Time-Varying Momentum Payoffs and Illiquidity*

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Abstract

This paper shows that the momentum payoffs strongly vary with market illiquidity, consistent with behavioral models of investor overconfidence. Periods of high market illiquidity are associated with overconfident investors staying out of the market as well as widening differences in the illiquidity of winner and loser stocks. Consequently, illiquid periods are followed by low, and often massively negative, momentum payoffs. The predictive power of market illiquidity uniformly exceeds that of competing state variables, including market-return states, market volatility, and investor sentiment. While price and earnings momentum are nonexistent in the most recent decade, they become significant following low market illiquidity.

1. Introduction

The momentum trading strategy of buying past winner stocks and selling past loser stocks, as documented by Jegadeesh and Titman (1993), yields a significant 1.18 percent return per month over the 1928 through 2011 period. Momentum payoff realizations, however, could be low, often massively negative. For example, the momentum strategy records huge losses of 79 percent in August 1932 and 46 percent in April 2009. Indeed, recent work documents the time-series dependence of momentum payoffs on down market states ($DOWN$) as well as market volatility (see Cooper, Gutierrez, and Hameed (2004), Wang and Xu (2010), and Daniel and Moskowitz (2012)). However, the role played by the aggregate market illiquidity in explaining the determinants and evolution of momentum payoffs has been overlooked.

From a modeling perspective, the momentum-illiquidity relation follows from Daniel, Hirshleifer, and Subrahmanyam (henceforth DHS, 1998). In DHS, investors overreact to private information due to overconfidence, which together with self-attribution bias in their reaction to subsequent public information, triggers return continuation. The DHS model suggests that when overconfidence, along with biased self-attribution, is high, there is excessive trading, liquidity is high, and the momentum effect is strong. Conversely, illiquid market conditions are associated with reducing momentum payoffs. Theoretical predictions of the relation between market illiquidity (or excessive trading) and variation in investor overconfidence are also made by Odean (1998), Gervais and Odean (2001), and Baker and Stein (2004). For example, in the Baker and Stein (2004) model, overconfident investors underreact to information in order flow and lower the price impact of trades and hence improve liquidity. Baker and Stein assert that during pessimistic periods, overconfident investors keep out of the market due to short-sale constraints, and thus reduce market liquidity.[1] Hence, market illiquidity provides an indicator of the relative prominence of overconfident investors, who, according to DHS, drive the momentum effect.[2]

Indeed, this paper shows that momentum profitability crucially depends on the state of market illiquidity, as measured by Amihud (2002). For one, the momentum effect is strong (weak) when liquidity is high (low). Moreover, the predictive effect of market illiquidity on momentum subsumes the explanatory power of $DOWN$ and market volatility states, which have been shown to forecast momentum payoffs. To start, time-series regressions reveal that a one standard deviation increase in market illiquidity reduces the momentum profits by 0.87% per month, while the unconditional mean of the momentum payoff is 1.18%. Moreover, $DOWN$ and market volatility states display diminishing, often nonexistent, predictive power in the presence of market illiquidity. A cross-sectional analysis applied to individual stocks further reinforces the illiquidity-momentum relation. The slope coefficients in the regressions of stock returns on their own lags are the lowest following illiquid market states. While $DOWN$ and market volatility may indirectly capture variations in aggregate liquidity associated with the presence of overconfident traders, the direct effect of market illiquidity stands out.

Next, a two-stage procedure shows that controlling for the influence of the market state variables, particularly market illiquidity, on individual stock returns significantly diminishes the firm level momentum payoffs. The first stage removes the pure effect of market illiquidity, $DOWN$, and volatility states on expected stock returns. This is accomplished by

[1] An alternative explanation for the illiquidity-momentum relation is that positive feedback (or momentum) traders enter the market when cost of trading is low and stay out of the market when the cost of trading is high. To the extent that these momentum traders are uninformed, their absence (presence) is associated with illiquid (liquid) markets and low (high) momentum. We thank Yakov Amihud for this insight.

[2] 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.

running time-series predictive regressions of individual stock returns on these state variables. In the second stage, we estimate the cross-sectional relation of the unexpected part of individual stock returns with its own past returns. The resulting stock level momentum is considerably reduced and even completely disappears in several specifications (all of which account for market illiquidity). These findings suggest that aggregate illiquidity predicts individual stock price momentum and that removing the component in stock returns that varies with the illiquidity state significantly reduces the momentum effects.

The analysis is then extended to the most recent decade wherein the unconditional price momentum yields insignificant profits (Chordia, Subrahmanyam, and Tong (2013)). Strikingly, momentum profitability does resurface upon conditioning on the market states, particularly when the market is liquid. Although the introduction of decimal pricing in 2001 considerably reduced trading costs, we detect significant remnants of momentum profits after accounting for variations in aggregate market illiquidity. Specifically, the momentum profits increases dramatically from −0.69 percent when markets are illiquid to 1.09 percent during relatively liquid market states. 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. Indeed, in DHS, the same psychological forces of investor overconfidence and self-attribution bias also bring about the price continuations in response to (public) earnings information.[3] Consistent with DHS predictions, earning momentum payoffs are significantly lower following periods of low market liquidity, reducing market valuations, and high market volatility. Examining all these three market state variables jointly, the effect of aggregate market illiquidity dominates.

We essentially account for the recent evidence that momentum payoffs depend on inter-temporal variation in investor sentiment, as documented by Stambaugh, Yu, and Yuan (2012)

[3] Barberis, Shleifer, and Vishny (1998) also develop a model where earnings and price momentum is generated by the psychological biases of representative heuristic and conservatism.

and Antoniou, Doukas, and Subrahmanyam (2013). The predictive effect of illiquidity on momentum payoffs is robust even in the presence of the investor sentiment index of Baker and Wurgler (2006, 2007). When the equity market is illiquid, momentum is unprofitable in all sentiment states, and negative momentum payoffs are recorded even during optimistic states. Clearly, market illiquidity represents a unique economic determinant of the momentum effect.

The momentum strategy goes long on winners (less illiquid stocks) and short on losers (more illiquid stocks). Thus, by construction, momentum is a long-short liquidity minus illiquidity strategy. Further, a positive cross-sectional relation between illiquidity level and stock return is well established (Amihud and Mendelson (1986) and Amihud (2002)). Therefore, conditioning on market liquidity states could potentially predict the time variation in momentum payoffs by affecting the illiquidity spread between the long and short sides of the momentum strategy. Indeed, our empirical findings confirm this intuition. 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, two reinforcing effects are at work. First, the high trading costs diminish the prominence of overconfident investors. Second, the illiquidity gap between 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 portfolio level and market level illiquidity on momentum payoffs add 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). Indeed, while there is a general positive correlation between liquidity risk and illiquidity level as documented in Archarya and Pedersen (2005), the correlation turns negative among the extreme winner and loser portfolios.

As a final remark, it should be noted that our evidence holds when the sample is restricted exclusively to large firms, indicating that the overall findings are not limited to illiquid stocks that make up a small fraction of the equity market. Moreover, we also examine the interaction of momentum and market illiquidity in subsets of stocks grouped by firm volatility. Jiang, Lee, and Zhang (2005), for example, argue that the investor overconfidence in DHS model is exacerbated with greater volatility, generating stronger momentum in high volatility stocks. We add to the evidence by showing that the state of aggregate illiquidity has a bigger impact on momentum profits in high volatility stocks, consistent with momentum payoffs varying with the psychological biases in DHS.

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 1928 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 (Jegadeesh (1990)). 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 are gathered from COMPUSTAT. The earnings announcement dates are obtained from I/B/E/S and COMPUSTAT following the procedure outlined by DellaVigna and Pollet (2009).

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 instance, 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 return increases to 1.5 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 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 of the momentum strategy is potentially linked to the overall illiquidity at the market level.

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[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.

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 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.

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

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. All 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 (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:

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

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 these two competing variables is essential.

The vector F stands for the Fama-French three factors, including the market factor, the size factor, and the book-to-market factor. The regression model gauges the ability of the three state variables, i.e., the market illiquidity, $DOWN$ market states, and the market volatility, to predict the risk-adjusted returns on the momentum portfolio. We also run 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 as well as the Newey-West adjusted t-statistics are reported in Panel A of Table 2. The evidence in 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. This supports the notion that illiquid markets are associated with less trading by overconfident investors and therefore lower momentum payoffs, as suggested by the DHS model.

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 10% 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% during the entire sample.[6] Indeed, the evidence arising 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 the winner and loser payoffs separately as the dependent variables. In particular, we regress excess returns on the value-weighted loser and winner portfolios separately on the same set 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 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 $MKTILLIQ$ for loser stocks ranges between 0.133 and 0.199, while the corresponding figures for winner stocks are −0.12 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 $MKTVOL$. Conversely, 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.

[6]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] Running the regression using $INNOV\_MKTILLIQ$ reveals that market illiquidity continues to be significant at conventional levels.

In sum, 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). Including aggregate market illiquidity weakens, often eliminates, the explanatory power of these alternative market state and volatility variables in time-series predictive regressions.

The dominance of market illiquidity is consistent with recent empirical and theoretical work. In particular, Hameed, Kang, and Viswanathan (2010) demonstrate that negative market returns and high market volatility are related to stock illiquidity. The volatility-illiquidity interaction is also confirmed 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. From a modeling perspective, the volatility, return, and illiquidity relation is consistent with equilibrium models that predict liquidity dry-ups following periods of increasing market volatility.[8]

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

[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).

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.

In our context, expanding the analysis to individual stocks is also useful as the WML portfolio considers only the extreme winner and loser stocks. We propose a two-stage analysis here. The first stage entails 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, $ILLIQ_{i,t-1}$, which would account for firm level liquidity effects. The second regression is similar except that we not only account for past returns but also for past negative returns. This allows one to examine if firm level momentum is different for loser stocks.

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

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

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

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 considers time-series regressions. 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. The time-series regressions are formulated as

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

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

The empirical analysis excludes NASDAQ stocks to make sure that the trading volume-related Amihud (2002) illiquidity is comparable across stocks. The time-series averages of the first cross-sectional regression coefficients are reported in Panel A of Table 3.

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 negative past return variable is highly significant recording a slope coefficient equal to 0.015, and illiquid stocks earn higher future returns than more liquid stocks. 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.

Next, in Panel B of Table 3, we estimate the 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 (Models 2 and 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. The predictive ability of the $DOWN$

market state (Model 4) and $MKTVOL$ (Model 5) vanishes in the presence of market illiquidity. For example, the estimated slope coefficient in Model 4 is -0.521 and its t-value is -0.39. In contrast, in all specifications, the level of market illiquidity displays a robust negative effect on momentum in individual securities.

In Panel C of Table 3, the dependent variable is the individual stock momentum following negative past stock returns (β_{Nt}), 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, $MKTILLIQ$ records negative and strongly significant slope coefficients across the board. In un-tabulated analysis, we control for the effect of individual stock volatility on stock returns in Equations (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 the prominence of investor overconfidence affects the momentum-illiquidity relation and the momentum 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 $DOWN$ market 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 predictive effect of these state variables accounts for the documented price momentum.

The proposed analysis is based on a two-pass regression method, 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,

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

(4)

where $R_{i,t}^{e}$ is the excess return of stock i in month t, $MKTILLIQ_{t-1}$, $DOWN_{t-1}$, $MKTVOL_{t-1}$stand for market illiquidity, down market return dummy, and market volatility, respectively. The vector F stacks the 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 co-variation with lagged state variables captures the momentum effect. Specifically, we estimate the following monthly cross-sectional regressions,

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

(5)

Panel A of Table 4 presents the cross-sectional average of first-stage results in Equation (4). Model 2 indicates that high aggregate market illiquidity ($MKTILLIQ$) predicts a higher risk-adjusted 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). Accounting for all three state variables (Model 8), the evidence shows that $MKTILLIQ$ 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.

Panel B presents the estimate of the second-stage regression in Equation (5). Interestingly, accounting for the predictability of individual stock returns using the aggregate state variables lowers the stock level momentum. In the presence of $MKTILLIQ$, the slope coefficient, which represents the residual momentum effect, reduces from 0.006 (Model 1) to 0.003 (Model 2). The slope coefficient also 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 these market state variables, and market illiquidity in particular, predict stock returns, but that the proper adjustment for market states substantially eliminates the 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 analyses, for both value-weighted portfolios and individual stocks. Momentum strategy payoffs are significantly reduced following illiquid market states. Furthermore, the market illiquidity provides additional explanatory power to the previously documented effects of down market and market volatility.

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:

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

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-

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

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

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

5. Further Analyses and Robustness Checks

5.1 Momentum-Volatility Interactions and Market States

Prior work shows that the momentum trading strategy delivers payoffs that vary across firms as well as through time with the level of investor overconfidence, consistent with the predictions in DHS. Jiang, Lee, and Zhang (2005) provide several arguments for investor overconfidence, and thus momentum, to be exacerbated with greater uncertainty about firm value. First, investor overconfidence is amplified when the difference between the investor's subjective (narrower) distribution of firm values and actual distributions are likely to be greater. Second, overconfident investors trade more aggressively on their private signals since the quality of public signals is difficult to access. Third, public signals are noisier with greater information uncertainty. These reasoning imply that the overconfidence bias induced momentum is likely to have a bigger effect for firms with greater uncertainty or price volatility. Evidence in support of this hypothesis is provided in Jiang, Lee, and Zhang (2005) and Zhang (2006). A natural question that arises is whether the market state variables considered here, which proxy for the state of aggregate overconfidence, are able to explain the differential drift in stock prices across firms grouped by uncertainty.

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 information uncertainty measures, we focus on portfolios of stocks sorted by stock volatility.[10] 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. 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 A of Table 6, the risk-adjusted momentum payoff for the high volatility stocks is significant at 1.98 percent per

[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.

month (Model 1). In Model 2, we find that the momentum payoffs are significantly lower following 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 payoff decreases monotonically across the volatility groups.

Next, we regress the difference in momentum payoffs between the high and low volatility stocks on the explanatory variables, considering all the eight specifications. The results are reported in Panel C of Table 6. As shown in Model 1 of Panel C, the additional momentum profits of 0.64 percent attributable to the high volatility stocks is significant. If the stronger momentum among high volatility stocks is related to greater investor overconfidence bias, we ought to see variations in aggregate overconfidence to have a bigger impact as well. Consistent with this expectation, variations in the state of $MKTILLIQ$ significantly explain the higher momentum in stocks with greater overconfidence bias, 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 add to the evidence on the ability of psychological biases in the DHS model, as measured by the state of aggregate market illiquidity, to explain the variation in momentum payoffs across firms and through time.

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 for 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 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, $MKTILLIQ$ also stands out as the strongest predictor in the sub-sample of large firms in all specifications, emphasizing our main contention that the 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 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 eight models studied earlier. Trading strategies that exploit the post earnings announcement drift effect have been shown to be profitable (e.g., Ball and Brown (1968), Bernard and Thomas (1989), Chan, Jegadeesh, and Lakonishok (1996), and Chordia and Shivakumar (2006)). DHS assert that the same psychological biases that generate price momentum in their model also give rise to 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 in 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. To gauge the economic magnitude of the effect of $MKTILLIQ$ states, we compute WML in illiquid (liquid) sub-periods defined as those months with above (below) the median value of $MKTILLIQ$ in the 2001−2011 sample. There is a marked increase in WML, from −0.69 percent (t-stats = −0.50) when the market is illiquid to 1.09 percent (t-stats = 2.20) per month in liquid market states.

Additionally, we obtain similar evidence that months following $DOWN$ markets and 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 complements the cumulative results we have presented thus far: the

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

state of market illiquidity dominantly governs the (lack of) profitability of price momentum strategies.

Panels B to D in Table 8 lay 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 Fama-French risk factors. Unlike the disappearance of price momentum, significant earnings momentum is recorded 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, $MKTILLIQ$ 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 predictive regression is estimated with only one explanatory 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 (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 (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 complements the cumulative evidence we have presented. Consistent with the prediction in DHS, 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 the Illiquidity Effect?

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 stems 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 examine whether the predictive effect of illiquidity on momentum payoffs are subsumed by variation in investor sentiment.

We first document the momentum payoffs across states of investor sentiment. Our investor sentiment index is based on 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 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, a significant positive WML payoff of 2.69 percent per month is recorded 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 lowest (highest) $MKTILLIQ_{t-1}$ tercile corresponds to the most liquid (illiquid) period. Within each of the three $MKTILLIQ_{t-1}$ terciles, the observations are further sorted 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.

The evidence shows a strong influence of market illiquidity states on the momentum payoffs. When the equity market is illiquid, momentum is unprofitable in all sentiment states, including the most optimistic state. Moreover, the WML portfolio displays negative payoffs when sentiment is High but the market is illiquid.

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. To address this correlation, we run various predictive regressions with different combinations of the predictive variables. We consider two alternative definitions of the sentiment variable. The

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

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 display low momentum payoffs. The exception is in Model 1, 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 specifications and the two sentiment variables are only significant at the 10% level.

5.5 Momentum and the Illiquidity Gap

The evidence thus far indicates that the momentum strategy is unprofitable 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 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 lower payoffs in times when the cross-sectional difference in illiquidity between the loser and winner portfolio is large. Moreover, the cross-sectional differences in illiquidity are expected 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 examine whether momentum payoffs are significantly lower following periods when the loser portfolio is relatively more illiquid than winners. To pursue the task, the regression in Equation (1) is estimated with $ILLIQGAP_{t-1}$ as an additional explanatory variable.

Our analysis of the effect of illiquidity level differs from the important work of Pastor and Stambaugh (2003), Sadka (2006) and Assness, Moskowitz, and Pedersen (2013) − all of which examine the liquidity risk (beta) exposure of the momentum strategies. Their investigations show that the momentum portfolio has significant exposure to variations in the systematic liquidity factor, which, in turn, explains some, albeit small, portion of momentum payoffs. 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).

The results are reported in Table 11. Starting with Model 2, $ILLIQGAP_{t-1}$ predicts significantly lower momentum profits when the loser portfolio is more illiquid than the winner portfolio. Model 3 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 the estimated coefficients either.

We note that $ILLIQGAP_{t-1}$ and $MKTILLIQ_{t-1}$have a strong contemporaneous correlation of −0.66, implying that the illiquidity gap between the winners and losers is more negative when the market is highly illiquid. We consider the interaction of these two variables and find the effect to be highly significant, as depicted in Model 6. The latter findings emphasize that the gap in the liquidity between losers and winner has the biggest impact on expected momentum profits when the aggregate market is most illiquid. Interacting $ILLIQGAP_{t-1}$ with excess return on the market portfolio $RMRF_t$ yields a significant positive coefficient (Model 7). 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 by Daniel and Moskowitz (2012).

Our findings in Table 11 highlight 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 (more illiquid) loser 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 due to high trading costs, 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 negative momentum payoffs, and in some extreme scenarios, momentum crashes.

[13] There is a positive relation between liquidity betas and illiquidity level in portfolios sorted by illiquidity levels (see, e.g. Acharya and Pedersen (2005)). However, 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.

6. Conclusion

This paper implements comprehensive in- and out-of-sample experiments, using both time-series and cross-sectional specifications, to show that payoffs to momentum trading strategies are predicted by the state of market illiquidity. Periods of high (low) market illiquidity are followed by low (high) momentum payoffs. In the presence of market illiquidity, the power of the competing state variables that have been shown to predict variation in momentum profits, namely down market states and market volatility, is attenuated and often even disappears altogether.

From a modeling perspective, the momentum-illiquidity relation is implied by the behavioral theory of Daniel, Hirshleifer, and Subrahmanyam (1998) and is also supported by Odean (1998), Gervais and Odean (2001), and Baker and Stein (2004). In these models, high market illiquidity is associated with low investor overconfidence and self-attribution bias, and hence, low momentum payoffs. Consistent with a positive relation between volatility and investor overconfidence, we find that high volatility stocks generate higher momentum payoffs than low volatility stocks, and the state of market illiquidity has a bigger impact on high volatility stocks. Moreover, our evidence of lower profits to the momentum portfolio strategy following illiquid market states holds when the sample is restricted exclusively to large firms, indicating that the overall findings are not limited to small illiquid stocks that make up a small fraction of the equity market.

Examining momentum profitability in the most recent decade reveals several intriguing findings. While the price momentum strategy is no longer profitable in this period with an insignificant profit of 0.24 percent per month, significant profitability is regained upon conditioning on the state of the market illiquidity. Specifically, the momentum profit rises dramatically from an insignificant −0.69 percent when the aggregate market is illiquid to a significant 1.09 percent in relatively liquid markets. 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. Analogous findings are attained: the drift in stock prices following the release of earnings information is weaker when the market is illiquid. Our findings are consistent with the model in Daniel, Hirshleifer, and Subrahmanyam (1998) in that the same psychological biases drive price as well as earnings momentum. The results point to the dependence of both price and earnings momentum payoffs on the state of market illiquidity, which often subsumes the predictive power of market states defined by $DOWN$ market returns and market volatility. Moreover, when the market is illiquid, momentum is unprofitable in all investor sentiment states, and negative momentum payoffs are recorded even in the most optimistic state.

We note that the long-short momentum investment is, by construction, a liquid (winner) minus illiquid (loser) portfolio strategy. A positive cross-sectional relation between stock illiquidity and expected returns (Amihud (2002)) implies that this negative illiquidity gap reduces the returns to the momentum strategy. We show that in normal (liquid) market states, this reduction is overwhelmed by the presence of overconfident investors that trigger return continuation. However, the negative illiquidity gap between the winner and loser stocks widens sharply when the aggregate market is illiquid. This effect in conjunction with the disappearance of overconfident investors gives rise to low, and often massively negative, momentum profits, or momentum crashes.

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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	-6.217

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,

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

where $R^e_{i,t}$ 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 the 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.