12:t-2}$ is the accumulated stock return between month $t-12$ and $t-2$. Newey-West adjusted t-statistics are reported in parenthesis and numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: First-Stage Excess Stock Returns Regressed on Lagged State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-0.047***	0.143***	-0.130***	-0.037	0.124**	0.286***	-0.042	0.277***
	(-2.84)	(2.93)	(-6.99)	(-0.88)	(2.49)	(4.87)	(-0.98)	(4.65)
MKTILLIQ		0.087**			0.031	0.225***		0.165***
		(2.16)			(0.69)	(4.40)		(3.04)
DOWN			-0.055		0.066		-0.016	0.126*
			(-0.86)		(0.92)		(-0.24)	(1.74)
MKTVOL				-0.063		-0.140**	-0.127**	-0.146**
				(-1.24)		(-2.40)	(-2.41)	(-2.50)
RMRF	0.967***	0.972***	0.969***	0.967***	0.972***	0.969***	0.967***	0.968***
	(177.14)	(176.32)	(175.16)	(176.05)	(174.27)	(175.94)	(174.35)	(173.73)
SMB	0.975***	0.969***	0.970***	0.975***	0.969***	0.965***	0.971***	0.963***
	(111.95)	(110.18)	(110.07)	(111.24)	(109.18)	(107.83)	(109.57)	(106.79)
HML	0.226***	0.233***	0.231***	0.229***	0.234***	0.223***	0.229***	0.223***
	(23.86)	(24.55)	(24.44)	(23.84)	(24.54)	(23.07)	(23.88)	(22.94)
Panel B: Second-Stage Risk and Market State Adjusted Stock Returns Regressed on its Own Lagged Returns								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.001	-0.011	-0.070*	-0.135***	-0.025	-0.067	-0.119**	-0.045
	(0.03)	(-0.24)	(-1.66)	(-2.88)	(-0.58)	(-1.44)	(-2.55)	(-0.97)
$Ret_{t-12:t-2}$	0.006***	0.003**	0.004***	0.004***	0.002*	0.002	0.003**	0.001
	(5.08)	(2.50)	(3.85)	(3.30)	(1.75)	(1.32)	(2.36)	(0.64)
Adj-Rsq	0.009	0.009	0.009	0.009	0.009	0.009	0.009	0.009
Obs	2,839,507	2,839,507	2,839,507	2,839,507	2,839,507	2,839,507	2,839,507	2,839,507

Table 5: The Out-of-Sample Forecasting Power of Market States

This table presents the summary statistics of the mean, standard deviation (Std.Dev) and mean squared error (MSE) of the forecast error based on out-of-sample forecasts. At the beginning of each month t, all common stocks listed on NYSE, AMEX and NASDAQ are sorted into deciles based on their lagged eleven-month returns (formation period ranges from $t-12$ to $t-2$, skipping month $t-1$). The portfolio breakpoints are based on NYSE firms only. The momentum profits (WML, winner minus loser deciles) are regressed on an intercept, Fama-French three factors and a combination of three market state proxies (market illiquidity, down market dummy and market volatility). The model specifications are in the same sequence as those in Table 2. The forecasted momentum profits refer to the fitted value of the time-series regressions using all historical data, with at least five years' data. In Panel A, the forecast error is the difference between realized momentum profit and the forecasted one. In Panel B, we define the predicted negative momentum profit dummy to take the value of one if the predicted momentum profit is negative and zero otherwise, and the forecast error is the difference between the realized and predicted dummy variable.

Panel A: Out-of-Sample Forecast Errors of Momentum Payoffs								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mean	0.313	-0.336	0.126	0.089	-0.323	-0.326	0.012	-0.330
Std.Dev	6.889	6.806	6.867	6.879	6.805	6.821	6.872	6.826
MSE	47.502	46.382	47.122	47.281	46.369	46.589	47.171	46.647
Panel B: Out-of-Sample Forecast Errors of Negative Momentum Payoff Dummy								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Mean	0.050	0.149	0.083	0.084	0.150	0.146	0.091	0.147
Std.Dev	0.627	0.587	0.610	0.619	0.584	0.590	0.613	0.585
MSE	0.396	0.366	0.379	0.390	0.363	0.369	0.384	0.364

Table 6: Momentum-Volatility Interactions and Market States

Panel A presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles for high volatility portfolio in month t. At the beginning of each month t, all common stocks listed on NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged eleven-month returns (formation period is from $t-12$ to $t-2$, skipping month $t-1$). For each momentum decile, we further sort stocks into five groups based on stock volatility ($\sigma_{i,t-1}$), which is defined as the standard deviation of weekly market excess returns over the year ending at the end of month $t-1$. All portfolio breakpoints are based on NYSE firms only. $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). Panels B and C report similar regression parameters, where the dependent variable is the momentum payoff (WML) for low volatility portfolio and the difference between high and low volatility portfolios, respectively. Numbers with “*”, “**” and “***” are significant at the 10%, 5% and 1% level, respectively.

Panel A: Momentum Profit (High Volatility Portfolio) Regressed on Lagged Market Conditions								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.977***	2.314***	2.381***	2.936***	2.507***	2.569***	2.841***	2.531***
	(7.23)	(7.11)	(7.68)	(5.17)	(8.13)	(3.99)	(5.18)	(4.06)
MKTILLIQ		-0.369***			-0.319**	-0.345**		-0.317**
		(-2.90)			(-2.23)	(-2.32)		(-2.00)
DOWN			-2.211**		-1.307		-1.814**	-1.291
			(-2.37)		(-1.12)		(-2.14)	(-1.32)
MKTVOL				-1.096*		-0.316	-0.608	-0.033
				(-1.82)		(-0.36)	(-1.10)	(-0.04)
RMRF	-0.253*	-0.239	-0.259*	-0.256*	-0.244	-0.241	-0.260*	-0.244
	(-1.67)	(-1.56)	(-1.67)	(-1.67)	(-1.60)	(-1.58)	(-1.68)	(-1.60)
SMB	0.002	0.038	0.023	0.013	0.046	0.039	0.026	0.046
	(0.01)	(0.25)	(0.17)	(0.09)	(0.31)	(0.26)	(0.18)	(0.31)
HML	-0.582**	-0.512**	-0.576**	-0.583**	-0.518**	-0.517**	-0.578**	-0.519**
	(-2.34)	(-2.41)	(-2.35)	(-2.38)	(-2.42)	(-2.44)	(-2.37)	(-2.44)
Adj-Rsq	0.088	0.105	0.096	0.093	0.108	0.106	0.097	0.108
Obs	1,008	1,008	1,008	1,008	1,008	1,008	1,008	1,008

Table 6—Continued

Panel B: Momentum Profit (Low Volatility Portfolio) Regressed on Lagged Market Conditions								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.336***	1.531***	1.647***	2.196***	1.713***	2.016***	2.128***	1.986***
	(7.07)	(7.45)	(7.75)	(5.66)	(8.14)	(4.49)	(5.54)	(4.51)
MKTILLIQ		-0.214***			-0.167**	-0.169**		-0.147*
		(-3.08)			(-2.28)	(-2.03)		(-1.73)
DOWN			-1.702***		-1.229**		-1.286**	-1.044*
			(-3.40)		(-2.04)		(-2.55)	(-1.96)
MKTVOL				-0.983**		-0.601	-0.637	-0.371
				(-2.48)		(-1.05)	(-1.51)	(-0.67)
RMRF	-0.312***	-0.304***	-0.317***	-0.315***	-0.309***	-0.307***	-0.317***	-0.310***
	(-3.16)	(-3.01)	(-3.13)	(-3.13)	(-3.03)	(-3.02)	(-3.12)	(-3.03)
SMB	-0.011	0.010	0.005	-0.001	0.017	0.012	0.008	0.017
	(-0.09)	(0.07)	(0.04)	(-0.01)	(0.13)	(0.09)	(0.06)	(0.13)
HML	-0.577***	-0.537***	-0.573***	-0.578***	-0.543***	-0.546***	-0.575***	-0.547***
	(-3.75)	(-3.85)	(-3.80)	(-3.84)	(-3.86)	(-3.89)	(-3.84)	(-3.88)
Adj-Rsq	0.167	0.177	0.175	0.174	0.181	0.179	0.178	0.181
Obs	1,008	1,008	1,008	1,008	1,008	1,008	1,008	1,008
Panel C: Momentum Profit (High − Low Volatility Portfolio) Regressed on Lagged Market Conditions								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.641***	0.783***	0.734***	0.740*	0.794***	0.553	0.712*	0.546
	(2.68)	(2.91)	(2.74)	(1.87)	(2.90)	(1.39)	(1.83)	(1.39)
MKTILLIQ		-0.155*			-0.152	-0.176*		-0.171*
		(-1.76)			(-1.61)	(-1.82)		(-1.69)
DOWN			-0.509		-0.078		-0.528	-0.247
			(-0.70)		(-0.10)		(-0.69)	(-0.31)
MKTVOL				-0.113		0.284	0.029	0.338
				(-0.27)		(0.56)	(0.07)	(0.71)
RMRF	0.059	0.065	0.058	0.059	0.065	0.067	0.058	0.066
	(0.64)	(0.71)	(0.62)	(0.64)	(0.71)	(0.73)	(0.62)	(0.73)
SMB	0.013	0.028	0.018	0.014	0.029	0.027	0.018	0.029
	(0.12)	(0.26)	(0.17)	(0.13)	(0.26)	(0.25)	(0.17)	(0.26)
HML	-0.005	0.024	-0.004	-0.005	0.024	0.029	-0.003	0.028
	(-0.03)	(0.19)	(-0.03)	(-0.04)	(0.19)	(0.23)	(-0.02)	(0.22)
Adj-Rsq	0.002	0.006	0.002	0.002	0.006	0.006	0.002	0.006
Obs	1,008	1,008	1,008	1,008	1,008	1,008	1,008	1,008

Table 7: Momentum in Big Firms and Market States

This table presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles for big firms in month t, $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). At the beginning of each month t, all common stocks listed on NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged eleven-month returns (formation period is from $t-12$ to $t-2$, skipping month $t-1$). For each momentum decile, big stocks are above the NYSE median based on market capitalization at the end of month $t-1$. All portfolio breakpoints are based on NYSE firms only. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Momentum Profit (WML) Regressed on Lagged Market Conditions								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.569***	1.856***	1.923***	2.628***	2.030***	2.340***	2.555***	2.311***
	(8.38)	(8.96)	(8.71)	(5.97)	(9.64)	(5.33)	(5.98)	(5.37)
MKTILLIQ		-0.315***			-0.271***	-0.271***		-0.250**
		(-3.45)			(-2.79)	(-2.62)		(-2.37)
DOWN			-1.938***		-1.171*		-1.391***	-0.980*
			(-3.43)		(-1.86)		(-2.75)	(-1.79)
MKTVOL				-1.211***		-0.599	-0.836*	-0.384
				(-2.77)		(-1.09)	(-1.94)	(-0.75)
RMRF	-0.364***	-0.352***	-0.370***	-0.367***	-0.357***	-0.355***	-0.370***	-0.358***
	(-3.09)	(-2.93)	(-3.06)	(-3.07)	(-2.94)	(-2.93)	(-3.06)	(-2.94)
SMB	-0.022	0.008	-0.004	-0.010	0.015	0.010	-0.000	0.015
	(-0.16)	(0.06)	(-0.03)	(-0.07)	(0.11)	(0.07)	(-0.00)	(0.11)
HML	-0.630***	-0.571***	-0.625***	-0.632***	-0.576***	-0.580***	-0.628***	-0.581***
	(-3.17)	(-3.29)	(-3.21)	(-3.25)	(-3.29)	(-3.31)	(-3.25)	(-3.30)
Adj-Rsq	0.201	0.221	0.211	0.211	0.224	0.223	0.215	0.225
Obs	1,008	1,008	1,008	1,008	1,008	1,008	1,008	1,008

Table 8: Price Momentum, Earnings Momentum, and Market States in Recent Years

This table presents the results of the following monthly time-series regressions,

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted portfolio return (WML, winner minus loser deciles) from the momentum strategy in month t. In Panels B to D, stocks are sorted into deciles according to the lagged earnings news in each month (Panel B) or quarter (Panels C and D), and the Loser (Winner) portfolio comprises of the bottom (top) decile of stocks with extreme earnings surprise. In Panel A, WML refers to the winner minus loser portfolio sorted on past eleven-month stock returns. In Panel B, earnings news is proxied by the changes in analysts' forecasts of earnings (REV), and $REV_{it} = \sum_{j=0}^{6}(f_{it-j} - f_{it-j-1})\,/P_{it-j-1}$, where f_{it-j} is the mean estimate of firm i's earnings in month $t-j$ for the current fiscal year, and P_{it-j-1} is the stock price. In Panel C, earnings news is proxied by the standardized unexpected earnings (SUE), and $SUE_{it} = (e_{iq} - e_{iq-4})/\sigma_{it}$, where e_{iq} and e_{iq-4} refer to quarterly earnings per share for stock i in quarter q and $q-4$, σ_{it} is the standard deviation of unexpected earnings $(e_{iq} - e_{iq-4})$ over the previous eight quarters. In Panel D, earnings news is proxied by the cumulative abnormal stock return (CAR) from day -2 to day $+1$ around the earnings announcement, where day 0 is the announcement day and the abnormal return is stock return adjusted by the equally-weighted market return. $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). The sample period is from May 2001 to 2011. Newey-West adjusted t-statistics are reported in parenthesis and numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Panel A: Price Momentum Profit Regressed on Lagged Market Conditions								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.237	3.371***	1.575***	3.716**	3.371***	4.476**	3.770**	4.532***
	(0.35)	(2.91)	(2.94)	(2.50)	(2.93)	(2.52)	(2.31)	(2.63)
MKTILLIQ		-4.764**			-4.901**	-3.728**		-4.104***
		(-2.01)			(-2.44)	(-2.32)		(-3.06)
DOWN			-3.319*		0.222		-1.731	0.698
			(-1.96)		(0.16)		(-1.29)	(0.47)
MKTVOL				-2.933**		-1.507	-2.390*	-1.582
				(-2.26)		(-1.41)	(-1.70)	(-1.40)
RMRF	-1.034***	-1.082***	-1.070***	-1.083***	-1.081***	-1.097***	-1.093***	-1.094***
	(-3.83)	(-4.08)	(-3.91)	(-3.86)	(-4.10)	(-4.02)	(-3.91)	(-4.03)
SMB	0.531**	0.685**	0.647**	0.569**	0.682**	0.671**	0.622**	0.660**
	(2.00)	(2.44)	(2.31)	(2.22)	(2.31)	(2.47)	(2.32)	(2.32)
HML	-0.224	-0.285	-0.260	-0.466	-0.285	-0.396	-0.439	-0.399
	(-0.35)	(-0.44)	(-0.38)	(-0.64)	(-0.44)	(-0.57)	(-0.59)	(-0.58)
Adj-Rsq	0.253	0.323	0.282	0.301	0.323	0.332	0.307	0.333
Obs	128	128	128	128	128	128	128	128

Table 8—Continued

Panel B: Earnings Momentum Profit (based on REV) Regressed on Lagged State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.120***	2.180***	1.767***	0.940*	2.179***	1.415**	1.007	1.325**
	(3.09)	(5.27)	(4.76)	(1.72)	(4.97)	(2.35)	(1.58)	(2.05)
MKTILLIQ		-1.611***			-1.126***	-2.328***		-1.713***
		(-3.15)			(-2.62)	(-3.51)		(-3.28)
DOWN			-1.603***		-0.789		-2.153***	-1.139*
			(-3.18)		(-1.38)		(-4.71)	(-1.94)
MKTVOL				0.152		1.043**	0.828	1.165**
				(0.29)		(2.18)	(1.62)	(2.49)
RMRF	-0.475***	-0.491***	-0.492***	-0.472***	-0.495***	-0.481***	-0.484***	-0.485***
	(-4.07)	(-4.31)	(-4.20)	(-3.91)	(-4.33)	(-4.24)	(-4.08)	(-4.26)
SMB	-0.223*	-0.171	-0.167	-0.225*	-0.159	-0.161	-0.159	-0.143
	(-1.81)	(-1.35)	(-1.29)	(-1.81)	(-1.22)	(-1.19)	(-1.15)	(-1.01)
HML	-0.343	-0.363	-0.360	-0.330	-0.366	-0.287	-0.298	-0.281
	(-0.94)	(-1.00)	(-0.94)	(-0.87)	(-0.97)	(-0.79)	(-0.76)	(-0.75)
Adj-Rsq	0.261	0.284	0.280	0.262	0.287	0.297	0.289	0.302
Obs	128	128	128	128	128	128	128	128
Panel C: Earnings Momentum Profit (based on SUE) Regressed on Lagged State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	0.763**	1.389***	1.003***	0.843**	1.389***	1.093**	0.864*	1.097*
	(2.52)	(3.02)	(3.44)	(2.02)	(3.01)	(2.09)	(1.89)	(1.93)
MKTILLIQ		-0.951***			-1.054	-1.228***		-1.255*
		(-2.83)			(-1.38)	(-3.41)		(-1.71)
DOWN			-0.593		0.169		-0.694	0.049
			(-1.60)		(0.20)		(-1.46)	(0.06)
MKTVOL				-0.067		0.403*	0.151	0.398
				(-0.27)		(1.72)	(0.45)	(1.51)
RMRF	-0.270***	-0.279***	-0.276***	-0.271***	-0.278***	-0.275***	-0.275***	-0.275***
	(-3.46)	(-3.49)	(-3.45)	(-3.36)	(-3.60)	(-3.39)	(-3.33)	(-3.46)
SMB	-0.008	0.023	0.013	-0.007	0.020	0.027	0.014	0.026
	(-0.06)	(0.18)	(0.09)	(-0.05)	(0.15)	(0.20)	(0.10)	(0.19)
HML	-0.262	-0.274	-0.268	-0.267	-0.274	-0.244	-0.257	-0.245
	(-0.89)	(-0.92)	(-0.89)	(-0.89)	(-0.93)	(-0.83)	(-0.83)	(-0.83)
Adj-Rsq	0.184	0.202	0.190	0.184	0.202	0.206	0.190	0.207
Obs	128	128	128	128	128	128	128	128
Panel D: Earnings Momentum Profit (based on CAR) Regressed on Lagged State Variables								
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	-0.170	1.198***	0.496**	1.200**	1.198***	1.555***	1.234**	1.545***
	(-0.57)	(3.93)	(2.23)	(2.25)	(3.92)	(2.79)	(2.16)	(2.68)
MKTILLIQ		-2.079***			-1.915***	-1.744***		-1.677***
		(-6.16)			(-3.44)	(-4.05)		(-2.68)
DOWN			-1.651***		-0.267		-1.117*	-0.125
			(-4.92)		(-0.38)		(-1.97)	(-0.17)
MKTVOL				-1.154***		-0.487	-0.804	-0.473
				(-3.11)		(-0.90)	(-1.52)	(-0.85)
RMRF	-0.297***	-0.318***	-0.315***	-0.316***	-0.319***	-0.322***	-0.323***	-0.323***
	(-4.53)	(-5.47)	(-5.08)	(-4.37)	(-5.61)	(-5.12)	(-4.77)	(-5.23)
SMB	0.242***	0.309***	0.300***	0.257***	0.313***	0.305***	0.291***	0.307***
	(2.83)	(3.72)	(3.18)	(2.97)	(3.69)	(3.62)	(3.13)	(3.61)
HML	-0.026	-0.052	-0.043	-0.121	-0.053	-0.088	-0.104	-0.087
	(-0.18)	(-0.41)	(-0.29)	(-0.72)	(-0.41)	(-0.56)	(-0.58)	(-0.55)
Adj-Rsq	0.120	0.200	0.163	0.165	0.201	0.206	0.180	0.206
Obs	128	128	128	128	128	128	128	128

Table 9: Momentum, Investor Sentiment and Market Illiquidity

At the beginning of each month t, all common stocks listed on NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged eleven-month returns (formation period is from $t-12$ to $t-2$, skipping month $t-1$). The portfolio breakpoints are based on NYSE firms only. This table reports the average monthly value-weighted holding period (month t) Fama-French three-factor adjusted returns of the bottom (loser) and top (winner) decile portfolios, as well as the momentum profits (WML, winner minus loser deciles). Models 1 to 3 report one-way sort results following high, median and low levels of investor sentiment, as classified based on the tercile of Baker and Wurgler (2007) sentiment index (in month $t-1$) over the entire sample period. Models 4 to 12 focus on a two-way sort, that is first sort into terciles by market illiquidity (proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms) in month $t-1$, and within each market illiquidity state, we further sort into terciles according to the contemporaneous investor sentiment. The sample period is from May 2001 to 2010. Newey-West adjusted t-statistics are reported in parentheses, and the numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

3-Factor Alpha of Momentum Decile Portfolios												
Rank of SENTIMENT	One-Way Sort			Low MKTILLIQ (Liquid)			Med MKTILLIQ			High MKTILLIQ (Illiquid)		
	1 (Loser)	10 (Winner)	WML	1 (Loser)	10 (Winner)	WML	1 (Loser)	10 (Winner)	WML	1 (Loser)	10 (Winner)	WML
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Low	1.661	-0.578	-2.238	0.864*	-0.459	-1.324*	-2.244***	0.203	2.447**	0.461	0.340	-0.121
	(1.49)	(-1.10)	(-1.47)	(1.92)	(-1.61)	(-1.93)	(-2.89)	(0.61)	(2.39)	(0.60)	(1.35)	(-0.13)
Med	0.449	0.433	-0.017	-0.270	0.100	0.369	0.466	0.841*	0.375	8.065***	-1.905*	-9.970**
	(0.81)	(1.66)	(-0.03)	(-0.59)	(0.33)	(0.72)	(0.57)	(1.92)	(0.43)	(2.79)	(-1.80)	(-2.57)
High	-2.275***	0.415	2.689**	-0.306	0.067	0.373	-3.529***	1.039	4.568***	-0.274	-0.909	-0.636
	(-2.85)	(0.70)	(2.02)	(-1.25)	(0.19)	(0.70)	(-5.64)	(1.32)	(3.31)	(-0.37)	(-1.29)	(-0.69)
High − Low	-3.935**	0.992	4.928**	-1.170**	0.527*	1.697***	-1.284	0.836	2.121	-0.735	-1.250*	-0.515
	(-2.58)	(1.04)	(2.09)	(-2.73)	(1.89)	(2.90)	(-1.35)	(0.90)	(1.23)	(-0.57)	(-1.96)	(-0.38)

Table 10: Momentum Profits and Investor Sentiment

This table presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + \beta_4 SENTIMENT_{t-1} + c'F_t + e_t,$$

$$WML_t = \alpha_0 + \beta_1 MKTILLIQ_{t-1} + \beta_2 DOWN_{t-1} + \beta_3 MKTVOL_{t-1} + \beta_4 Dummy(Low\ SENTIMENT)_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles in month t, $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return, $SENTIMENT_{t-1}$ is the monthly Baker and Wurgler (2007) market sentiment index, and $Dummy(Low\ SENTIMENT)_{t-1}$ is a dummy variable that takes the value of one if the investor sentiment is in the bottom tercile over the entire sample period. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). The sample period is from May 2001 to 2010. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

	Momentum Profit (WML) Regressed on Lagged Market Conditions					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	0.060	3.976***	4.932***	1.305*	4.157***	5.331***
	(0.09)	(2.86)	(2.78)	(1.71)	(2.82)	(2.83)
MKTILLIQ		-5.698**	-5.286***		-4.569**	-4.214***
		(-2.18)	(-2.89)		(-2.07)	(-3.25)
DOWN			1.154			1.580
			(0.87)			(0.93)
MKTVOL			-1.490			-1.754
			(-1.30)			(-1.51)
SENTIMENT	1.859	3.232*	3.122*			
	(1.21)	(1.84)	(1.90)			
Dummy (Low SENTIMENT)				-3.483*	-2.476*	-2.660*
				(-1.76)	(-1.66)	(-1.80)
RMRF	-1.059***	-1.069***	-1.081***	-1.022***	-1.097***	-1.100***
	(-3.66)	(-3.89)	(-3.86)	(-3.99)	(-4.28)	(-4.36)
SMB	0.477*	0.632**	0.610**	0.495*	0.635**	0.605**
	(1.72)	(2.33)	(2.24)	(1.84)	(2.43)	(2.25)
HML	-0.159	-0.305	-0.403	-0.192	-0.253	-0.376
	(-0.23)	(-0.44)	(-0.55)	(-0.27)	(-0.37)	(-0.52)
Adj-Rsq	0.283	0.373	0.380	0.298	0.357	0.369
Obs	117	117	117	117	117	117

Table 11: Momentum Profits and Cross-Sectional Illiquidity Gap

This table presents the results of the following monthly time-series regressions, as well as their corresponding Newey-West adjusted t-statistics,

$$WML_t = \alpha_0 + \beta_1 ILLIQGAP_{t-1} + \beta_2 MKTILLIQ_{t-1} + \beta_3 DOWN_{t-1} + \beta_4 MKTVOL_{t-1} + \beta_5 PSLIQ_t + c'F_t + e_t,$$

where WML_t is the value-weighted return on the winner minus loser momentum deciles in month t, $ILLIQGAP_{t-1}$ is the portfolio illiquidity gap between winner and loser momentum deciles, and the portfolio illiquidity is proxied by the value-weighted average of stock-level Amihud (2002) illiquidity, $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, $DOWN_{t-1}$ is a dummy variable that takes the value of one if the return on the value-weighted CRSP market index during the past twenty-four months ($t-24$ to $t-1$) is negative and zero otherwise, $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return, and $PSLIQ_t$ is the Pastor-Stambaugh liquidity factor. The vector F stacks Fama-French three factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). The sample consists of all common stocks listed on NYSE and AMEX over the period from May 2001 to 2011. Numbers with "*", "**" and "***" are significant at the 10%, 5% and 1% level, respectively.

Momentum Profit (WML) Regressed on Lagged Portfolio Illiquidity Gap and Market Conditions							
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	0.694	2.824***	4.059***	3.900***	4.591***	3.708**	1.538
	(0.94)	(3.43)	(3.62)	(2.71)	(3.01)	(2.39)	(1.12)
ILLIQGAP		0.380***	0.234**	0.293***	0.204**	-0.192	0.045
		(3.53)	(2.12)	(3.30)	(2.21)	(-1.39)	(0.55)
MKTILLIQ			-3.134**		-2.981***	-2.169*	-3.427**
			(-2.27)		(-2.66)	(-1.82)	(-2.20)
DOWN				-1.374	0.132	-0.375	0.301
				(-0.85)	(0.07)	(-0.25)	(0.15)
MKTVOL				-0.852	-0.719	-1.228	-1.086
				(-0.84)	(-0.70)	(-1.16)	(-1.09)
PSLIQ	0.095	0.009	-0.003	0.017	0.001	0.040	-0.064
	(0.61)	(0.08)	(-0.02)	(0.15)	(0.00)	(0.39)	(-0.72)
ILLIQGAP × MKTILLIQ						0.537**	
						(2.44)	
ILLIQGAP × RMRF							0.076***
							(4.93)
RMRF	-1.124***	-1.141***	-1.154***	-1.163***	-1.161***	-1.072***	-0.809***
	(-3.71)	(-3.98)	(-4.05)	(-3.93)	(-3.99)	(-3.67)	(-3.69)
SMB	0.717***	0.886***	0.930***	0.909***	0.918***	0.734***	0.866***
	(2.98)	(3.53)	(3.80)	(3.56)	(3.62)	(2.71)	(4.32)
HML	-0.315	-0.469	-0.445	-0.517	-0.488	-0.519	-0.100
	(-0.49)	(-0.67)	(-0.65)	(-0.71)	(-0.69)	(-0.79)	(-0.17)
Adj-Rsq	0.267	0.341	0.357	0.349	0.359	0.395	0.480
Obs	128	128	128	128	128	128	128

Figure 1: Time Series of Momentum Payoff and Market States (2001 − 2011)

This figure plots the time series of momentum portfolio payoff and market states, over the period between May 2001 and December 2011. At the beginning of each month t, all common stocks listed on NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged eleven-month returns (formation period is from $t-12$ to $t-2$, skipping month $t-1$) or lagged earnings news at month $t-2$, proxied by changes in analysts' forecasts of earnings (REV). The portfolio breakpoints are based on NYSE firms only. We report the average monthly value-weighted price momentum profits (WML, winner minus loser deciles) as well as earnings momentum profits (REV, extreme positive earnings surprise minus extreme negative earnings surprise deciles) in the holding period (month t). Market state variables (lagged at month $t-1$) include the aggregate market illiquidity ($MKTILLIQ$) and market return volatility ($MKTVOL$). $MKTILLIQ_{t-1}$ is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all NYSE and AMEX firms, and $MKTVOL_{t-1}$ is the standard deviation of daily CRSP value-weighted market return.