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Time-Varying Liquidity and Momentum Profits

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Abstract

A basic intuition is that arbitrage is easier when markets are most liquid. Surprisingly, we find that momentum profits are markedly larger in liquid market states. This finding is not explained by variation in liquidity risk, time-varying exposure to risk factors, or changes in macroeconomic condition, cross-sectional return dispersion, and investor sentiment. The predictive performance of aggregate market illiquidity for momentum profits uniformly exceeds that of market return and market volatility states. While momentum strategies have been unconditionally unprofitable in the United States, in Japan, and in the Eurozone countries in the last decade, they are substantial following liquid market states.

I. Introduction

The economic notion of limits to arbitrage suggests that the profitability of anomaly-based trading strategies should be lower when markets are liquid. The evidence concerning many of these anomalies has typically been supportive of this notion. For example, Chordia, Subrahmanyam, and Tong (2014) offer this interpretation of their finding that the recent regime of increased stock market liquidity is contemporaneous with the attenuation of equity return anomalies due to increased arbitrage. They find that the decrease in tick size due to decimalization in the U.S. stock exchanges has lowered trading costs and attenuated the profitability of prominent anomaly-based trading strategies in the recent decade, consistent with the effect of greater arbitrage activities. To test more directly the

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role of liquidity for arbitrage, we examine the systematic relation between variations in market liquidity and the strength of the momentum anomaly (Jegadeesh and Titman (1993)).[1] We focus on momentum because it is a robust and well-known anomaly that is not explained as a risk premium and, therefore, is subject to arbitrage.

If variations in momentum payoffs reflect changes in arbitrage constraints, we expect a positive relation between momentum profits and aggregate market illiquidity. We find that the effect goes in the opposite direction, and strongly so. The evidence is that momentum profits are large (weak) when the markets are highly liquid (illiquid). On the basis of the Amihud (2002) illiquidity measure, time-series regressions reveal that a 1-standard-deviation increase in aggregate market illiquidity reduces the momentum profits by 0.87% per month over the 1928–2011 period. For perspective, the unconditional raw monthly long-short momentum payoff is 1.18%, and the Fama–French alpha is 1.73%. Our findings are contrary to the intuition that arbitrage of the momentum anomaly is easier when markets are most liquid.

The negative momentum-illiquidity relation is also quite robust. For example, the findings survive after controlling for 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 (2015), and Daniel and Moskowitz (2014)). Similar results emerge when the Amihud measure is replaced by the illiquidity measure recently developed by Corwin and Schultz (2012). The predictive effect of market illiquidity is also significant when the sample is restricted exclusively to large firms, indicating that the findings are not limited to illiquid stocks, which make up a small fraction of the aggregate market capitalization.

The findings on the association between market illiquidity and momentum payoffs complement the important studies on the liquidity risk (beta) exposure of the momentum portfolio in Pástor and Stambaugh (2003), Sadka (2006), and Asness, Moskowitz, and Pedersen (2013). After limiting the exposure of our portfolios to liquidity risk, we continue to find a significant negative loading of market-illiquidity state on momentum payoffs. Hence, the predictive effect of market illiquidity on momentum payoffs is different from the exposure of momentum to liquidity risk. Additionally, the negative illiquidity-momentum relation is not subsumed by time variation in the factor risk exposures emphasized by Grundy and Martin (2001), Korajczyk and Sadka (2004), and Daniel and Moskowitz (2014).

To explore more deeply the dynamics of momentum and illiquidity, we examine the association between aggregate illiquidity and the difference in the degree of illiquidity of winner and loser portfolios. The momentum strategy goes long on winners (which tend to be liquid) and short on losers (which tend to be illiquid). A positive cross-sectional relation between illiquidity level and stock return (Amihud and Mendelson (1986), Amihud (2002)) implies that loser stocks should earn *higher* return. We find that when markets are liquid, price

[1]Different from the evidence in Chordia et al. (2014), we examine the time-varying nature of the relation between market liquidity and momentum payoffs.

continuations dominate the cross-sectional liquidity effects, hence generating a positive momentum payoff. On the other hand, when the market as a whole is illiquid, the large illiquidity gap between the loser and winner portfolios further reduces the momentum payoff, as the loser portfolio earns a much higher subsequent return. Consequently, momentum payoffs are considerably lower following illiquid markets.

The analysis is then narrowed to the most recent decade, wherein technological developments have lowered the barriers to arbitrage and the unconditional momentum strategy yields insignificant profits, as noted in Chordia et al. (2014). Remarkably, the momentum profitability resurfaces upon conditioning on the market states, particularly when the market is highly liquid. Although the introduction of decimal pricing in 2001 considerably reduced trading costs, we detect substantial remaining momentum profits after accounting for variations in aggregate market illiquidity. Specifically, the monthly momentum profits increase dramatically from −0.69% when markets are illiquid to 1.09% during relatively liquid market states.

Moreover, over the past decade, there has been an almost identical predictive effect of the lagged market state variables on the profitability of the earnings momentum strategy. Indeed, earnings momentum payoffs are significantly lower following periods of low market liquidity, reduced market valuations, and high market volatility. When examining these three market state variables jointly, we find that the effect of aggregate market illiquidity dominates.

We consider the possibility that stock market illiquidity is an indicator of the state of the real economy, as suggested by Næs, Skjeltorp, and Ødegaard (2011), and that variation in momentum payoffs reflects time-varying expected returns over the business cycle (Chordia and Shivakumar (2002)). Our findings on the predictive effect of market illiquidity on momentum payoffs are unaffected when we control for various measures of the macroeconomy. The effect of liquidity is also robust to, and partially subsumes, the recent evidence that momentum payoffs depend on intertemporal variation in investor sentiment, as documented by Stambaugh, Yu, and Yuan (2012) and Antoniou, Doukas, and Subrahmanyam (2013). Clearly, market illiquidity captures a unique dimension of the time-varying momentum profits.

When we extend the analysis to the non-U.S. markets of Japan and the 10 countries establishing the Eurozone, we find similar evidence of significant time variation in momentum payoffs in relation to market illiquidity. Most strikingly, while it is well known that momentum is unprofitable in Japan (e.g., Griffin, Ji, and Martin (2003), Chui, Titman, and Wei (2010)), the strategy yields substantial and significant profits following periods of low market illiquidity.

The paper is organized as follows: Section II presents a description of the characteristics of the momentum portfolios. In Section III, we provide evidence on the effect of market illiquidity and other state variables on momentum payoffs. Further analyses of the momentum-illiquidity relation using the recent sample period are presented in Section IV. Several robustness checks are provided in Section V, followed by some concluding remarks in Section VI.

II. Data Description

The sample consists of all common stocks listed on the New York Stock Exchange (NYSE), American Stock Exchange (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 Jan. 1928–Dec. 2011 period. Our portfolio formation method closely follows the approach in Daniel and Moskowitz (2014). Specifically, at the beginning of each month t, all common stocks are sorted into deciles based on their lagged 11-month returns. Stock returns over the portfolio formation months, $t-12$ to $t-2$, are used to sort stocks into 10 portfolios. The top (bottom) 10% of stocks constitute the winner (loser) portfolios. The breakpoints for these portfolios are based on returns of those stocks listed on the NYSE only, so that the extreme portfolios are not dominated by the more volatile NASDAQ firms. The holding period returns for each stock are 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 (2014), we require the stock to have a valid share price and number of shares outstanding at the formation date and at least eight valid monthly returns over the 11-month formation period.

We first provide some summary statistics on the portfolios used in evaluating the momentum strategy. As shown in Panel A of Table 1, 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%. Consistent with the existing literature, these profits are not due to exposure to common risk factors. For instance, the WML returns are higher after adjusting for the Fama–French (1993) common risk factors: market (excess return on the value-weighted CRSP market index over the 1-month T-bill rate, RMRF), size (small-minus-big return premium, SMB), and value (high book-to-market minus low book-to-market return premium, HML).[2] The Fama–French 3-factor risk-adjusted return for the WML portfolio is highly significant at 1.73% per month.

Table 1 also presents other characteristics of the portfolios. For instance, the momentum profit (WML) is highly negatively skewed (skewness $=-6.25$), suggesting that momentum strategies come with occasional large crashes (Daniel and Moskowitz (2014)). To compute the portfolio average illiquidity, we employ the Amihud (2002) measure, $\text{ILLIQ}_{i,t}$, defined as $[\sum_{d=1}^{n}|R_{i,d}|/(P_{i,d}\times N_{i,d})]/n$, where n is the number of trading days in each month t, $|R_{i,d}|$ is the absolute value of the 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 the value of the Amihud illiquidity measure.

We find striking cross-sectional differences in the (value-weighted) average illiquidity of these portfolios. In particular, the average ILLIQ of the loser portfolio is 8.4, which is markedly higher compared to the ILLIQ of between 0.8 and 2.2

[2]We thank Kenneth French for making the common factor returns available via his Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

TABLE 1

Descriptive Statistics for Momentum Portfolios and Market States

Panel A of Table 1 presents characteristics of the monthly momentum portfolio in our sample during the period 1928–2011. At the beginning of each month t, all common stocks listed on the NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged 11-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 deciles). The returns are further adjusted by the CAPM and Fama–French 3-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). The 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 (2014). 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 (1987) adjusted t-statistics are reported below in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, 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

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)

for the other nine portfolios. We explore the effect of cross-sectional differences in the average illiquidity of the loser and winner portfolios on the performance of the momentum strategy in Section III.D.

In Panel B of Table 1, 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 the NYSE/AMEX and NASDAQ stock exchanges (Atkins and Dyl (1997)).[3] 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.[4]

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, following Cooper et al. (2004), 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}), which takes the value of 1 only if a negative cumulative two-year return is recorded in month $t-1$. The correlation between DOWN market states and momentum profits is a significant −0.13, consistent with Cooper et al. (2004).

Wang and Xu (2015) document that, in addition to DOWN market states, the aggregate market volatility significantly predicts momentum profits. Using 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}, we find a significant negative correlation between MKTVOL_{t-1} and WML_t (−0.12), confirming the findings in Wang and Xu (2015).

Moreover, as we show in Panel B of Table 1, all three aggregate market-level variables (MKTILLIQ, DOWN, and MKTVOL) are reasonably correlated, with correlations ranging from 0.33 to 0.42. While the univariate correlation between WML_t and MKTILLIQ_{t-1} is supportive of a significant role for aggregate liquidity, it is important to evaluate the relative predictive power of the three dimensions of market conditions. Indeed, we show in our analysis that the market illiquidity appears to be the strongest predictor of momentum profitability.

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 described in Amihud and Hurvich (2004).

[3]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).

[4]In unreported results, we consider an alternative measure that captures the innovations in aggregate market illiquidity, $\text{INNOV\_MKTILLIQ}_{t-1}$. 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: We obtain a significant correlation of −0.12 between $\text{INNOV\_MKTILLIQ}_{t-1}$ and WML_t.

III. Time Variation in Momentum Payoffs

A. Price Momentum in Portfolio Returns

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

$$(1) \qquad \mathrm{WML}_t = \alpha_0 + \beta_1 \mathrm{MKTILLIQ}_{t-1} + \beta_2 \mathrm{DOWN}_{t-1} + \beta_3 \mathrm{MKTVOL}_{t-1} + c' F_t + e_t.$$

More precisely, we consider all eight combinations of the predictive variables, starting with the IID model, which drops all predictors and retains the intercept only, and ending with the all-inclusive model, which retains all predictors. The predictive variables include three aggregate measures of the market conditions in the prior month: MKTILLIQ, the level of market illiquidity; DOWN, the state of the market return; and MKTVOL, the aggregate market volatility. The vector F stands for the Fama–French three factors, including the market factor, the size factor, and the book-to-market factor. We also run predictive regressions excluding the Fama–French risk factors and obtain similar results (which are not reported to conserve space but available from the authors).

The estimates of the eight regression specifications are reported in Panel A of Table 2. The evidence 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).

Consistent with Cooper et al. (2004) and Wang and Xu (2015), we also find that momentum payoffs are lower in DOWN market states and when market volatility (MKTVOL) is high. Panel A of Table 2 shows that the inclusion of MKTILLIQ weakens the predictive influence of DOWN and MKTVOL on WML. To illustrate, consider Model 8, which is an all-inclusive specification. While market illiquidity is statistically significant at conventional levels, market volatility is insignificant and the market states variable is significant only at the 10% level. Further, a 1-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 of 1.18% during the entire sample.[5] 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.[6]

We consider the same eight regression specifications using the winner and loser payoffs separately as the dependent variables and present the results in

[5]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.

[6]Running the regression using INNOV_MKTILLIQ reveals that innovation in market illiquidity continues to be significant at conventional levels.

Panels B and C of Table 2. 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 slightly 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 return states and market volatility weakens considerably, often disappearing, in the presence of market illiquidity (see, e.g., Model 8 of Panel C).

TABLE 2
Momentum Profits and Market States

Panel A of Table 2 presents the results of the following monthly time-series regressions as well as their corresponding Newey–West (1987) adjusted t-statistics (reported below in parentheses):

$$\mathrm{WML}_t \quad = \quad \alpha_0 + \beta_1 \mathrm{MKTILLIQ}_{t-1} + \beta_2 \mathrm{DOWN}_{t-1} + \beta_3 \mathrm{MKTVOL}_{t-1} + c' F_t + e_t,$$

where WML_t is the value-weighted return on the WML momentum deciles in month t; $\mathrm{MKTILLIQ}_{t-1}$ 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 1 if the return on the value-weighted CRSP market index during the past 24 months ($t-24$ to $t-1$) is negative, and 0 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 variables are the excess value-weighted portfolio return in loser and winner deciles, respectively. The sample period is 1928–2011. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel A. Momentum Profit (WML) Regressed on Lagged Market State Variables								
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. R^2	0.232	0.254	0.246	0.247	0.259	0.259	0.252	0.261
Panel B. Excess Loser Portfolio Return Regressed on Lagged Market State Variables								
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. R^2	0.783	0.787	0.787	0.786	0.789	0.788	0.788	0.790

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TABLE 2 (continued)
Momentum Profits and Market States

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel C. Excess Winner Portfolio Return Regressed on Lagged Market State Variables								
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. R^2	0.757	0.763	0.759	0.761	0.764	0.764	0.761	0.764

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 et al. (2004), Wang and Xu (2015)).

B. Liquidity Risk Effects

Our analysis of the effect of illiquidity level differs from the important work of Pástor and Stambaugh (2003), Sadka (2006), and Asness et al. (2013), all of whom 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. Hence, we examine whether the momentum-illiquidity relation is explained by variations in its liquidity risk exposures.

We start by constructing the momentum portfolio, which is liquidity risk neutral. Specifically, at the beginning of each month t, the liquidity beta is estimated for each NYSE/AMEX stock based on a 4-factor model estimated over the previous (rolling) 60 months, where the factors are the Fama–French three factors and the shock to the Amihud (2002) market-illiquidity factor. The market-illiquidity shock is measured as the residual of the logarithm of market liquidity in an AR(1) process (Amihud (2002)). The stocks are then sorted into quintiles depending on their liquidity beta. Within each liquidity-beta group, we compute the (value-weighted) returns of the winner and loser deciles, which are defined according to their formation period returns from months $t-12$ to $t-2$. The overall loser (winner) portfolio return is the equal-weighted average of all the bottom (top) decile portfolios across all liquidity-beta quintiles. The resulting liquidity-beta neutral momentum portfolio returns are regressed on the four factors as well as MKTILLIQ and other state variables.

As shown in Table 3, the liquidity-beta neutral momentum portfolio has slightly lower risk-adjusted momentum profits. Of particular interest is the coefficient associated with the state of the market illiquidity, which is lower for the

TABLE 3

Momentum Profits in Liquidity-Beta Neutral Portfolios

In Table 3, stocks are first sorted into quintiles according to their lagged liquidity beta. Within each liquidity-beta group, stocks are sorted into deciles according to their lagged 11-month accumulated returns to generate 50 (5×10) portfolios. Value-weighted portfolio returns are calculated after skipping one month following the formation period, and the loser (winner) portfolio return is the average return on the bottom (top) past the 11-month return decile portfolios across the five liquidity-beta groups. Table 3 presents the results of the following monthly time-series regressions as well as their corresponding Newey–West (1987) adjusted t-statistics (reported below in parentheses):

$$\text{WML}_t = \alpha_0 + \beta_1 \text{MKTILLIQ}_{t-1} + \beta_2 \text{DOWN}_{t-1} + \beta_3 \text{MKTVOL}_{t-1} + c'F_t + e_t,$$

where WML_t, MKTILLIQ_{t-1}, DOWN_{t-1}, MKTVOL_{t-1}, and vector F are defined as before. The liquidity betas of each stock are estimated as the exposures of the stock to the liquidity factor with a five-year estimation period. Specifically, excess stock returns are regressed on Fama–French three factors and the shock in Amihud (2002) market illiquidity, defined as the residual of the logarithm of market illiquidity in an AR(1) process. The sample period is 1931–2011. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Intercept	1.678***	1.904***	2.055***	2.793***	2.129***	2.561***	2.689***	2.503***
	(9.19)	(8.92)	(9.73)	(6.15)	(10.61)	(4.43)	(5.99)	(4.46)
MKTILLIQ		−0.251***			−0.196**	−0.191**		−0.168*
		(−3.04)			(−2.05)	(−2.22)		(−1.91)
DOWN			−2.040***		−1.486*		−1.467***	−1.218**
			(−3.20)		(−1.78)		(−2.62)	(−2.48)
MKTVOL				−1.294**		−0.825	−0.859	−0.520
				(−2.45)		(−0.95)	(−1.62)	(−0.64)
RMRF	−0.378***	−0.368***	−0.382***	−0.378***	−0.373***	−0.370***	−0.381***	−0.374***
	(−3.33)	(−3.19)	(−3.27)	(−3.27)	(−3.18)	(−3.07)	(−3.25)	(−3.05)
SMB	−0.282**	−0.257**	−0.263**	−0.266**	−0.249*	−0.253**	−0.258**	−0.248**
	(−2.13)	(−1.96)	(−2.03)	(−2.01)	(−1.92)	(−2.16)	(−1.97)	(−2.12)
HML	−0.721***	−0.673***	−0.715***	−0.724***	−0.679***	−0.686***	−0.719***	−0.686***
	(−3.68)	(−3.76)	(−3.71)	(−3.76)	(−3.75)	(−4.18)	(−3.76)	(−4.15)
Adj. R^2	0.256	0.268	0.266	0.265	0.272	0.270	0.269	0.273

liquidity-beta neutral momentum payoffs: the coefficient reduces from −0.35 to −0.25. More importantly, we find that the state of the market illiquidity continues to have a significant predictive effect on momentum profits. As we show in Section IV, the predictive effect of market illiquidity on momentum payoffs remains significant when we directly control for the Pástor and Stambaugh (2003) or Sadka (2006) liquidity factors in the regressions. These results show that the effect of market liquidity on momentum payoffs is different from the liquidity risk exposure of the momentum portfolio.

C. Effects of Time-Varying Factor Risks

The existing literature shows that the factor risk exposures of the momentum portfolio are time varying (Grundy and Martin (2001), Korajczyk and Sadka (2004), and Daniel and Moskowitz (2014)). A natural question is whether the predictive effect of aggregate market illiquidity is explained by variations in the risk loadings on the market (RMRF), size (SMB), and book-to-market (HML) factors.

We start by measuring the conditional factor risk exposures in momentum portfolios, which have been shown to be linear functions of the ranking-period factor portfolio returns in the Grundy and Martin (2001) model. Following Korajczyk and Sadka (2004), we define $11\text{MRMRF}_{t-12:t-2}$ ($11\text{MSMB}_{t-12:t-2}$ and $11\text{MHML}_{t-12:t-2}$) as the cumulative (excess) returns of the market (size and book-to-market) factor over the ranking period (months $t-12$ to $t-2$) used to define the momentum strategy, and interact them with each of the three contemporaneous risk factors in the holding period t. The results are reported in Table 4 as

Models 1 and 2. Model 1 shows significant time variation in the exposure of the momentum portfolio to the three common factors. In general, the factor exposures are higher following a positive own-past realization of the factor (Grundy and Martin (2001), Korajczyk and Sadka (2004)). While the coefficient associated with the state of the market illiquidity is lower after controlling for the variation in the factor loadings, it remains economically significant (Model 2): a 1-standard-deviation increase in market illiquidity reduces the momentum profits by 0.29% per month.

Alternatively, we adopt the methodology in Daniel and Moskowitz (2014) to model the time-varying nature of the exposure of the momentum payoffs to factor risk. Following Daniel and Moskowitz (2014), we consider interacting the (excess) returns of the market factor (RMRF) with the DOWN market state as well as the contemporaneous market state variable, UP_t, defined as a dummy variable that takes the value of 1 if the excess return on the value-weighted CRSP market index in month t is positive, and 0 otherwise. Models 3 and 4 of Table 4 reproduce the findings in Daniel and Moskowitz (2014): The momentum portfolio has a negative market exposure following DOWN market states, and the exposure is even more negative when the contemporaneous market state (UP_t) exhibits a reversal. For example, the market beta of the momentum portfolio decreases by -1.14 in DOWN markets, with a t-value of -7.67 on the difference. When the contemporaneous market return is positive, the market beta of the momentum portfolio is even more negative, with an aggregate beta of -1.48. Models 5 and 6 of Table 4 show that the negative momentum-illiquidity relationship remains robust after controlling for the time-varying market exposures, with a slightly lower predictive coefficient: It reduces from -0.35 to -0.31 (Model 5) or -0.21 (Model 6). These results confirm that the predictive effect of market illiquidity on momentum payoffs goes beyond the time-varying exposure of the momentum portfolio to common risk factors.

D. Momentum and the Illiquidity Gap

The evidence thus far indicates that the momentum strategy is unprofitable when the aggregate market is illiquid. 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 depends 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 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.

Next, we introduce the notion of an illiquidity gap, defined as follows:

$$\mathrm{ILLIQGAP}_{t-1} = \mathrm{ILLIQ}_{\mathrm{WINNER},t-1} - \mathrm{ILLIQ}_{\mathrm{LOSER},t-1}, \tag{2}$$

where $\mathrm{ILLIQ}_{\mathrm{WINNER},t-1}$ ($\mathrm{ILLIQ}_{\mathrm{LOSER},t-1}$) is the average of the stock-level Amihud (2002) illiquidity measure of all stocks in the winner (loser) decile during

TABLE 4
Momentum Profits and Time-Varying Market Beta

In Table 4, Models 1 and 2 present the results of the following monthly time-series regressions as well as their corresponding Newey–West (1987) adjusted t-statistics (reported below in parentheses):

$$\begin{aligned}\text{WML}_t \quad = \quad & \alpha_0+\beta_1\,\text{MKTILLIQ}_{t-1}+\beta_2\,\text{RMRF}_t\times 11\text{MRMRF}_{t-12:t-2}+\beta_3\text{RMRF}_t\times 11\text{MSMB}_{t-12:t-2}\\ & +\beta_4\text{RMRF}_t\times 11\text{MHML}_{t-12:t-2}+\beta_5\text{SMB}_t\times 11\text{MRMRF}_{t-12:t-2}+\beta_6\text{SMB}_t\times 11\text{MSMB}_{t-12:t-2}\\ & +\beta_7\text{SMB}_t\times 11\text{MHML}_{t-12:t-2}+\beta_8\text{HML}_t\times 11\text{MRMRF}_{t-12:t-2}+\beta_9\text{HML}_t\times 11\text{MSMB}_{t-12:t-2}\\ & +\beta_{10}\text{HML}_t\times 11\text{MHML}_{t-12:t-2}+c'F_t+e_t,\end{aligned}$$

where WML_t, MKTILLIQ_{t-1}, and vector F are defined as before, and $11\text{MRMRF}_{t-12:t-2}$, $11\text{MSMB}_{t-12:t-2}$, and $11\text{MHML}_{t-12:t-2}$ refer to the cumulative (excess) returns of the Fama–French three factors over the ranking period ($t-12$ to $t-2$) used to define the momentum strategy, following Korajczyk and Sadka (2004). Models 3–6 report similar regression parameters:

$$\begin{aligned}\text{WML}_t \quad = \quad & \alpha_0+\beta_1\text{MKTILLIQ}_{t-1}+\beta_2\text{DOWN}_{t-1}+\beta_3\text{DOWN}_{t-1}\times\text{RMRF}_t\\ & +\beta_4\text{DOWN}_{t-1}\times\text{UP}_t\times\text{RMRF}_t+c'F_t+e_t,\end{aligned}$$

where DOWN_{t-1} is a dummy variable that takes the value of 1 if the return on the value-weighted CRSP market index during the past 24 months ($t-24$ to $t-1$) is negative, and 0 otherwise; UP_t is a dummy variable that takes the value of 1 if the excess return on the value-weighted CRSP market index in month t is positive, and 0 otherwise, following Daniel and Moskowitz (2014); and all other variables are defined as before. The sample period is 1928–2011. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	1.453***	1.534***	1.656***	1.656***	1.809***	1.759***
	(8.05)	(8.45)	(8.82)	(8.82)	(9.42)	(9.25)
MKTILLIQ		−0.084***			−0.314***	−0.211**
		(−2.74)			(−3.77)	(−2.29)
DOWN			−2.050***	0.543	−1.161	0.429
			(−2.82)	(0.70)	(−1.49)	(0.55)
DOWN × RMRF			−1.136***	−0.668***	−1.089***	−0.765***
			(−7.67)	(−4.98)	(−8.10)	(−5.55)
DOWN × UP × RMRF				−0.813***		−0.589***
				(−3.90)		(−2.93)
RMRF	−0.232***	−0.235***	0.020	0.020	0.024	0.022
	(−2.92)	(−2.97)	(0.28)	(0.28)	(0.34)	(0.32)
RMRF × 11MRMRF	0.016***	0.017***				
	(5.56)	(5.58)				
RMRF × 11MSMB	0.006	0.006				
	(1.01)	(1.05)				
RMRF × 11MHML	−0.007*	−0.007*				
	(−1.79)	(−1.73)				
SMB	−0.567***	−0.555***				
	(−7.67)	(−7.64)				
SMB × 11MRMRF	0.008***	0.007***				
	(5.48)	(5.07)				
SMB × 11MSMB	0.029**	0.030**				
	(2.25)	(2.29)				
SMB × 11MHML	−0.007***	−0.007***				
	(−3.13)	(−3.12)				
HML	−0.575***	−0.563***				
	(−8.37)	(−8.22)				
HML × 11MRMRF	−0.001	−0.002				
	(−0.43)	(−0.69)				
HML × 11MSMB	0.003	0.003				
	(0.34)	(0.37)				
HML × 11MHML	0.030***	0.030***				
	(9.09)	(8.46)				
Adj. R^2	0.541	0.542	0.308	0.325	0.323	0.331

the momentum portfolio formation period (months $t-12$ to $t-2$). 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 the winner portfolio. To pursue the task, the regression in equation (1) is estimated with ILLIQGAP_{t-1} as an additional explanatory variable. Since Amihud illiquidity is not comparable across NYSE/AMEX and NASDAQ stocks, we restrict the sample to firms listed on the NYSE/AMEX only.

The results are reported in Table 5. Starting with Model 2, ILLIQGAP_{t-1} predicts significantly lower momentum profits when the loser portfolio is relatively more illiquid. Model 3 shows that the predictive effect of ILLIQGAP_{t-1} is incremental to the prediction that illiquid market states produce lower momentum payoffs. We note that the contemporaneous correlation between ILLIQGAP_{t-1} and MKTILLIQ_{t-1} is -0.14, implying that the illiquidity gap between the winners and losers is more negative as the market becomes more illiquid. The interaction of these two variables is highly significant, as depicted in Model 6. The latter findings emphasize that the gap in the liquidity between losers and winners has the biggest impact on expected momentum profits when the aggregate market is most illiquid.

Our findings in Table 5 highlight the nature of the relation between price momentum and illiquidity. When the stock market is liquid, the positive future return attributable to the (more illiquid) loser portfolio attenuates but does not eliminate the positive momentum payoffs. In illiquid periods, however, there are two reinforcing effects. First, high aggregate market illiquidity lowers the momentum in stock prices. Second, the illiquidity gap between the losers and winners

TABLE 5

Momentum Profits and the Cross-Sectional Illiquidity Gap

Table 5 presents the results of the following monthly time-series regressions as well as their corresponding Newey–West (1987) adjusted t-statistics (reported below in parentheses):

$$\text{WML}_t = \alpha_0 + \beta_1\,\text{ILLIQGAP}_{t-1} + \beta_2\,\text{MKTILLIQ}_{t-1} + \beta_3\text{DOWN}_{t-1} + \beta_4\text{MKTVOL}_{t-1} + c'F_t + e_t,$$

where WML_t, MKTILLIQ_{t-1}, DOWN_{t-1}, MKTVOL_{t-1}, and vector F are defined as before; ILLIQGAP_{t-1} is the portfolio illiquidity gap between winner and loser momentum deciles; and the portfolio illiquidity is proxied by the average monthly equal-weighted stock-level Amihud (2002) illiquidity during the portfolio formation period ($t-12$ to $t-2$). The sample period is 1928–2011. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Intercept	1.679***	1.708***	2.003***	2.993***	2.745***	2.743***
	(9.29)	(13.87)	(9.09)	(7.31)	(5.92)	(5.98)
ILLIQGAP		0.184***	0.101**	0.149***	0.098**	0.030
		(4.45)	(2.24)	(4.27)	(2.44)	(0.46)
MKTILLIQ			−0.338***		−0.246***	−0.220***
			(−9.40)		(−3.52)	(−2.97)
DOWN				−1.390***	−1.019**	−1.072**
				(−4.89)	(−2.25)	(−2.43)
MKTVOL				−1.185***	−0.731	−0.748
				(−3.08)	(−1.18)	(−1.23)
ILLIQGAP × MKTILLIQ						0.009**
						(2.03)
RMRF	−0.403***	−0.405***	−0.391***	−0.411***	−0.399***	−0.399***
	(−3.61)	(−3.63)	(−3.48)	(−3.53)	(−3.39)	(−3.39)
SMB	−0.238*	−0.237*	−0.204*	−0.211*	−0.196	−0.202
	(−1.82)	(−1.93)	(−1.76)	(−1.66)	(−1.60)	(−1.62)
HML	−0.650***	−0.646***	−0.584***	−0.645***	−0.600***	−0.598***
	(−3.60)	(−5.34)	(−5.81)	(−5.56)	(−5.85)	(−5.85)
Adj. R^2	0.227	0.229	0.249	0.247	0.255	0.255

widens, and the corresponding higher returns associated with illiquid stocks lower momentum payoffs and, in some extreme scenarios, lead to negative momentum profits.

E. Momentum in Large Firms

Fama and French (2008) find that the momentum strategy yields significant returns in big, small, and microcap stocks, although small and microcap 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 subsection, we examine whether market illiquidity explains the time variation in expected momentum payoffs among the sample of large firms, defined as those above the median NYSE firm size each month (Fama and French (2008)). We also filter out firms with a stock price below \$5 each month.

As shown in Table 6, we continue to find that the state of the 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, MKTILLIQ also stands out as the strongest predictor in the subsample of large firms in all specifications, emphasizing our main contention that the effect of the state of the market illiquidity is robust.

TABLE 6

Momentum in Big Firms and Market States

Table 6 presents the results of the following monthly time-series regressions as well as their corresponding Newey–West (1987) adjusted t-statistics (reported below in parentheses):

$$\text{WML}_t = \alpha_0 + \beta_1 \text{MKTILLIQ}_{t-1} + \beta_2 \text{DOWN}_{t-1} + \beta_3 \text{MKTVOL}_{t-1} + c' F_t + e_t,$$

where WML_t, MKTILLIQ_{t-1}, DOWN_{t-1}, MKTVOL_{t-1}, and vector F are defined as before. At the beginning of each month t, all common stocks listed on the NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged 11-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 $t-1$. The sample period is 1928–2011, and all portfolio breakpoints are based on NYSE firms only. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	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. R^2	0.201	0.221	0.211	0.211	0.224	0.223	0.215	0.225

IV. Evidence from Recent Period (2001–2011)

While most of the research papers on the profitability of momentum strategies employ data from before 2000, Chordia et al. (2014) show that price and earnings momentum payoffs are insignificant in the postdecimalization period, starting in Apr. 2001. While the evidence in Chordia et al. (2014) is unconditional, the main focus of our paper is the time-varying nature of momentum payoffs. Indeed, improvements in marketwide liquidity in the recent decade due to technological and structural changes in the infrastructure have largely minimized the constraints to arbitrage; hence, they provide an interesting setting to perform our analysis.

A. Price and Earnings Momentum

In addition to the price momentum strategies explored in Section III, we also analyze earnings momentum. 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)). The data for our earnings momentum strategies come from analyst (consensus) earnings forecasts in Institutional Brokers' Estimate System (IBES), while the actual earnings are gathered from Compustat. The earnings announcement dates are obtained from IBES and Compustat following the procedure outlined by Dellavigna and Pollet (2009).

We follow Chan et al. (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) 10% 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 the 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

$$\text{REV}_{it} = \sum_{j=0}^{6} \frac{f_{it-j} - f_{it-j-1}}{P_{it-j-1}}, \tag{3}$$

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

$$(4) \qquad \mathrm{SUE}_{it} = \frac{e_{iq} - e_{iq-4}}{\sigma_{it}},$$

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 in 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:

$$(5) \qquad \mathrm{CAR}_{it} = \sum_{d=-2}^{+1} (r_{id} - r_{md}),$$

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

We begin with the presentation of estimates of the regression in equation (1) for the price momentum portfolio during the recent period from Apr. 2001 to Dec. 2011. Consistent with Chordia et al. (2014), the risk-adjusted price momentum profit in Panel A of Table 7 is insignificant at 0.24%.[7] 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 generates significant momentum profits, as indicated by the intercept in Model 2 of Panel A (Table 7). To gauge the economic magnitude of the effect of MKTILLIQ states, we compute WML in illiquid (liquid) subperiods 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% (t-value $= -0.50$) when the market is illiquid to 1.09% (t-value $= 2.20$) 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, 6, and 8 in Panel A of Table 7 complement the cumulative results we have presented thus far: The state of the market illiquidity dominantly governs the (lack of) profitability of price momentum strategies.

[7]The raw price momentum returns in 2001–2011 are also insignificant at 0.18% per month.

Panels B–D in Table 7 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 the estimate of Model 1 in Panel B, we obtain a significant earnings momentum profit of 1.12% 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 display 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.

TABLE 7

Price Momentum, Earnings Momentum, and Market States in Recent Years (2001–2011)

Table 7 presents the results of the following monthly time-series regressions:

$$\text{WML}_t \quad = \quad \alpha_0 + \beta_1 \text{MKTILLIQ}_{t-1} + \beta_2 \text{DOWN}_{t-1} + \beta_3 \text{MKTVOL}_{t-1} + c' F_t + e_t,$$

where WML_t is the value-weighted portfolio return (WML deciles) from the momentum strategy in month t. In Panels B–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 the bottom (top) decile of stocks with extreme earnings surprise. In Panel A, WML refers to the WML portfolio sorted on past 11-month stock returns. In Panels B–D, earnings news is proxied by the changes in analysts' forecasts of earnings (REV), standardized unexpected earnings (SUE), and cumulative abnormal stock return (CAR) from day −2 to day +1 around the earnings announcement. MKTILLIQ_{t-1}, DOWN_{t-1}, MKTVOL_{t-1}, and vector F are defined as before. The sample period is from May 2001 to 2011. Newey–West (1987) adjusted t-statistics are reported in below in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel A. Price Momentum Profit Regressed on Lagged Market State Variables								
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. R^2	0.253	0.323	0.282	0.301	0.323	0.332	0.307	0.333
Panel B. Earnings Momentum Profit (Based on REV) Regressed on Lagged Market State Variables								
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. R^2	0.261	0.284	0.280	0.262	0.287	0.297	0.289	0.302

(continued on next page)

TABLE 7 (continued)

Price Momentum, Earnings Momentum, and Market States in Recent Years (2001–2011)

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel C. Earnings Momentum Profit (Based on SUE) Regressed on Lagged Market State Variables								
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. R^2	0.184	0.202	0.190	0.184	0.202	0.206	0.190	0.207
Panel D. Earnings Momentum Profit (Based on CAR) Regressed on Lagged Market State Variables								
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. R^2	0.120	0.200	0.163	0.165	0.201	0.206	0.180	0.206

Earnings momentum profitability is significantly lower following illiquid aggregate market (MKTILLIQ) states (Model 2 of Table 7) 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.

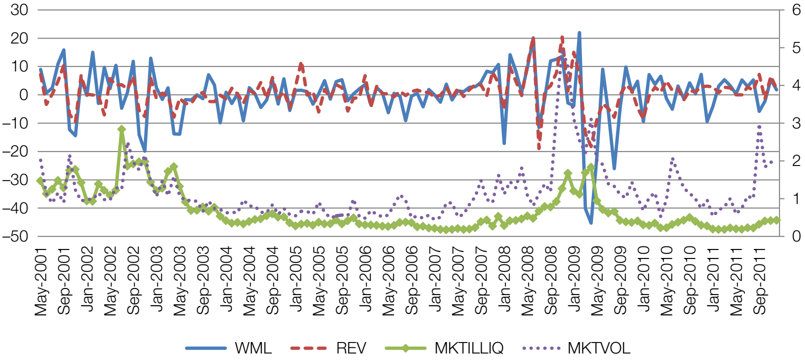
We obtain similar results when earnings surprise at the firm level is measured by changes in its standardized unexpected earnings (SUE) or is constructed using the abnormal stock price reactions in the announcement month t (CAR). As displayed in Panels C and D of Table 7, MKTILLIQ enters significantly into the prediction of earnings momentum. When all the state variables are considered together, the state of the market illiquidity is able to significantly capture a drop in earnings momentum in the following month (Model 8).

In summary, the analysis of price and earnings momentum in the recent decade complements the cumulative evidence we have presented: The state of the market illiquidity is a dominant predictor of the profitability of momentum strategies.

FIGURE 1

Time Series of Momentum Payoff and Market States (2001–2011)

Figure 1 plots the time series of momentum portfolio payoff and market states over the period between May 2001 and Dec. 2011. At the beginning of each month t, all common stocks listed on the NYSE, AMEX, and NASDAQ are sorted into deciles based on their lagged 11-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 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) defined as before.



B. Do Investor Sentiment and Macroeconomic Conditions Explain the Market-Illiquidity Effect?

Stambaugh et al. (2012) show that various cross-sectional return anomalies, including price momentum, are profitable when investor sentiment is high. In particular, profitability of these long-short strategies stems from the short leg of the strategies, reflecting binding short-sale constraints following high sentiment (see also Antoniou et al. (2013)). We examine whether the market-illiquidity effects simply reflect the influence of investor sentiment on momentum profits. We continue to use the regression models with controls for exposure to the Fama–French three factors (RMRF, SMB, and HML). In addition, we also include exposures to the liquidity risk factor obtained from Pástor and Stambaugh (2003) or Sadka (2006). In general, both proxies for the liquidity factor load significantly on the momentum portfolio, consistent with the findings in Pástor and Stambaugh (2003) and Sadka (2006), as shown in Table 8.[8]

We consider two alternative definitions of the sentiment variable. The first is the level of sentiment index obtained from Baker and Wurgler (2006), (2007).[9] The second is a low-sentiment dummy variable that takes a value of 1 only if the sentiment index value belongs to the bottom tercile over the sample period 2001–2011. The results presented in Table 8 show that sentiment has a positive effect on momentum profits, as low-sentiment periods display low-momentum payoffs (Model 1). Of special interest to our analysis is the finding that MKTILLIQ is

[8]We get similar results when we control for any predictive effect of other variables that may proxy for funding liquidity, including the TED spread and VIX (the implied volatility of the S&P 500 index options) in Asness et al. (2013).

[9]We thank Jeffrey Wurgler for making the index of investor sentiment publicly available.

TABLE 8
Momentum Profits, Sentiment, and Macroeconomic Conditions

Table 8 presents the results of the following monthly time-series regressions as well as their corresponding Newey–West (1987) adjusted t-statistics (reported below in parentheses):

$$\text{WML}_t = \alpha_0 + \beta_1 \text{MKTILLIQ}_{t-1} + \beta_2 \text{DOWN}_{t-1} + \beta_3 \text{MKTVOL}_{t-1} + \beta_4 \text{DUMMY(LOW\_SENTIMENT)}_{t-1} + \beta_4 M_{t-1} + \beta_5 \text{CSRD}_{t-1} + c' F_t + e_t,$$

where WML_t, MKTILLIQ_{t-1}, DOWN_{t-1}, and MKTVOL_{t-1} are defined as before; SENTIMENT_{t-1} is the monthly Baker and Wurgler (2007) market sentiment index; and $\text{DUMMY(LOW\_SENTIMENT)}_{t-1}$ is a dummy variable that takes the value of 1 if the investor sentiment is in the bottom tercile over the entire sample period. M_{t-1} refers to a set of macroeconomic variables, including dividend yield, defined as the total dividend payments accruing to the CRSP value-weighted index over the previous 12 months divided by the current level of the index; 3-month T-bill yield; term spread, defined as the difference between the average yield of 10-year Treasury bonds and 3-month T-bills; and default spread, defined as the difference between the average yield of bonds rated BAA and AAA by Moody's. CSRD_{t-1} is the 3-month moving average of the monthly cross-sectional return dispersion ($t-3$ to $t-1$), constructed from 10×10 stock portfolios formed on size and book-to-market ratio, following Stivers and Sun (2010). The vector F stacks Fama–French three factors, including the market factor (RMRF), the size factor (SMB), the book-to-market factor (HML), the Pástor and Stambaugh (2003) liquidity factor (PSLIQ), and the Sadka permanent-variable liquidity factor (SADKALIQ), or the Chen, Roll, and Ross (CRR) (1986) five factors, including the growth rate of industrial production, unexpected inflation, change in expected inflation, term premium, and default premium. The sample period is from May 2001–Dec. 2010. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
Intercept	1.302*	3.257***	3.142***	21.161**	4.822**	3.381*	4.014**	6.793**	19.975*	23.858**
	(1.68)	(2.75)	(2.80)	(2.30)	(2.38)	(1.67)	(2.06)	(2.62)	(1.71)	(2.40)
MKTILLIQ		−4.259**	−5.283**	−6.309***		−4.154***	−3.955***	−5.557**	−6.947***	−6.731***
		(−2.35)	(−2.32)	(−3.22)		(−3.00)	(−3.41)	(−2.28)	(−3.54)	(−3.87)
DOWN							0.871	2.634	0.694	0.099
							(0.55)	(0.92)	(0.36)	(0.05)
MKTVOL							−1.308	3.110	1.860	1.279
							(−1.23)	(0.72)	(1.10)	(1.15)
DUMMY(LOW_SENTIMENT)	−3.516*	−2.181					−2.310		−1.335	−1.733
	(−1.72)	(−1.41)					(−1.54)		(−0.85)	(−0.99)
SENTIMENT			2.884							
			(1.64)							
CSRD					−1.397**	−0.279	0.076			
					(−2.27)	(−0.58)	(0.15)			
PSLIQ		0.558***	0.543***	0.492***		0.574***	0.532***	0.467	0.498***	
		(4.01)	(4.25)	(4.75)		(4.07)	(4.22)	(1.32)	(3.73)	
SADKALIQ										2.052***
										(3.23)
Macro Controls	No	No	No	Yes	No	No	No	No	Yes	Yes
FF 3-Factor	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes
CRR 5-Factor	No	No	No	No	No	No	No	Yes	No	No
Adj. R^2	0.298	0.410	0.423	0.480	0.308	0.402	0.416	0.137	0.490	0.467

highly significant in the presence of sentiment indicators in Models 2 and 3, indicating that our findings are not subsumed by investor sentiment.

Næs et al. (2011) show that the aggregate stock market illiquidity is countercyclical and significantly predicts the real economy. Chordia and Shivakumar (CS) (2002) argue that the profits of momentum strategies are explained by common macroeconomic variables and are related to the business cycle. Specifically, CS find that the momentum profits are strong (weak) in expansionary (recessionary) periods. Taken together, these findings imply that the profitability of the momentum strategies could be due to variations in the common macroeconomic factors, and presumably changes in risks. Following CS, we use dividend yield, yield on 3-month T-bills, default spread, and term spread as our macroeconomic variables. We add the lagged values of these variables to the time-series regression models in equation (1). As shown in Model 4 of Table 8, adding these macroeconomic variables does not attenuate the strong negative influence of market illiquidity.

Stivers and Sun (2010) use the cross-sectional dispersion in stock returns (CSRD) as a countercyclical state variable to explain time variation in momentum profits. They find that the high CSRD coincides with economic recessions and significantly predicts lower momentum payoffs, after controlling for the macroeconomic variables in CS. Following Stivers and Sun (2010), CSRD is the 3-month moving average of the monthly cross-sectional return dispersion, constructed from 10×10 stock portfolios formed on firm size and book-to-market ratio. Specifically, CSRD is computed over months $t-3$ to $t-1$ to predict WML in month t. In Model 5 of Table 8, we report that CSRD is a significant predictor of momentum payoffs, consistent with Stivers and Sun (2010). However, when we include both MKTILLIQ and CSRD, only the state of the market liquidity remains significant, as shown in Model 6.[10]

In Model 7 of Table 8, we report a joint regression model that includes DOWN market state, market volatility, investor sentiment, cross-sectional return dispersion, the Fama–French three risk factors, and the Pástor–Stambaugh liquidity factor. In Model 9, we further control for macroeconomic variables, and in Model 10, the Pástor–Stambaugh liquidity factor is replaced by the Sadka liquidity factor. In all these joint models, the state of the market liquidity makes a significant contribution in determining future momentum payoffs.

In a recent paper, Liu and Zhang (2008) suggest that the macroeconomic risk factors in Chen et al. (1986), and in particular the growth rate of industrial production, explain a significant portion of momentum profits. We consider replacing the Fama–French risk factors with Chen et al.'s (1986) five macroeconomic factors: the growth rate of industrial production, unexpected inflation, change in expected inflation, term premium, and default premium. Adjusting for these risk factors, which are contemporaneous with the momentum profits, does not alter the findings on the negative impact of the market-illiquidity state on subsequent momentum payoffs (Model 8 of Table 8). Our findings reinforce the results in Liu

[10]Unreported result shows that if we exclude PSLIQ from Model 6, the coefficient of CSRD is -0.197 (t-value $=-0.35$), and MKTILLIQ remains to be highly significant with a coefficient of -4.642 (t-value $=-2.89$).

and Zhang (2014): Their real investment model of asset prices does not generate the time variation in momentum profits that we observe in the data.

V. Other Robustness Checks

A. Alternative Measure of Aggregate Market Illiquidity

We consider an alternative measure of liquidity introduced recently by Corwin and Schultz (2012), who estimate the bid–ask spreads (or the cost of trading) using only daily high and low stock prices. They show that their spread estimator is highly correlated with high-frequency measures of bid–ask spreads in both time-series and cross-sectional analyses, has similar power to the Amihud (2002) illiquidity measure, and outperforms several other low-frequency estimators of liquidity. Specifically, the monthly Corwin–Schultz (2012) spread estimator (SPREAD) for each stock is computed based on the high-to-low price ratio for a single two-day period and the high-to-low ratio over two consecutive single days.[11] The value-weighted average of Spread across all stocks in the market, MKTSPREAD, is our alternative measure of the state of aggregate market illiquidity. As expected, MKTSPREAD is (but not perfectly) correlated with MKTILLIQ, with a correlation coefficient of 0.57 over the period 1928–2011.

In the analysis that follows, we reestimate equation (1), replacing MKTILLIQ with MKTSPREAD, and present the estimates in Table 9. The overall results confirm our main findings that momentum payoffs are low when the aggregate market is highly illiquid. For example, Model 1 shows that a 1-standard-deviation increase in MKTSPREAD reduces the risk-adjusted monthly momentum profits by an economically significant 1.17%. Similar to our findings in Table 2, Models 2–4 in Table 9 show that adding the other state variables (DOWN and MKTVOL) does not fully explain the strong negative effect of marketwide illiquidity on the returns to the momentum strategy. Hence, our finding on the momentum-illiquidity relation is robust to alternate measures of market illiquidity.

B. International Evidence

We also examine the time variation of momentum profits in an international sample. Our non-U.S. sample, which spans the 2001–2010 period, consists of Japan and the set of 10 countries that belong to the Eurozone at the beginning of our sample period, including Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, and Spain. We obtain price and volume

[11] The Corwin–Schultz (2012) spread estimator is given by

$$\text{SPREAD} = \frac{2(e^{\alpha}-1)}{1+e^{\alpha}},$$

where
$$\alpha = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}}, \quad \beta = E\left\{\sum_{j=0}^{1}\left[\ln\frac{H_{t+j}}{L_{t+j}}\right]^2\right\},$$

and
$$\gamma = \left[\ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2.$$

In these notations, $H_t(L_t)$ refers to the observed high (low) stock price in day t, and negative two-day spreads are set to 0.

TABLE 9
Momentum Profits and Market Spreads

Table 9 presents the results of the following monthly time-series regression as well as its corresponding Newey–West (1987) adjusted t-statistics (reported below in parentheses):

$$\text{WML}_t = \alpha_0 + \beta_1 \text{MKTSPREAD}_{t-1} + \beta_2 \text{DOWN}_{t-1} + \beta_3 \text{MKTVOL}_{t-1} + c'F_t + e_t,$$

where WML_t, DOWN_{t-1}, MKTVOL_{t-1}, and vector F are defined as before, and MKTSPREAD_{t-1} is the market spread, proxied by the value-weighted average of stock-level Corwin and Schultz (2012) bid–ask spread (with negative 2-day spreads set to 0) of all NYSE and AMEX firms. The sample period is 1928–2011. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1	Model 2	Model 3	Model 4
Intercept	4.573***	4.226***	4.656***	4.302***
	(6.22)	(5.36)	(5.41)	(4.64)
MKTSPREAD	−5.131***	−4.110***	−5.629**	−4.559*
	(−3.96)	(−2.80)	(−2.33)	(−1.74)
DOWN		−1.197*		−1.194*
		(−1.81)		(−1.78)
MKTVOL			0.220	0.196
			(0.29)	(0.26)
RMRF	−0.397***	−0.398***	−0.398***	−0.399***
	(−3.38)	(−3.37)	(−3.37)	(−3.36)
SMB	−0.217	−0.212	−0.217	−0.211
	(−1.62)	(−1.58)	(−1.62)	(−1.59)
HML	−0.653***	−0.652***	−0.652***	−0.651***
	(−3.72)	(−3.72)	(−3.76)	(−3.76)
Adj. R^2	0.254	0.256	0.254	0.257

data for all common stocks traded on the primary exchange in each country from Datastream. After converting all prices to U.S. dollars, we exclude stocks with extreme prices, that is, those below \$1 or above \$1,000, to minimize microstructure biases and potential data errors.

The methodologies for computing the main variables in our analyses are similar to those described in Section II. Within each country, we form winner and loser decile portfolios based on the stock returns over the previous 11 months, from $t-12$ to $t-2$. The WML portfolio returns are computed each month as the difference in the returns of the value-weighted winner and loser decile portfolios in month $t+1$. For the Eurozone sample, we form country-neutral value-weighted WML portfolio returns based on the combined sample of all stocks in the 10 countries. For Japan, the state variables, MKTILLIQ, DOWN, and MKTVOL, are based on the value-weighted average of all stocks traded on the Tokyo Stock Exchange. The corresponding values of the state variables for the Eurozone stock market reflect the value-weighted average of all stocks traded in the 10 markets. Finally, the Fama–French three common risk factors (market, size, and value) for Japan and the European market are downloaded from Kenneth French's Web site (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html).

The estimate of equation (1) for Japan is presented in Panel A of Table 10. As documented in recent papers, Model 1 shows that, unconditionally, momentum strategies do not work in the Japanese market. Chui et al. (2010), for example, argue that investors in less individualistic cultures, such as Japan, exhibit smaller overconfident/self-attribution bias; hence, there is no evidence of price momentum in these markets. However, conditioning the time series of momentum payoffs on MKTILLIQ leads to significant momentum profits (see Model 2). In other

TABLE 10

International Evidence on Momentum Profits and Market States

Panel A in Table 10 presents the results of the following monthly time-series regression as well as its corresponding Newey–West (1987) adjusted t-statistics (reported below in parentheses):

$$\text{WML}_t = \alpha_0 + \beta_1 \text{MKTILLIQ}_{t-1} + \beta_2 \text{DOWN}_{t-1} + \beta_3 \text{MKTVOL}_{t-1} + c'F_t + e_t,$$

where WML_t is the value-weighted return on the WML momentum deciles in month t in Japan; MKTILLIQ_{t-1} is the market illiquidity, proxied by the value-weighted average of stock-level Amihud (2002) illiquidity of all firms listed in the Tokyo Stock Exchange; DOWN_{t-1} is a dummy variable that takes the value of 1 if the return on the value-weighted market return in Japan during the past 24 months ($t-24$ to $t-1$) is negative, and 0 otherwise; and MKTVOL_{t-1} is the standard deviation of the daily value-weighted market return in Japan. The vector F stacks Fama–French three Japanese factors, including the market factor (RMRF), the size factor (SMB), and the book-to-market factor (HML). Panel B reports similar regression parameters in 10 Eurozone countries, including Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, and Spain. Winner and loser portfolios are sorted within each country. The sample period is 2001–2010. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
Panel A. Momentum Profit (WML) Regressed on Lagged Market State Variables (Japan)								
Intercept	−0.381	1.789**	0.692	0.843	1.801**	1.527	1.111	1.522
	(−0.44)	(2.13)	(0.79)	(0.68)	(2.10)	(1.31)	(0.93)	(1.30)
MKTILLIQ		−57.681**			−50.825**	−60.154***		−53.277**
		(−2.45)			(−2.39)	(−2.69)		(−2.51)
DOWN			−2.202**		−0.554		−2.083**	−0.569
			(−2.09)		(−0.59)		(−2.19)	(−0.61)
MKTVOL				−0.925		0.268	−0.360	0.286
				(−1.21)		(0.46)	(−0.57)	(0.51)
RMRF	−0.122	−0.125	−0.142	−0.118	−0.130	−0.127	−0.140	−0.132
	(−0.56)	(−0.59)	(−0.64)	(−0.55)	(−0.59)	(−0.59)	(−0.64)	(−0.60)
SMB	0.424*	0.435**	0.427**	0.409*	0.435**	0.440*	0.421*	0.440*
	(1.86)	(1.98)	(2.02)	(1.74)	(2.00)	(1.96)	(1.93)	(1.97)
HML	0.629*	0.688**	0.662**	0.632*	0.690**	0.690**	0.661**	0.691**
	(1.97)	(2.38)	(2.25)	(1.96)	(2.39)	(2.40)	(2.23)	(2.41)
Adj. R^2	0.103	0.148	0.128	0.109	0.149	0.149	0.129	0.150
Panel B. Momentum Profit (WML) Regressed on Lagged Market State Variables (Eurozone)								
Intercept	0.734	1.503*	1.594***	4.392***	1.905**	4.523***	4.407***	4.585***
	(1.57)	(1.97)	(2.70)	(8.73)	(2.50)	(8.62)	(8.77)	(8.70)
MKTILLIQ		−1.402**			−0.985*	−0.650*		−0.766**
		(−2.10)			(−1.88)	(−1.76)		(−2.07)
DOWN			−1.945***		−1.426***		0.236	0.589
			(−2.87)		(−3.07)		(0.43)	(1.24)
MKTVOL				−2.864***		−2.688***	−2.958***	−2.891***
				(−6.23)		(−5.51)	(−5.54)	(−4.80)
RMRF	−0.797***	−0.779***	−0.802***	−0.788***	−0.789***	−0.780***	−0.787***	−0.777***
	(−9.90)	(−9.29)	(−9.73)	(−8.57)	(−9.24)	(−8.42)	(−8.59)	(−8.55)
SMB	0.375	0.428	0.392	0.266	0.425	0.297	0.260	0.288
	(0.93)	(1.19)	(1.02)	(0.67)	(1.19)	(0.78)	(0.65)	(0.75)
HML	0.460	0.463	0.478	0.277	0.476	0.290	0.269	0.272
	(1.00)	(1.00)	(0.99)	(0.60)	(0.99)	(0.63)	(0.59)	(0.61)
Adj. R^2	0.344	0.357	0.358	0.401	0.363	0.403	0.401	0.404

words, we find significant momentum even in the Japanese stocks when aggregate illiquidity is low. Similar to our findings for the U.S. market, MKTILLIQ as an aggregate variable has the greatest influence on momentum payoffs in Japan as well. The DOWN state predicts momentum payoffs on a stand-alone basis (Model 3) but loses its significance in the presence of MKTILLIQ (Models 5 and 8). The time variation in MKTVOL, on the other hand, is not related to (the absence of) momentum in Japan.

The results for the Eurozone market, reported in Panel B of Table 10, confirm the absence of unconditional momentum in that market. However, momentum emerges as a significant phenomenon when we condition on the state variables; momentum is positive and significant, except in bad times: after decreases in aggregate market valuations (DOWN), when markets are volatile (MKTVOL), and especially when the market is illiquid (MKTILLIQ). Of these three state variables, MKTILLIQ and MKTVOL have the strongest effect on momentum payoffs.

The overwhelming evidence across the United States, Japan, and the Eurozone samples is that market illiquidity predicts momentum payoffs, and its impact is pervasive across all these markets.

VI. Conclusion

In this paper, we examine the association between the variation in market liquidity and the momentum anomaly and provide a direct test of the role of liquidity for arbitrage. If variations in momentum profits reflect changes in arbitrage constraints, we expect a positive relation between momentum profits and aggregate market liquidity. Surprisingly, we find that the effect goes in the opposite direction, and rather sharply. We find that the momentum strategy generates large (weak) profits in liquid (illiquid) market states, which contrasts with the arbitrage prediction.

The negative momentum-illiquidity relation is robust. In the presence of market illiquidity, the power of the competing variables, such as market return states and market volatility, is attenuated and often even disappears altogether. We uncover that the same negative momentum-illiquidity relation governs the variation of the profits to the earnings momentum strategy in the United States and the price momentum in the Japan and Eurozone countries.

The negative momentum-illiquidity relation is also not subsumed by other known explanations. Our main finding remains intact when we allow for time-varying exposure to systematic risk factors (Korajczyk and Sadka (2004), Daniel and Moskowitz (2014)) and is different from the liquidity risk exposure of the momentum portfolio (Pástor and Stambaugh (2003), Sadka (2006), and Asness et al. (2013)). The evidence is also unaffected when we control for the state of the macroeconomy (Chordia and Shivakumar (2002)) or intertemporal variation in investor sentiment (Stambaugh et al. (2012)).

Our findings have implications for various models explaining the momentum anomaly. In particular, the aggregate liquidity state may be a useful point to distinguish different models. In the behavioral model by Daniel, Hirshleifer, and Subrahmanyam (1998), for example, investors overreact to private information due to overconfidence, which, together with self-attribution bias in their reaction to subsequent public information, triggers return continuation. Consequently, when overconfidence, along with biased self-attribution, is high, there is excessive trading, and the momentum effect is strong. Although the model of Daniel et al. (1998) does not formally examine liquidity, it is consistent with interpreting periods of heavy trading as more liquid.[12] Hence, our findings are consistent with (although they do not prove) market liquidity as an indicator of investor

[12]This interpretation is reinforced by the point that, when investors think highly of their ability to value the stock accurately, they will underreact to information in order flow of others and, hence, increase liquidity (Odean (1998)). Alternatively, during pessimistic periods, overconfident investors

overconfidence, and where overconfidence in turn drives the variation in the momentum effect, implying an association between illiquidity and momentum.[13] We leave additional work using the aggregate liquidity state to distinguish various models of momentum (whether behavioral or rational) to future research.

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keep out of the market due to short-sale constraints, thus reducing market liquidity (Baker and Stein (2004)).

[13]The predictions of other behavioral models, such as Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), and Grinblatt and Han (2005), for momentum profits when conditioned on market illiquidity are more difficult to ascertain. For example, in the Hong and Stein (1999) model, momentum profits come from the gradual diffusion of private information across investors and the interaction between heterogeneous agents, that is, newswatchers, who exclusively rely on their private information and momentum traders who trade only on past returns. While private information diffusion may be slower in illiquid markets, the relation between momentum and market illiquidity also depends on the aggressiveness of the trading by momentum investors in different liquidity states.

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