Momentum crashes and variations to market liquidity

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Abstract

We document that the variation in market liquidity is an important determinant of momentum crashes that is independent of other known explanations surfaced on this topic. This relationship is driven by the asymmetric large return sensitivity of short-leg of momentum portfolio to changes in market liquidity that flares the tail risk of momentum strategy in panic states. This identification explains the forecasting ability of known predictors of tail risk of momentum strategy such that the contemporaneous increase in market liquidity predominantly sums up the trademark negative relationship between predictors and future momentum returns. Our results are robust using a different momentum portfolio and alternative measures of market liquidity that make a substantial part of the common source of variation in aggregate liquidity.

JEL Codes: G10, G12, G15

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1. Introduction

The large returns, including the Sharpe ratio, and even larger risk adjusted returns on momentum anomaly relative to common benchmarks such as Fama and French (1996) three factor (FF3) model point to substantial financial gains for investing in such strategies.[1] However, the substantial negative skewness and persistent large drawdowns, also known as crashes, in momentum strategy highlight the large momentum tail risk (Barroso and Santa-Clara 2015, Daniel and Moskowitz 2016).

Understanding the level of returns and risk of momentum in asset prices has resulted in numerous explanations, one area particularly unresolved is comprehending time variation in momentum payoffs. Grundy and Martin (2001) document that buying recent winners and selling recent losers symbolizes time-varying factor exposures that is well supported by their evidence, however, this dynamic factor structure remains unsuccessful in describing the level of the winner-minus-loser (WML) momentum strategy. Cooper, Gutierrez and Hameed (2004) provide empirical evidence that momentum profits are high/low following up/down-market states. Daniel and Moskowitz (2016) extend this line of evidence and show that momentum crashes happen following down-market states (DMS hereafter).[2]

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[1] A conventional momentum strategy, first introduced by Jegadeesh and Titman (1993), is constructed monthly: 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 i.e. *t-12* to *t-2*, are sorted into ten deciles. 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 to avoid small firm effect of NASDAQ firms. The standard practice of skipping the last month at the end of the ranking period and the start of the holding period is adhered to avoid the short-term reversals shown by Jegadeesh (1990) and Lehmann (1990). The monthly portfolio return in month *t* is the value-weighted average of stocks in each decile. Here, we like to thank Ken French for maintaining a database through which we fetch momentum deciles as well FF3 model factor returns.

[2] We use, interchangeably, market downturns, market declines, DMS and *d* (in regression equations and Tables) to imply bearish market states.

Cooper et al. (2004) evidence shows that market return can predict time variations of momentum payoffs, other forecasting variables identified by the literature are lagged market volatility (Wang and Xu 2015), previous period aggregate liquidity (Avramov, Cheng and Hameed 2016), and momentum gap i.e. the cross-sectional dispersion of formation period winner and loser portfolio returns (Huang 2015), among others. Likewise, the literature on the predictability of momentum crashes is fast growing. Daniel and Moskowitz (2016) show that these crashes are partially predictable as they occur following DMS when contemporaneous, not ex-ante, excess return on market index is positive, a condition known as market rebound. Other predictors for large down swings in momentum strategies include market variance (Daniel and Moskowitz 2016), crowding effects (Yan 2013, Huang 2015, Barroso, Edelen, and Karehnke 2017), and momentum risk i.e. the volatility of momentum strategy (Barroso and Santa-Clara 2015, Daniel and Moskowitz 2016). In sum, changes in market return and market volatility are some of the strong predictors of variations in momentum returns and momentum crashes. While Avramov et al. (2016) investigate the predictive ability of aggregate liquidity for momentum returns, none of the noted studies account for the role of market liquidity in understanding momentum crashes. We provide this evidence and report new insights in grasping the large downswings in momentum returns. Our results show that the changes to market liquidity adds to the explanation of momentum crashes along with the market rebounds. We find that contemporaneous positive (or liquid) shocks to market liquidity augment this additional explanation in DMS. Daniel and Moskowitz (2016) show that large momentum risk is an outcome of an option-like feature of momentum strategy which is short a call option on market. We show that the optionality effect and predictive ability of lagged market variance is statistically significant, but only irregularly, for momentum crashes once we control for changes to market liquidity in market downturns, [3] although the known meaningfulness of both for momentum crashes remains intact.

Another significant contribution from our work shows that the negative relationship between momentum returns and known predictive variables is conditional on the contemporaneous variation in market liquidity for the US market for the period of 1965:06-2012:12. That is, the negative relationship between the predictive variables and momentum returns, except for Huang's (2015) momentum gap, is concentrated in periods when market liquidity contemporaneously rises in DMS. We show this interrelation also drives the predictive ability of time variation in momentum returns for lagged market illiquidity, and lagged market variance and momentum risk.

The motivation for exploring the role of changes to market liquidity for momentum crashes is the explanations available in the literature: DMS, high volatility and market rebounds all have strong linkages to changes in market liquidity vis a vis variation in momentum returns. Where DMS and high volatility characterize reduced market liquidity, market rebounds link well to improvements in market liquidity. Likewise, the analogy in Daniel and Moskowitz (2016) linking the expected returns on momentum strategy to a call option, which is short on the market, justifies huge momentum losses following bearish market states when market variance is high. Under the noted market conditions, these losses on momentum strategy are shown to be essentially a consequence of conditionally high premium attached to the option-like payoffs of past losers. This also points towards the higher equity premium associated with illiquid stocks.[4] We relate our claim to three

[3] The optionality effect is a central explanation of momentum crashes surfaced so far because studies such as Barroso et al. (2017) suggest that the dynamic exposures of momentum strategy to common sources of risk (Grundy and Martin 2001) and the crowding effect (Yan 2013, Huang 2015, among others) are not the main explanation for momentum crashes.

[4] The forecasting ability of realized market variance entails a fascinating design i.e. the lower momentum profits following DMS are a function of higher lagged variance of market returns. Daniel and Moskowitz (2016) show that the large momentum declines are due to higher returns for the loser portfolio (short position) following DMS in comparison to the winner portfolio (long position). During DMS, the underlying firm values among past losers generally suffer greatly e.g. for the so-called financial distress of the firms

distinctive types of empirical evidence on momentum returns and liquidity. First, this is because the loser portfolio is more illiquid, as reported in Lesmond, Schill and Zhou (2004) and Avramov et al. (2015) relative to the winner portfolio. Second, the inherent illiquidity of the loser portfolio potentially has a larger sensitivity to unexpected changes in aggregate liquidity relative to the more liquid winner portfolio (Avramov et al 2016, Butt and Virk 2018, among others). Third, the firm values among loser portfolio suffer from large drops during market declines, compared to the firms in the winner portfolio, due to their relatively increased illiquidity. Daniel and Moskowitz (2016) refer to this as high financial distress. Taken together, the variations in market dynamics that have strong linkages to changes in market liquidity, and differences in illiquidity and liquidity risk, of winner and loser portfolios of the WML strategy stresses the inclusion of changes to market liquidity to understand momentum crashes.

We argue that negative momentum returns are more probable in DMS when market liquidity suddenly rises. The loser portfolio, by its inherent illiquidity, displays larger sensitivity and return variation to this unexpected change in market liquidity. This is consistent with theoretical and empirical explanations in Amihud (2002): the rise in market liquidity increases the return on the illiquid portfolios relatively more compared to return on the liquid portfolios. Thus, this may result in lower returns on WML strategy when return on loser (illiquid) portfolio post large return as market liquidity increases in DMS.

We specify that this increase in returns for the loser portfolio, which must be higher than the comparable decrease in its returns when market liquidity unexpectedly falls in DMS, is a necessary condition for momentum crashes. We find consistent evidence: the relationship between momentum returns and changes to market liquidity is asymmetric. During market declines

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and thus are near the level at which the option convexity is strong. With the same token this option convexity that enlarges return is not applicable to the past winners.

momentum returns observe large drops when market liquidity rises relative to the increase in returns when market liquidity falls. For instance, following bearish market states the momentum exposure to rises in contemporaneous market liquidity shows momentum pay-offs drop by an amount of -9.665 with a t-stat of -8.92, whereas the momentum returns increase only by 1.233 (t-stat: 2.19) when market liquidity falls in period *t*. This liquidity asymmetry in DMS stays substantial and statistically significant after controlling for the predicting and explanatory variables, including the optionality effect, noted in Daniel and Moskowitz (2016). To investigate if the optionality effect is driving this strong relationship, we repeat our estimations using a momentum strategy that is neutral to the optionality effect as proposed in Grobys (2018). Our results show that including market liquidity in understanding the return variations of this synthetic momentum strategy is plausible and, more importantly, the increase in market liquidity in DMS is systematically and significantly associated with the returns of this momentum risk adjusted strategy as well.

We consistently find the strong negative relationship between predictive variables and momentum returns reported in literature. However, we show that this predictive relationship mainly captures the downside risk of momentum strategies[5], and this relationship is mostly significant when interacted with DMS dummy *d* and an increase in market liquidity. That is, the predictive variables such as lagged market liquidity, the optionality effect explanation, and lagged momentum risk do not stand a significant chance to explain variations in momentum returns. Most importantly, we show that this strong negative interconnection between the predictive variables and momentum returns is conditional on the contemporaneous increase in market liquidity in DMS.

[5] One exception here is the momentum gap of Huang (2015).

Grundy and Martin (2001) describe how the higher negative market exposure of the momentum strategy indicates that when market returns increase, the returns on momentum strategies decrease. This relationship becomes important in bear market conditions: during the formation period of momentum strategy (in our case from *t-12* to *t-2*), there is a strong chance that stocks with positive market risk will rise with the market after DMS. Following this, Daniel and Moskowitz (2016) explore another plausible explanation for momentum crashes that entails dramatic time variation in the factor exposures of momentum payoffs: in DMS up-market beta for the momentum strategy is negative and almost double the size of the down-market beta. This asymmetry in market exposures is indicative of momentum crashes when market returns rebounds suddenly in DMS, because momentum payoffs have a conditionally large negative market beta. To this effect, we show that even after controlling for factor exposures of the momentum strategy contemporaneously and dynamically, i.e. interacting FF3 factors with DMS dummy *d*, the explanation of momentum crashes in DMS through increase in market liquidity is robust.

Our study contributes to the literature by providing insights on how momentum crashes are systemically linked to changes to market liquidity because of the well-established illiquidity differences in the winner and loser portfolios of WML strategy. These results are of great importance to regulators, investors and manager because of the tail risk of the enigmatic momentum anomaly to unexpected changes in market liquidity can not only influence the fortune of market participants but also the financial stability of markets.

The paper is designed so that in section (2) we discuss the asymmetric relationship between market liquidity and momentum returns in DMS. In section (3) we contrast the significance of market liquidity with other explanatory and predictive variables proposed by the literature. Lastly, in section (4), we conclude.

2. Down Market States and Asymmetric Effect of Illiquidity for Momentum Profits

2.1 Illiquidity Measures

The illiquidity measure for the US market is estimated through the price impact (PI) measure of Amihud (2002). For that the stocks prices, returns and traded volume are obtained from the Center for Research in Security Prices (CRSP) at daily and monthly frequency for all common stocks with the share code 10 or 11 listed on NYSE, AMEX and NASDAQ stock exchanges for the period of 1965:06-2012:12. The PI measure is estimated as $ILLQ_{i,t} = 1/n \sum_{d=1}^{n} \left|R_{i,d,t}\right| / [P_{i,d,t} X\, Vol_{i,d,t}]$. Where $|R_{i,d,t}|$ is the absolute return on stock i on day d in month *t*, and ($P_{i,d,t} X\, Vol_{i,d,t}$) is a dollar traded volume of stock i on day d in month *t*. The *n* indicates the number of days in a month when this ratio of absolute return and dollar traded volume is available. This ratio gauges price responses for a stock given per unit of its dollar volume traded. These daily responses, for the number of days a stock is traded, are averaged across months for each stock in month t. This gives us stock specific monthly illiquidity. Subsequently, cross-sectional average of the $ILLQ_{i,t}$ ratios across all stocks in the month t gives the estimate for monthly market illiquidity for month *t*.

The use of shocks to market liquidity instead of the level of series is a common practice in the liquidity related asset pricing literature (Amihud, 2002, Acharya and Pedersen 2005, Sadka 2006 and others). Following that we collect the shocks from autoregressive (AR) filter of order 2 for market illiquidity. We make an adjustment following Sadka (2006) and multiply the series of shocks to market illiquidity by minus one. This eases out the interpretation of coefficient of market liquidity on momentum profits that we see in coming sections. It may be added that now, whenever the shocks to market liquidity have a positive sign, that is $S\_LIQ_t > 0$, it is interpreted as an unexpected increase in market liquidity and conversely the negative signed shocks (where $S\_LIQ_t < 0$) are interpreted as a sudden decrease in market liquidity.

2.2 Predictors of momentum returns and momentum crashes

In exploring the role of changes to aggregate market liquidity to explain momentum crashes we account for several known predictors of momentum returns and momentum crashes in the literature to gauge the strength of our evidence. Below we note the definitions and construction procedures of these forecasting variables.

1. *d,* we define a dummy variable following the procedure adopted in Daniel and Moskowitz (2016): $d=1$ when the lagged last two-year cumulative return on CRSP VW index return is negative and $d=0$ otherwise.[6]
2. *u* (Market rebounds), Daniel and Moskowitz (2016) note that the infrequent yet unrelenting large falls in momentum returns are contemporaneous with market rebounds following market declines. To account for the forecasting variables in relation to the optionality effect, we define an up-market dummy variable *u*. This indicator variable is one if the excess CRSP VW index return is greater than the risk-free rate in month *t* i.e. $u=1$ when $R_{ex,t} > 0$, and is zero otherwise. Furthermore, their optionality effects specification also includes interaction terms of $d.u.R_{ex,t}$.
3. *Hedging market risk and DMS*, Grundy and Martin (2001) provide evidence that momentum strategies dynamically hedge market risk, and this is one of the reasons for their poor performance following DMS. Daniel and Moskowitz (2016) further this claim by showing that the momentum portfolio mimic the payoffs of short a call option on market

[6] Where Cooper et al. (2004) report that momentum returns rise/fall following up/down-market states, Daniel and Moskowitz (2016) show that momentum crashes happen following DMS when the market is in panic state: market volatility is high. Cooper et al. (2004) proxy market states by using the last three-year cumulative returns on market index i.e. if the lagged three years' cumulative return is positive, the market is referred to be in an up state and negative cumulative imply the contrary i.e. a market downturn. However, Daniel and Moskowitz (2016) measures the same using last two-year cumulative returns on market index.

portfolio in market downturns that incur large negative returns when the market contemporaneously rebounds. To this effect, the regression estimate on the interaction of $d.R_{ex,t}$ aims to describe the Grundy and Martin (2001) evidence on time varying market exposure of momentum returns. The co-efficient on the interaction term $d.u.R_{ex,t}$, in our regression equations and tables, replicates Daniel and Moskowitz (2016) results.

4. *Illiq* (lagged aggregate market liquidity), Avramov et al. (2016) report that momentum returns are higher(lower) following liquid(illiquid) market states. They show that aggregate market illiquidity retains its predictive ability while controlling for several predictors as well as explanatory variables. To keep the comparisons consistent, we compute aggregate market illiquidity using the price impact measure of Amihud (2002) and notate it by *Illiq*. In all instances, *Illiq* represents the previous month level of aggregate market illiquidity. We have also used the interaction of level of lagged market illiquidity with the dummy d and increase in market liquidity dummy $L=1$ whenever $S\_LIQ_t > 0$.

5. $\hat{\sigma}^2_{m,t-1}$ (Market variance), Daniel and Moskowitz (2016) report that momentum crashes occur in DMS and can be forecasted by the ex-ante market volatility. The market variance is estimated using market returns of the 126 days before the start of the next month's momentum returns. In our estimations $d.\hat{\sigma}^2_{m,t-1}$ is the interaction of dummy d and lagged market variance. We have also used the interaction of market variance, with the dummy d and increase in market liquidity dummy $L=1$ whenever $S\_LIQ_t > 0$

6. Momentum risk, Barroso and Santa-Clara (2015) show that the ex-ante variance of the momentum returns, i.e. momentum risk, can be used to hedge large momentum drawdowns. They estimate this variance using the momentum returns of the 126 days before the start of contemporaneous month t. Following the procedure laid in Barroso and

Santa-Clara (2015), we estimate the trailing volatility of momentum returns and denote it as *BS.Vol*. The conditional version of momentum risk using the momentum returns of the 126 days before the start of contemporaneous month t is estimated using a GARCH-type model as proposed in Daniel and Moskowitz (2016). This volatility is indicated as *DM.Vol* in our estimations. We have also used the interaction of both types of momentum risks with the dummy d and increase in market liquidity dummy $L=1$ whenever $S\_LIQ_t > 0$.

7. *M.Gap* (Momentum gap), Huang (2015) report that the momentum gap, i.e. returns differences of past winners and losers during the formation period, predicts a sizeable chunk of momentum crashes and momentum returns as well as momentum returns excluding panic periods. He shows that the predictive power of the momentum gap remains economically and statistically significant after controlling for market return (Cooper et al. 2004), market volatility (Wang and Xu 2015), and market illiquidity (Avramov et al. 2016). We have also used the interaction of the momentum gap with the dummy d and increase in market liquidity dummy $L=1$ whenever $S\_LIQ_t > 0$.

2.3 Characteristics of Momentum Profits in Down Market States

Daniel and Moskowitz (2016) suggest that although momentum strategies offer sizable economic returns, they have frequently incurred huge losses. They show that these losses are partially predictable as they follow DMS when overall market volatility is high and market returns contemporaneously rebound. In Table 2 of Daniel and Moskowitz (2016), the 15 momentum crashes that are shown, result in skewness of -4.70 for the momentum strategy. Further, they argue that the high returns on the momentum strategy is a compensation for the downside risk of WML strategy. Barroso and Santa-Clara (2015) compute that because of these large losses one dollar invested in a momentum strategy in July 1932 is recovered by April 1963. This suggests that higher average returns of momentum strategy come along with extreme negative returns that may ruin the professed profitability of momentum strategy for substantially longer periods than expected.

Daniel and Moskowitz (2016) give the intuitive explanation of this behavior of momentum profits: that is the loser portfolio is an underpriced call option in DMS on market returns and its price increases as market volatility rises when the market posts positive returns. As a result, the, call option on the loser portfolio, which is deep in the money, earns huge profits when market returns contemporaneously increases, and its payoff does not worsen by the same amount when market returns deteriorate in market downturns. This pattern of returns of the loser portfolio results in momentum crashes because the momentum strategy is short in loser stocks. This optionality effect of Daniel and Moskowitz (2016) is the main explanation of momentum crashes that has surfaced so far. This is also consistent with the studies of Cooper et al. (2004) who find that momentum returns are lower following DMS, and of Stivers and Sun (2002) that shows a negative relationship market volatility and momentum returns. Studies such as Kothari and Shanken (1992), and Grundy and Martin (2001) report the dynamic exposure of the momentum strategy to systematic factors as a major reason for the momentum collapse. In particular, the asymmetric response of market beta of loser stocks in bear market states, when market contemporaneously rebounds, turns momentum strategy as negatively exposed to market performance.

Daniel and Moskowitz (2016) describe this asymmetric response as an optionality effect of momentum strategy.[7] Yan (2013) further elaborates that this optionality effect is mainly driven by the asymmetric effect of the loser stocks. He then points out that why this asymmetric response is restricted to the loser stocks does not receive much attention. Resultantly, in this paper, we explore an alternative explanation for momentum crashes within the market liquidity and asset pricing

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[7] Precisely, a momentum strategy is written (short) call option on the market returns in DMS, which finds huge loses once market return increases and gains little when market return decreases.

framework as this important link is ignored in previous studies. To elucidate this connection, we discuss how the existing literature on liquidity risk and asset pricing suggests that the returns on the illiquid assets appreciate/depreciate more when market liquidity rises/falls (Amihud 2002, Pastor and Stambaugh 2003, and others).

Lesmond et al. (2006) and Avramov et al. (2015) document that the loser portfolio is more illiquid than the winner portfolio. Resultantly, the returns on the loser portfolio should be large when market liquidity rises and this increase lowers momentum profits and vice versa. In the remainder of this paper we test this reasoning and show that changes in market liquidity are an important determinant of momentum crashes.

To see this effect, we download the monthly momentum deciles from Kenneth French's website. The momentum strategy, i.e. WML, is the difference between the returns on the winner portfolio (10th decile) and the loser portfolio (1st decile) and is represented by $R_{WML,t}$ in our work. The sample period comprises July 1963 to December 2012. The beginning of the data period in our work is more of a convention than a choice for asset pricing literature studying the role of liquidity (see Amihud 2002, Acharya and Pedersen 2005, among others). As we identify DMS in our work the first two years of data is further clipped and regressions in our work are run from 1965:06 to 2012:12.

Table 1 shows the relationship between the returns on the loser portfolio, the winner portfolio and momentum and market liquidity in DMS. Here, the DMS dummy d is interacted with a contemporaneous increase and decrease in market liquidity, separately, that are shown as $d.S\_LIQ_t > 0$ and $d.S\_LIQ_t < 0$, to report the respective summary stats. In the full sample the average momentum returns are roughly three times higher than market returns whereas the loser portfolio performs the worst. Whereas, the momentum returns in DMS that comprises 90 months in our sample period are lower in comparison to their performance in the full sample. However, now the performance of the loser portfolio is better than the winner portfolio and this results in an overall negative return for the momentum strategy in DMS. Importantly, the clear distinction between the performance of the loser and winner portfolios emerges once momentum returns are averaged for these 90 observations in DMS, when market liquidity contemporaneously increases/decreases. Of the 47 months in DMS when liquidity increases, shown as $d.S\_LIQ_t > 0$, loser and winner portfolios have average monthly returns of 3.507% and 0.702%. Resultantly, the average of momentum returns is -2.805% in DMS when market liquidity increases. Not surprisingly the average returns for the markets are 1.110%, that is, as market liquidity increases the overall market performs well.

Similarly, the opposite effect is seen when market liquidity suddenly decreases in DMS ($d.S\_LIQ_t < 0$): market returns drop overall. However, these statistics across $d.S\_LIQ_t > 0$ and $d.S\_LIQ_t < 0$ do not explain the asymmetric effect for momentum returns for unexpected variations in market liquidity as we argued, because the average momentum losses and gains are respectively -2.805% and 2.246%, and these averages, one may argue, are not substantially different.

To understand the asymmetric response, we analyzed the worst five losses and gains in momentum returns in DMS when market liquidity contemporaneously increases and decreases. Table 2 panel A shows the results when market liquidity improves and there is a substantial increase in returns for losers i.e. largest return of 46.65% is posted in April 2009, whereas the largest return on winners is only 4.79% in March 2009. On the other hand, the positive return on the WML strategy is driven by the large losses on losers when market liquidity falls, see panel B of Table 2. Overall, the gains for the loser portfolio when market liquidity improves are higher than the losses on the loser portfolio when market liquidity falls in DMS. Resultantly, this asymmetric relationship of the loser portfolio to market liquidity in DMS results in momentum crashes.

The results in these tables have two aspects, the first aspect alludes to the diametrically opposite pattern of returns on loser and winner portfolios to an unexpected rise or fall in market liquidity in DMS. The second aspect is that this response is asymmetric for loser stocks as their returns increase more when market liquidity rises than their comparable decrease when market liquidity falls. The negative skewness in momentum returns, which has been pointed out by Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016), is attributable to later aspect of momentum returns. [8]

2.4 Momentum Profits and Asymmetric Effect of Liquidity

To test for the asymmetric effect of market liquidity on momentum profits, we estimate the coefficients on the interacting variables $d.S\_LIQ_t > 0$ and $d.S\_LIQ_t < 0$. To ease out an interpretation of the coefficients associated with increases and decreases of market liquidity, we take the absolute value of the decrease in market liquidity in DMS, such as $|d.S\_LIQ_t < 0|$, to estimate the following model. [9]

$$R_{it} = \alpha + \beta_1 d.S\_LIQ_t > 0 + \beta_2 \mid d.S\_LIQ_t < 0 \mid + \varepsilon_t \tag{1}$$

where R_{it} is the monthly return series of the loser, winner or momentum portfolios. The main reason for estimating separate effects of increases and decreases in market liquidity is to uncover the return sensitivities of the loser, winner and momentum portfolio returns given our expectations discussed earlier. Table 3 contains these outputs. For momentum returns, the increase in market liquidity in DMS has β_1 of -9.665 with a t-stat of -8.92, which is approximately eight times bigger than the coefficient associated with the decrease in market liquidity in DMS: that is β_2 of 1.233

[8] The momentum returns for 1965:06-2012:12 are negatively skewed by -1.491.
[9] The adjustment is essential to ease out the interpretation of the coefficients in the conventional sense. Without taking an absolute value of decrease in market liquidity the coefficients associated with increase and decrease in market liquidity, such as β_1 and β_2 will be the same but their meaning will be different.

with a t-statistics of 2.19. This indicates that in DMS the momentum profits decrease about 8 times more when market liquidity rises than the corresponding increase in momentum returns when market liquidity falls. This liquidity risk asymmetry is aligned to our expectations.

Furthermore, in Table 3, the asymmetry in liquidity exposures, and consequent return variation in the loser portfolio, is large: the estimated coefficient β_1 is 10.360 with an associated t-stat of 8.23, whereas the estimated coefficient β_2 is -2.328 with an associated t-stat of -3.56. On the other hand, there is no statistically reliable increase for the returns on the winner portfolio when market liquidity increases in DMS. However, when market liquidity abruptly deteriorates, the β_2 is significantly estimated with a coefficient of -1.096 with an associated t-stat of -2.03. Obviously, the results imply that return variations in winner and loser portfolios are not comparable and are asymmetric in relation to unexpected changes to market liquidity that result in momentum crashes in DMS.

This variation in the liquidity exposures of winner and loser portfolios is very much reconciled to the existing body of literature on liquidity risk and asset pricing. However, the asymmetric effect of liquidity risk following DMS that we identify is novel. We conjecture that one plausible explanation for this relationship is that the prices in DMS are already depressed. This is especially reasonable for illiquid stocks as a further decrease in their returns is less tenable during bearish market conditions when market liquidity falls. Instead, the rise in their returns is more maintainable once market liquidity improves. This could also be rationalized through the investor sentiment effect that inflates prices of stocks where information asymmetry, another feature of illiquid stocks, is higher as market sentiment improves (Baker and Wurgler 2006). To this effect Daniel and Moskowitz (2016) report that in one DMS the loser portfolio reduced its value by 84%. Combing this facet, i.e. the depressed price of the loser portfolio, with the asymmetric and large return sensitivity of the loser portfolio results in price recovery for the loser when market liquidity rises in DMS. Essentially this price appreciation in the loser portfolio is much higher than the simultaneous appreciation in the winner portfolio and has a large knock down effect on momentum profits following market downturns.

3. Robustness of various explanations of momentum crashes in DMS

3.1 Changes to market liquidity and market rebounds

As discussed in the previous section, the variation in market liquidity in DMS is linked with momentum downturns. However, we have yet to see if the market liquidity has some additional explanatory power for the momentum crashes along with the optionality effect (i.e. crash risk) of Daniel and Moskowitz (2016). For that we included the regression of Daniel and Moskowitz (2016, see page 228 and Table 3).[10] Furthermore, to corroborate their evidence, we augment their optionality effect with variables of interest under the scope of our study:

$$R_{WML,t} = \alpha + \beta_1 R_{ex,t} + \beta_2 d + \beta_3 d.R_{ex,t} + \beta_4 d.u.R_{ex,t} + \beta_5 .S\_LIQ_t + \beta_6 d.S\_LIQ_t + \varepsilon_t \tag{2}$$

In equation (2), the R_{WMLt} shows the returns on the conventional WML self-financed portfolio and S_LIQ_t is the liquidity related shocks and $d.S\_LIQ_t$ is the interaction between innovations in market liquidity and the DMS dummy. In Table 4, the regression outputs 1, 2 and 3 show that the shocks to market liquidity in DMS have additional explanatory power for momentum crashes over and above the optionality specification, or the so-called forecasting variables of Daniel and Moskowitz (2016).[11] The results in panel A of Table 4, for the negative coefficient of β_6 indicates that

[10] Daniel and Moskowitz (2016) find that in bear market conditions the up-market beta is -1.51, which is more than double the down-market beta of -0.70, and the difference in betas is also statistically significant.
[11] For instance, the adjusted R^2 of optionality effect regression i.e. excluding $d.S\_ILLQ_t$ from equation (2) is 0.13. This result is available upon request.

unexpected change in market liquidity is negatively related to momentum profits following DMS and is statistically significant.

Subsequently, we segregate the variable $d.S\_LIQ_t$ into two components, representing increase and decrease in market liquidity following market declines, as explained earlier. To gauge the relevance of the reported asymmetric market liquidity effect, we add these two terms together with the Daniel and Moskowitz's (2016) optionality effect regression:

$$R_{WML,t} = \alpha + \beta_1 R_{ex,t} + \beta_2 d + \beta_3 d.R_{ex,t} + \beta_4 d.u.R_{ex,t} + \beta_5 .S\_LIQ_t + \beta_7 d.S\_LIQ_t > 0 + \beta_8 \mid d.S\_LIQ_t < 0 \mid + \varepsilon_t \quad (3)$$

The results of different specifications of equation 3 are presented in panel B of Table 4. These results show that the increase in market liquidity is an important determinant of the large losses on momentum returns in DMS and is highly significant. Furthermore, the large effect, and statistical significance, of increases in market liquidity compared to decreases in market liquidity indicates that the market liquidity impacts asymmetrically on momentum profits for the fact β_7 (coefficient on sudden increase in market liquidity) is more economically meaningful than β_8.

In fact, after the inclusion of $d.S\_LIQ_t>0$ the optionality effect – explanation in Daniel and Moskowitz (2016) for downside risk of momentum payoffs – has lost its statistically significance: the coefficient on $d.u.R_{ex,t}$ *i.e.* β_4 is insignificant in specification 5 although it maintains its economic meaningfulness. The importance of distinguishing asymmetric effects of liquidity to explain momentum crashes is reinforced by the increase in adjusted R^2 when compared to the baseline specification in Daniel and Moskowitz (2016). The model fit of the tested specifications in Panel B of Table 4 is even better than the specifications, not segregating the impact of rises and falls in market liquidity, in Panel A of Table 4.

We also test for the explanation of momentum crashes through an interactive variable that signifies the increase in market liquidity when the market rebounds in DMS. This variable is represented as

$d.u.S\_LIQ_t > 0$: we contrast the significance of this variable for momentum crashes against the optionality effect i.e. $d.u.R_{ex,t}$. This way we can directly compare the suitability of either the upmarket beta or the coefficient on the increase in market liquidity to explain momentum crashes in DMS. To test that we run the following regression:

$$R_{WML,t} = \alpha + \beta_1 R_{ex,t} + \beta_2 d + \beta_3 d.R_{ex,t} + \beta_4 d.u.R_{ex,t} + \beta_5 .S\_LIQ_t + \beta_9 d.u.S\_LIQ > 0 + \varepsilon_t \quad (4)$$

The regression outputs in panel C of Table 4 contain three specifications of equation 4 and the coefficient on $d.u.S\_LIQ_t > 0$ is sizeable and is precisely estimated, whereas the regression estimate on the optionality effect only retains its economic meaningfulness with less statistical reliability. This result indicates that when the market rebounds in DMS, the simultaneous improvement in market liquidity is a more reliable explanation for momentum crashes than the contemporaneous positive returns on market index.

Although the variation in market liquidity in DMS statistically dominates the optionality effect of Daniel and Moskowitz (2016), one may suspect that both effects are highly correlated. The correlation between these two variables is 40.75%. To further investigate the explanatory power of the sudden rise of market liquidity following DMS, as an out of sample test, we use the 52-week high industry momentum strategy proposed by Grobys (2018).[12] This momentum strategy uses the framework of George and Hwang (2004), the 52-week high momentum strategy, for the 48 value-weighted industry portfolios. Interestingly, Grobys (2018) claims that the optionality effect of Daniel and Moskowitz (2016) is not a relevant explanation for the George and Hwang (2004) 52-week high industry momentum strategy as well as for his momentum risk-scaled 52-week high

[12] Grobys (2018) investigate a synthetic version of George and Hwang's (2004) 52-week high momentum strategy in an industrial portfolio setting instead of the conventional WML price momentum strategy that we consider and is used in the studies of Barroso and Santa-Clara (2015) and Daniel and Moskowitz (2016). His results show that for the risk-scaled momentum strategy, the downside risk is reduced substantially to the extent that the optionality effect of Daniel and Moskowitz (2016) is no longer a reliable explanation. We are thankful to Klaus Grobys for providing the industry momentum data.

industry momentum strategy following Barroso and Santa-Clara (2015). If the increase in market liquidity in DMS is just another facet of the optionality effect, then arguably we may observe irrelevance of the role of variables underpinning in our work i.e. $d.S\_LIQ_t > 0$ and $d.u.S\_LIQ_t > 0$. We repeat the regressions in Table 4, using the Grobys (2018) synthetic version of 52-week high industry momentum strategy as the dependent variable and report results in Table 5. We find coefficients on both the variables $d.S\_LIQ_t > 0$ and $d.u.S\_LIQ_t > 0$ are significant, as can be seen in Panel B and C, and are economically meaningful. Nevertheless, the reduced coefficients on these variables are very understandable as the 52-week high industry momentum strategy is less risky with average returns, minimum and maximum returns are lower than the momentum strategy mainly used in this paper. [13]

3.2 Market variance and momentum returns in down market states

Given the optionality effect explanation of Daniel and Moskowitz (2016) of momentum crashes that occur, following DM when market variance is higher and when market rebounds contemporaneously, as an outcome of return variation in the portfolio of past losers. They argue that the loser portfolio behaves like an underpriced call option in DMS on the market portfolio, resulting in a low expected return for the momentum portfolio as this strategy shorts the losers. Since the value of a call option with underlying asset as market increases as market variance increases, therefore the momentum strategy which shorts this call option finds its returns to be a decreasing function of the future variance of the market.

[13] On a separate note, we identify that results in Grobys (2018) are sample specific even for optionality effect of Daniel and Moskowitz using synthetic momentum portfolios: he writes that (see page 6) “The point estimates for $\hat{\beta}_{B,U}$ are virtually zero and statistically insignificant.” Our results to this effect are evidently contrary to his findings.

To this effect we assess the strength of our evidence by augmenting the regression in Daniel and Moskowitz (2016, see page 230 equation 4) by including $d.S\_LIQ_t > 0$:

$$R_{WML,t} = \beta_0 + \beta_1 d + \beta_2 \hat{\sigma}^2_{m,t-1} + \beta_3 d.\hat{\sigma}^2_{m,t-1} + \beta_4 d.S\_LIQ_t > 0 + \varepsilon_t \tag{5}$$

Table 6 reports the results. Despite having a smaller sample in our study than Daniel and Moskowitz's work the outputs are similar. Specifically, see point estimates on $d.\hat{\sigma}^2_{m,t-1}$ in panel A; Daniel and Moskowitz (2016) regression shows that future momentum returns are a decreasing function of increasing market variance in DMS.

The outputs containing $d.S\_LIQ_t > 0$ are presented in panel B of Table 6. Once we account for sudden increases in market liquidity in periods of market declines, the coefficient on $d.S\_LIQ_t > 0$ is the only significant explanation. Although the contemporaneous explanation such as an increase in market liquidity and predicting variables like market volatility are not directly comparable, nevertheless we expect that these results indicate the nature of the predictive relationship: the negative relationship between the lagged market variance and future momentum returns is conditional on the increase in market liquidity in DMS for the following month. In the coming section we explore this proposition for the predictive performance of market variance and other known predicting variables.

3.3 Predictor variables of momentum returns and market liquidity

In the wake of the insignificance of ex-ante market variance, we explore our proposition that the market variance is only negatively related with momentum return when market liquidity increases contemporaneously in DMS. To explore this assertion, we also add other predictors for momentum crashes as well to explain the momentum returns. Namely, we add lagged aggregate market illiquidity (Avramov et al. 2016), unconditional and conditional versions of momentum risk (Barroso and Santa-Clara 2015 and Daniel and Moskowitz) and formation period of cross-sectional dispersion of WML strategy i.e. the momentum gap (Huang 2015). These variables are denoted as $Illiq_{m,t-1}$, $BS.Vol_{t-1}$, $DM.Vol_{t-1}$, and $M.Gap_{t-1}$, respectively and for details on the computational procedures of these variable please refer to section 2.2.[14] To understand the nature of the relationship between these predictive variables with momentum returns in connection with the increase in market liquidity in DMS denoted as $d.S\_LIQ_t > 0$, the different versions of the following regression are estimated:

$$R_{WML,t} = \beta_0 + \beta_1 d + \beta_i .P\_Variables_{t-1} + \beta_2 d.S\_LIQ_t > 0 + \varepsilon_t \qquad (6)$$

Panel A, Table 7, reports the results for running the regression of momentum returns $R_{WML,t}$ on a constant and takes each of the predictive variables from the set, [$Illiq_{m,t-1}$, $BS.Vol_{t-1}$, $DM.Vol_{t-1}$, and $M.Gap_{t-1}$]. These results confirm the findings of the original studies and that these predicting variables are strong predictors of changes in future momentum pay-offs.

Next, in panel B of Table 7, we repeat all specifications in panel A with the inclusion of $d.S\_LIQ_t > 0$, and in column 5 we have also reported the output of a regression which includes all variables. As we have already seen for ex-ante market variance in Table 6, that all the predicting variables except for momentum gap are insignificant in Table 7.

As we have shown in section 3.1 that the left tail risk of the momentum strategy is explained better by the increase in market liquidity in DMS than the optionality effect of Daniel and Moskowitz (2016), we conjecture that the significant negative relationship between the predicting variables and future momentum returns, as shown in Panel A for full sample, is mainly driven by left tail risk of momentum strategy, and is explained well by rises in market liquidity in DMS. [15] Therefore, once the more robust and informed signal of left tail risk of momentum strategy is included, the

[14] We are thankful to Huang for providing the series of momentum gap.

[15] In fact, when we reproduce the Panel B of Table 7 by replacing the optionality effect $d.u.R_{ex,t}$ for $d.S\_LIQ_t > 0$, then all the predicting variables despite the strong presence of optionality effect, remain significant except for lagged level of market illiquidity. These results can be supplied upon request.

effect of predictors subside and do not remain statistically reliable. The result of the full specification reported in column 5 of panel B (Table 7) shows that economic implication of momentum risk is as argued in Barroso and Santa Clara (2015), however, $d.S\_LIQ_t > 0$ and *M.Gap* are the ones that are reliably estimated. The importance of $d.S\_LIQ_t > 0$ is further boosted by the increased values of adjusted R^2 in panel B compared to panel A of Table 7. To say it explicitly, the negative association of all predictors (except for the momentum gap) at *t-1* with the momentum returns at *t* is only maintainable if market liquidity in DMS also increases at *t* and not otherwise. Implying that the ex-ante negative association of all predictors with the momentum returns is conditional on next-period rise in market liquidity following DMS only.

3.4 Momentum crash predictors and ex-post market liquidity

To understand the relationship between forecasting variables and ex-post market liquidity, we define liquid state as $L=1$, when the market liquidity contemporaneously increases $S\_LIQ_t > 0$ and 0 otherwise.[16] In this vein, we proceed by taking the interaction of the predicting variables such as $\hat{\sigma}^2_{m,t-1}$, $Illiq_{m,t-1}$, $BS.Vol_{t-1}$, $DM.Vol_{t-1}$, and $M.Gap_{t-1}$, with indicator functions of *d* and *L*. The set of these interacting variables is shown as $d.L.P\_Variables_{t-1} = [d.L.\hat{\sigma}^2_{m,t-1}$, $d.L.Illiq_{m,t-1}$, $d.L.BS.Vol_{t-1}$, $d.L.DM.Vol_{t-1}$, and $d.L.M.Gap_{t-1}]$. Now these predicting variables have become explanatory variables. Their construction facilitates in understanding what determines their forecasting ability in the contemporaneous sense. After constructing these interacting variables, we run different specifications of the following regression:

$$R_{WML,t} = \beta_0 + \beta_1.d + \beta_i.P\_Variables_{t-1} + \beta_j.d.L.P\_Variables_{t-1} + \varepsilon_t \quad (7).$$

[16] Similarly, we construct a dummy that depicts contemporaneously sudden falls in market liquidity, we notate it by *IL* i.e. market liquidity receives an illiquid shock. The results of regressions using both dummies interacted with DMS dummy *d* and each of predicting variable from the set $P\_Variables_{t-1} = [\hat{\sigma}^2_{m,t-1}$, $Illiq_{m,t-1}$, $B.Vol_{t-1}$, $D.Vol_{t-1}$, $M.Gap_{t-1}]$ are presented in Appendix A.

Now in the above equation (7), the β_i shows the relationship between the momentum returns $R_{WML,t}$ and predicting variables such as $\hat{\sigma}^2_{m,t-1}$, $Illiq_{m,t-1}$, $BS.Vol_{t-1}$, $DM.Vol_{t-1}$, and $M.Gap_{t-1}$ in all periods other than the periods in DMS, when market liquidity contemporaneously rises. Whereas, β_j captures the relationship in DMS, when ex-post market liquidity increases i.e. $d.L.\hat{\sigma}^2_{m,t-1}$, $d.L.Illiq_{m,t-1}$, $d.L.BS.Vol_{t-1}$, $d.L.DM.Vol_{t-1}$, *and* $d.L.M.Gap_{t-1}$.

These results are shown in Table 8, the coefficients on $\hat{\sigma}^2_{m,t-1}$, $Illiq_{m,t-1}$, $B.Vol_{t-1}$, $D.Vol_{t-1}$ are economically small and statistically insignificant. However, the coefficients on $d.L.\hat{\sigma}^2_{m,t-1}$, $d.L.Illiq_{m,t-1}$, $d.L.BS.Vol_{t-1}$, $d.L.DM.Vol_{t-1}$, in DMS when ex-post market liquidity increases are -0.024, -3.372, -3.081 and -3.838 with the t-stats of (-6.69), (-7.21), (-5.54) and (-6.05), respectively. Essentially, our results identify that the overall economically large, and statistically significant, negative predictive relationship – ability to predict momentum crashes – is conditional on ex-post change in market liquidity. Such that the results reported in panel A of Tables 6 and 7, showing a strong negative predictive relationship in full sample for the variables such as $\hat{\sigma}^2_{m,t-1}$, $Illiq_{m,t-1}$, $BS.Vol_{t-1}$, $DM.Vol_{t-1}$, turn insignificant in the presence of our latest interacting variables as shown across specifications in Panel B of Table 8.

With the only exception of the prediction of Huang's (2015) momentum gap, otherwise all predictors for momentum returns/crashes are not independent of contemporaneous market liquidity in DMS.

Lastly, we conclude that the evidence for predicting variables interacted to dummy L identifies an important systematic characteristic that determines why forecasting variables in the first place can predict momentum crashes. If this condition is not met, their forecasting ability is lost in most of the cases otherwise the degree of the prediction suffers i.e. *M.Gap*, see the results in Appendix A Table A.I.

3.5 Liquidity risk and exposure to other risk factors of momentum profits

So far we have explored explanatory effects of contemporaneous market rebounds, in DMS, i.e. the optionality effect of Daniel and Moskowitz (2016) and rises in market liquidity. This investigation is followed by why certain variables forecast momentum crashes and/or momentum returns. In this section we explore the robustness of the explanation put forward by our work compared to other strong explanations for momentum returns as well as momentum crashes. Momentum returns are shown to be negatively correlated with size and value (Barroso and Santa-Clara 2015, and others) whereas, Grundy and Martin (2001) have shown that momentum returns have time varying exposure on market and size factors. The significant and negative exposure, although time-varying, of the momentum strategy on the market index following DMS, is one plausible explanation for the momentum crashes.

For the reported time variation in exposures of systematic risk-factors on momentum returns, it is necessary to test the significance of a contemporaneous increase in market liquidity in DMS as an explanation of momentum crashes after controlling for other contemporaneous determinants of momentum returns. To do so, we adopt the procedure in Barroso et al. (2017) that controls for static as well as dynamic factor exposures (an instance when FF3 model factors i.e. market factor (R_{ex}), size factor (SMB_t) and value factor (HML_t) are interacted with DMS dummy d) of FF3 model. In panel A and B of Table 9, the momentum returns are orthogonalised over unconditional/conditional version of FF3 model. Column 1 shows that the optionality effect of Daniel and Moskowitz (2016) for momentum returns for unconditional FF3 model is strongly significant. However, importantly, the economic and statistical reliability of an increase in market liquidity in DMS remains present, even after controlling for FF3 factor exposures, for momentum returns/crashes. This impact of rising market liquidity remained unaffected across specifications incorporating the lagged market variance, unconditional and conditional volatility of momentum strategy and momentum gap. We note the same even after accounting for the dynamic factor exposures of FF3 model in DMS. However, we identify that the optionality effect is not significant when we account for dynamic exposures of FF3 model factors. Furthermore, we note that in full specifications reported under columns 7 and 14 in panels A and B, of Table 9, Huang's momentum gap loses its statistical significance, after controlling for all predictors both in unconditional and conditional specifications. In sum, we provide conclusive evidence that the increase in market liquidity in DMS is a determinant of momentum crashes independent of other explanations i.e. the optionality effect and FF3 model static and dynamic exposures.

4. Robustness tests

Liquidity is a multidimensional concept. Resultantly, there are plethora of liquidity measures proposed in the literature approximating different dimensions of liquidity. Cochrane (2011) notes that literature have struggled to define and measure liquidity. Goyenko, Holden and Trzcinka (2009) extensively study numerous proxy measures of liquidity for US stock returns and their linkages with refined measures of market liquidity constructed from high frequency data. They report that Amihud (2002) PI measure and zero returns (ZR) of Lesmond, Trzcinka, and Ogden (1999) are appropriate price impact and percent cost proxies, respectively. Fong, Holden and Trzcinka (2017, FHT) undertake the same work as of Goyenko et al. (2009) for the international markets and document that Amihud PI measure, ZR and FHT measure are strongly correlated with corresponding measures calculated from high frequency trade data. Another commonly used measure of liquidity is the Gamma measure of Pastor and Stambaugh (2003, PS), although Goyenko et al. (2009) and Fong et al. (2017) both document that Gamma measure is dominated by other approximations for market liquidity.

Notwithstanding the strong results that we have presented with the Amihud (2002) PI measure to understand momentum crashes, we demonstrate the reliability of our evidence by replicating our results with Gamma measure, FHT measure and ZR. These unreported results (available upon request) show that we find similar results with FHT measure and ZR. Although statistical significance is there; it is not as strong as we find with Amihud (2002) measure. However, using PS Gamma measure we do not find our results as robust as are available with other prominent measures for market liquidity.[17] It is likely that different proxies are capturing different dimensions of liquidity and only some of these relate to momentum crashes, however only concentrating on results with the better proxies for market liquidity might appear as a compromise on the reliability of our results. Therefore, we retrieve the common factor, in the unexpected changes to the cross-section of four market liquidity measures using principal component analysis, to examine if there is a common variation in measures of aggregate liquidity that is linked to momentum crashes. Using the second principal component that accounts for the second largest amount of variability in the factor structure, we replicate our results in Tables 4, 5 and 7.[18] Tables B.I, B.II and B.V

[17] The non-robustness of our results using Gamma measure, led us replicating Avramov et al. (2016) evidence. We find that their results also do not hold when we replace Amihud (2002) PI measure by the Pastor and Stambaugh (2003) Gamma measure. This is explained by the evidence in Li, Novy-Marx and Velikov (2017) that replicate the original study of Pastor and Stambaugh (2003). They show that momentum is unrelated with liquidity risk given by Gamma measure. They also note that the performance of PS liquidity factor is sensitive to mechanical details involved in the factor construction bringing difficulties in replication of the former work and even interpretation of new results.

[18] The results using first component are qualitatively appropriate to the motivation and reported results in the paper, however, statistical significance is only available for $d.u.S\_LIQ_{t} > 0$ in replications of tables 4 and 5. The replications of table 7 using first principal component are economically and statistically robust. Nonetheless, the better description of momentum crashes by second component is suggestive of the fact that not all dimensions of aggregate liquidity are linked to momentum crashes.

present the corresponding results in the file titled supplementary results. All the results endorse our evidence: mostly t-stats on the variables of interest i.e. $d.S\_LIQ_{,t}$, $d.S\_LIQ_{,t}$ >0, or $d.u.S\_LIQ_{,t}$ >0 are significant for conventional alpha level of 0.01. The results using common factor in the so-called better measures of market liquidity are statistically even more significant and are largely comparable to what we have presented in the paper, see Table B.II, B.IV and B.VI in the supplementary results file. Thus, we conclude that there is a common source of variation in unexpected changes to aggregate liquidity that is linked to momentum crashes.

5. Conclusion

We document a new explanation for the well-reported momentum crashes that follow market downturns by incorporating ex-post changes in market liquidity. Our investigation shows that the impact of contemporaneous changes to market liquidity on large momentum falls adds to the existing strong evidence base in multiple ways. First, in the most conservative manner, the explanation of optionality effect presented in Daniel and Moskowitz (2016) is a co-function of ex-post unexpected changes in market liquidity along with contemporaneous market rebounds. However, when taken together, contemporaneous changes to market liquidity dominate ex-post market rebounds and subsume ex-ante market variance related explanation of momentum crashes. Second, for the larger illiquidity of the loser portfolio than the winner portfolio the loser portfolio is asymmetrically linked to changes in market liquidity and responds more to the increase in market liquidity, in comparison to decrease in market liquidity in DMS. Arguably, this ex-post liquidity exposure asymmetry summarizes the prior period large losses on the firm values belonging to the loser portfolio that results in large contemporaneous returns on the loser portfolio vis a vis momentum drawdown in DMS as market liquidity unexpectedly improves. This return variation, because of asymmetric liquidity exposures in DMS, for the loser portfolio relative to the winner portfolio is consistent with the empirical evidence. This is described in literature (Baker and Wurgler (2006), Stambaugh, Yu and Yuan (2012), among others) such that the stocks in which information asymmetry is large witness considerable price appreciation relative to stocks where information asymmetry is low as market sentiment improves. One other explanation is the financial distress of past losers (Daniel and Moskowitz 2016). Our evidence shows that changes in market liquidity capture sentiment effect better than market rebounds in bearish market conditions, to the extent these changes are driven by sentiment, to explain the downside risk of momentum returns.

Finally, and most importantly, our evidence elucidates the nature of the relationship between the well-known predictors and momentum crashes. Our results conclude that, mostly, the predictive ability of lagged market illiquidity, ex-ante market variance as well as momentum risk and momentum gap encapsulate the ex-post market liquidity related explanation of momentum downside risk. Put simply, when we account for variations to market liquidity, the effects of forecasting variables are either subsumed altogether or the magnitude of their ex-ante predictions weakens. This conclusion holds, most of the times, even when we control for static as well as dynamic factor exposures of the FF3 model factors. Overall, the contributions from our study illuminate asset pricing literature on momentum crashes as well as time variation in momentum returns. We expect future research will identify firm level common sources of variations that will guide our ex-ante understanding of these crashes to develop better risk management tools for investors and managers alike.

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Table 1: Characteristics of Momentum related profits in Down Market States.

Table presents the returns related characteristics for the loser, winner, momentum and market for the sample comprising 1965:06-2012:12, in down market states (DMS). To identify DMS, we construct a dummy variable *d* that takes the value of 1 when the cumulative returns for last 24 months for the market portfolio is negative and is zero otherwise. This results in 90 months in the full period considered here. Following DMS, we further distinguish features of momentum returns when market liquidity increases $d.S\_LIQ_t > 0$ and when market liquidity decreases $d.S\_LIQ_t < 0$.

Sample	*Observations*	*Loser*	*Winner*	*Momentum*	*Market Returns*
Full-Sample	571	-0.737%	0.628%	1.365%	0.434%
DMS	90	-0.379%	-0.744%	-0.365%	-0.490%
$d.S\_LIQ_t > 0$	47	3.507%	0.702%	-2.805%	1.110%
$d.S\_LIQ_t < 0$	43	-4.362%	-2.116%	2.246%	-2.025%

Table 2: Asymmetric Momentum related profits in Down Market States.

In Panel A, the worst five monthly losses occurring during the sample period comprising 1965:06-2012:12 are shown. Under the column 'Date', months of occurrence of these losses on momentum strategy are reported when the market liquidity increases contemporaneously in DMS. We identify DMS when the cumulative returns for last 24 months for the market portfolio is negative: we construct a dummy *d* that takes the value of 1 the noted market state occurs and is zero otherwise. The returns on the short leg (Loser) and long leg (Winner) of the strategy are also shown. Similarly, the best five monthly returns for the momentum strategy following DMS are also shown in Panel B essentially when market liquidity suddenly decreases. Similarly, the returns on short leg (Loser) and long leg (winner) of the strategy are also shown.

Panel A: Increase in Market Liquidity				Panel B: Decrease in Market Liquidity			
Date	Loser	Winner	Momentum	Date	Loser	Winner	Momentum
2009-04	45.65%	-0.14%	-45.79%	2009-02	-25.65%	-4.57%	21.08%
2009-03	44.18%	4.79%	-39.39%	2002-02	-18.02%	-2.44%	15.58%
2009-08	25.01%	0.16%	-24.85%	2001-09	-23.35%	-7.93%	15.42%
2002-11	22.40%	2.00%	-20.40%	2001-03	-18.43%	-3.74%	14.69%
2009-05	21.27%	2.30%	-18.97%	2002-04	-14.11%	-0.17%	13.94%
AVG	31.70%	1.82%	-29.88%	AVG	-19.91%	-3.77%	16.14%

Table 3. Loser, Winner and Momentum Returns and Variation in Market Liquidity in DMS

Table provides the output of a regression to show the relationship of the excess returns on the loser, winners and momentum profits with positive and negative shocks to market liquidity in DMS. The variable $d.S\_LIQ_t > 0$ indicates that increased market liquidity and $|d.S\_LIQ_t < 0|$ indicates the effect decreased market liquidity, we take the absolute values of the former for the ease of interpretation. The OLS estimates from each regression are shown below the column title displaying the name of the portfolio (dependent variable) and respective *t-stats* are provided in parentheses. Adjusted R^2 are reported in the last row of the table.

Coefficients	Variables	Loser	Winner	Momentum
β_0	*Cons*	-0.009 (-2.88)	0.007 (2.46)	0.0161 (5.69)
β_1	$d.S\_LIQ_t > 0$	10.360 (8.23)	0.698 (0.67)	-9.665 (-8.92)
β_2	$\mid d.S\_LIQ_t < 0 \mid$	-2.328 (-3.56)	-1.096 (-2.03)	1.233 (2.19)
R^2_{adj}		0.122	0.005	0.127

Table 4: Momentum Crashes and Time Varying Market Liquidity

Table reports the estimation outputs for equations (2), (3) and (4) shown in the main text. Each of the regressions reported in this table have momentum returns $R_{WML,t}$, for the period of 1965:06-2012:12, as the dependent variable. The output of equation (2) is given in Panel A, the explanatory variables are $R_{ex,t}$, the excess return on the value weighted market portfolio, the dummy variable d that takes the value of 1, whenever the returns for the last 24 months of the US market is negative and 0 otherwise. Interaction term $d.\ R_{ex,t}$ traces the value weighted return on market portfolio after down-market states (DMS), and the variable $d.u.R_{ex,t}$ traces the value weighted return on market portfolio following DMS when the market returns contemporaneously increase i.e. market returns are strictly positive for this interacting variable. Lastly, the variable $d.S\_LIQ_{,t}$ captures market liquidity following DMS. The coefficients on these variables are β_1, β_2, β_3, β_4, β_5 and β_6 as shown in the equation 2. In Panel B the outputs of different types of the equation (3) are shown, all variables are the same as in Panel A, expect the variable $d.S\_LIQ_{,t}$ which is decomposed into two variables, i.e. $d.S\_LIQ_{,t} >0$ shows the increase in market liquidity and $|d.S\_LIQ_{,t}<0|$ shows the decrease in market liquidity following DMS. The coefficient on these variables are β_7 and β_8. Lastly in Panel C, the outputs of equation (4) are shown. In this set of estimations the impact of simultaneous increase in market and market liquidity is accounted for $d.u.S\_LIQ_{,t} >0$. Here u is an indicator variable that takes the value of 1 if the excess CRSP VW index return is greater than the risk-free rate in month t i.e. $u=1$ when $R_{ex,t} > 0$, and is zero otherwise. The coefficient on this variable is β_9. Estimated coefficients across the reported specifications are shown below numeric column headings along with their *t-stat* in parenthesis. The adjusted R^2 for each regression is also provided.

	Panel A:			Panel B:			Panel C:		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Const	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017	0.017
	(5.49)	(5.52)	(5.71)	(5.62)	(5.62)	(5.86)	(5.63)	(5.64)	(5.79)
$R_{ex,t}$	0.038	0.038	0.038	0.038	0.038	0.037	0.041	0.041	0.042
	(0.53)	(0.53)	(0.53)	(0.54)	(0.54)	(0.53)	(0.58)	(0.59)	(0.59)
d	-0.028	0.001		-0.010	0.004		-0.012	-0.001	
	(-3.62)	(0.11)		(-1.29)	(0.31)		(-1.55)	(-0.07)	
$d.\ R_{ex,t}$	-0.921	-0.375	-0.392	-0.840	-0.550	-0.598	-0.821	-0.617	-0.606
	(-6.67)	(-1.56)	(-2.19)	(-6.19)	(-2.30)	(-3.31)	(-6.10)	(-2.71)	(-3.59)
$d.u.R_{ex,t}$		-1.132	-1.096		-0.612	-0.514		-0.448	-0.472
		(-2.77)	(-4.58)		(-1.47)	(-1.94)		(-1.11)	(-1.90)
$S\_LIQ_{,t}$	-0.025	-0.025	-0.025	-0.025	-0.025	-0.025	-0.173	-0.219	-0.220
	(-0.07)	(-0.07)	(-0.07)	(-0.07)	(-0.07)	(-0.07)	(-0.60)	(-0.75)	(-0.75)
$d.S\_LIQ_{,t}$	-1.941	-2.187	-2.181						
	(-3.11)	(-3.49)	(-3.50)						
$d.S\_LIQ_{,t} >0$				-7.361	-7.086	-7.058			
				(-6.20)	(-5.90)	(-5.90)			
$\|d.S\_LIQ_{,t}<0\|$				0.462	0.706	0.695			
				(0.69)	(1.02)	(1.01)			
$d.u.S\_LIQ_{,t} >0$							-7.401	-7.133	-7.134
							(-6.26)	(-5.91)	(-5.92)
R^2_{adj}	0.151	0.161	0.163	0.190	0.192	0.193	0.193	0.193	0.194

Table 5: Different Momentum Strategy and Time Varying Market Liquidity

Table reports the estimation outputs for equations (2), (3) and (4) shown in the main text. Each of the regression reported in this table have momentum returns $R_{WML,t}$, for the period of 1965:06-2012:12, as the dependent variable. The output of equation (2) is given in Panel A, the explanatory variables are $R_{ex,t}$, the excess return on the value weighted market portfolio, the dummy variable *d* that takes the value of 1, whenever the returns for the last 24 months of the US market is negative and 0 otherwise. Interaction term $d.\ R_{ex,t}$ traces the value weighted return on market portfolio after down-market states (DMS), and the variable $d.u.R_{ex,t}$ traces the value weighted return on market portfolio following DMS when the market returns contemporaneously increase i.e. market returns are strictly positive for this interacting variable. Lastly, the variable $d.S\_LIQ_{,t}$ captures market liquidity following DMS. The coefficients on these variables are β_1, β_2, β_3, β_4, β_5 and β_6 as shown in the equation 2. In Panel B the outputs of different types of the equation (3) are shown, all variables are the same as in Panel A, expect the variable $d.S\_LIQ_{,t}$ which is decomposed into two variables, i.e. $d.S\_LIQ_{,t} > 0$ shows the increase in market liquidity and $|d.S\_LIQ_{,t} < 0|$ shows the decrease in market liquidity following DMS. The coefficient on these variables are β_7 and β_8. Lastly in Panel C, the outputs of equation (4) are shown. In this set of estimations the impact of simultaneous increase in market and market liquidity is accounted for $d.u.S\_LIQ_{,t} > 0$. Here *u* is an indicator variable that takes the value of 1 if the excess CRSP VW index return is greater than the risk-free rate in month t i.e. $u=1$ when $R_{ex,t} > 0$, and is zero otherwise. The coefficient on this variable is β_9. Estimated coefficients across the reported specifications are shown below numeric column headings along with their *t-stat* in parenthesis. The adjusted R^2 for each regression is also provided.

	Panel A:			Panel B:			Panel C:		
Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Const	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008	0.008
	(5.08)	(5.09)	(5.15)	(5.12)	(5.12)	(5.21)	(5.12)	(5.12)	(5.17)
$R_{ex,t}$	-0.233	-0.233	-0.233	-0.233	-0.233	-0.233	-0.233	-0.233	-0.233
	(-6.31)	(-6.32)	(-6.31)	(-6.36)	(-6.36)	(-6.36)	(-6.38)	(-6.37)	(-6.36)
d	-0.011	-0.002		-0.005	-0.002		-0.007	-0.003	
	(-2.77)	(-0.36)		(-1.30)	(-0.25)		(-1.64)	(-0.41)	
$d.\ R_{ex,t}$	-0.407	-0.249	-0.219	-0.381	-0.304	-0.284	-0.367	-0.296	-0.262
	(-5.75)	(-2.01)	(-2.38)	(-5.40)	(-2.44)	(-3.02)	(-5.25)	(-2.49)	(-2.99)
$d.u.R_{ex,t}$		-0.327	-0.389		-0.164	-0.205		-0.158	-0.227
		(-1.56)	(-3.16)		(-0.75)	(-1.48)		(-0.75)	(-1.76)
$S\_LIQ_{,t}$	0.029	0.029	0.030	0.029	0.029	0.029	0.052	0.036	0.034
	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.17)	(0.35)	(0.24)	(0.22)
$d.S\_LIQ_{,t}$	-0.329	-0.400	-0.409						
	(-1.03)	(-1.24)	(-1.27)						
$d.S\_LIQ_{,t} > 0$				-2.017	-1.943	-1.955			
				(-3.27)	(-3.11)	(-3.14)			
$\lvert d.S\_LIQ_{,t} < 0\rvert$				-0.132	-0.067	-0.062			
				(-0.38)	(-0.19)	(-0.17)			
$d.u.S\_LIQ_{,t} > 0$							-2.050	-1.956	-1.960
							(-3.33)	(-3.11)	(-3.12)
R^2_{adj}	0.232	0.234	0.236	0.245	0.244	0.245	0.246	0.245	0.246

Table 6: Momentum Profits, Variance of Market Returns and Liquidity

This table provides the results for running following regression,

$$R_{WML,t} = \beta_0 + \beta_1 d + \beta_2 \hat{\sigma}^2_{m,t-1} + \beta_3 d.\hat{\sigma}^2_{m,t-1} + \beta_4 d.S\_LIQ_t > 0 + \varepsilon_t ,$$

Where β_1 is a coefficient on the down-market states (DMS) dummy $d=1$ when the negative returns for the last 24 months of the US market occurs and $d=0$ otherwise. β_2 is the coefficient on the variance of the previous126 days of market returns, before the start of the days in month t, and is shown as $\hat{\sigma}^2_{m,t-1}$, β_3 is the coefficient on the interaction between d and $\hat{\sigma}^2_{m,t-1}$. Lastly β_4 is the coefficient on the interaction of d and instances of increasing market liquidity i.e. $S\_LIQ_{,t}$ >0. All estimated coefficients across the reported specifications are shown below numeric column headings and the t-stats associated with these coefficients are shown in parentheses. The associated R^2_{adj} with each regression is shown in the last row.

Panel A:						Panel B:				
Variables	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
Const.	0.0169 (5.20)	0.0259 (7.12)	0.0259 (7.12)	0.0184 (6.06)	0.0206 (4.66)	0.0169 (5.52)	0.0205 (5.72)	0.0202 (5.62)	0.0176 (6.01)	0.0206 (4.83)
d	-0.0205 (-2.51)		-0.0006 (-0.07)		0.0134 (1.20)	-0.0002 (-0.03)		0.0053 (0.61)		0.0042 (0.38)
$\hat{\sigma}^2_{m,t-1}$		-0.0119 (-5.63)	-0.0118 (-5.00)		-0.0049 (-1.21)		-0.0038 (-1.65)	-0.0044 (-1.76)		-0.0049 (-1.26)
$d.\hat{\sigma}^2_{m,t-1}$				-0.0123 (-5.66)	-0.0104 (-2.10)				-0.0025 (-0.97)	0.0009 (0.17)
$d.S\_LIQ_{,t} > 0$						-9.691 (-8.50)	-8.680 (-6.94)	-8.754 (-6.97)	-8.966 (-6.78)	-8.830 (-6.61)
R^2_{adj}	0.009	0.051	0.049	0.052	0.055	0.120	0.124	0.123	0.121	0.121

Table 7: Momentum profits, and other Predictive Variables

This table provides the results for running following regression, where $R_{wml,t}$ is the series of monthly momentum returns for the period 1965:06-2012:12.

$$R_{WML,t} = \beta_0 + \beta_1 d + \beta_i .P\_Variables_{t-1} + \beta_2 d.S\_LIQ_t > 0 + \varepsilon_t$$

the β_1 is a coefficient on the dummy of DMS indicated as d, which takes the value of 1, whenever the returns for the last 24 months of the US market is negative and 0 otherwise. Whereas $P\_Variables_{t-1}$ is the set of variables that predict momentum returns. These variables are the lagged market illiquidity (Avramov et al. 2016), the lagged volatility of the momentum strategy (Barroso and Santa-Clara 2015), the lagged conditional volatility of momentum strategy Daniel and Moskowitz (2016) and momentum gap (Huang 2015). We estimate different combinations of regression equation along with full specification. In Panel A, we exclude DMS dummy d and $d.S\_LIQ_{,t} > 0$ that shows the increase in market liquidity in DMS and run specifications that include each predicting variable from the set $[Illiq_{m,t-1}, B.Vol_{t-1}, D.Vol_{t-1}, M.Gap_{t-1}]$. Panel B repeat all the regressions in panel A after adding d and $d.S\_LIQ_{,t} > 0$ and also includes the full specification. Estimated coefficients are shown below, and the *t-stats* associated with these coefficients are shown in parentheses. The R^2_{adj} related to each regression is shown in the last row.

Variables	Panel A:				Panel B:				
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)
Const.	0.019	0.029	0.031	0.075	0.015	0.022	0.021	0.045	0.043
	(5.17)	(5.91)	(6.02)	(5.72)	(4.01)	(4.50)	(4.09)	(3.23)	(2.75)
d					-0.001	0.005	0.003	0.006	0.007
					(-0.10)	(0.57)	(0.34)	(0.75)	(0.76)
$Illiq_{m,t-1}$	-0.568				0.247				0.370
	(-2.50)				(1.05)				(1.54)
$BS.Vol_{t-1}$		-1.440				-0.536			-0.148
		(-3.92)				(-1.28)			(-0.16)
$DM.Vol_{t-1}$			-1.745				-0.464		0.921
			(-4.12)				(-0.98)		(0.91)
$M.Gap_{t-1}$				-0.175				-0.083	-0.095
				(-4.80)				(-2.06)	(-1.79)
$d.S\_LIQ_{,t} > 0$					-10.176	-9.345	-9.337	-9.031	-9.358
					(-8.28)	(-7.98)	(-7.81)	(-7.65)	(-6.97)
R^2_{adj}	0.009	0.025	0.027	0.037	0.120	0.121	0.119	0.125	0.124

Table 8: Predictive Variables, Increase in Market Liquidity in DMS, and Momentum Returns

This table reports the results of running the regression of momentum returns $R_{WML,t}$ for the period of 1965:06-2012:12 on DMS dummy d, which takes the value of 1, whenever the returns for the last 24 months of the US market is negative and 0 otherwise, on various predictive variables shown in the set of predicting variables $P\_Variables_{t-1} = [\hat{\sigma}^2_{m,t-1}, Illiq_{m,t-1}, B.Vol_{t-1}, D.Vol_{t-1}, M.Gap_{t-1}]$.

The set $d.L.P\_Variables_{t-1} = [d.L.\hat{\sigma}^2_{m,t-1}, d.L.Illiq_{m,t-1}, d.L.BS.Vol_{t-1}, d.L.DM.Vol_{t-1}, d.L.M.Gap_{t-1}]$ contains the corresponding interaction of these predictive variables with DMS dummy d that takes the value of 1 whenever the return on the US market in preceding 24 months is negative and 0 otherwise and dummy L that takes the value of 1 when contemporaneous market liquidity increases i.e. $S\_LIQ_{,t}>0$ and is zero otherwise. A full specification regression is estimated as follows

$$R_{WML,t} = \beta_0 + \beta_1.d + \beta_i.P\_Variables_{t-1} + \beta_j.d.L.P\_Variables_{t-1} + \varepsilon_t$$

The coefficients β_i are estimated on the predicting variables whereas coefficients β_j are estimates on the variables belonging to set with interacting terms. All estimated coefficients, across different specifications, are shown below. Corresponding t-stats associated to respective regression variables are shown in parentheses. The associated R^2_{adj} with each regression is shown in the last row.

Variables	(1)	(2)	(3)	(4)	(5)
Const.	0.018	0.015	0.019	0.019	0.059
	(4.98)	(3.96)	(3.76)	(3.48)	(4.20)
d	0.014	0.002	0.014	0.015	0.027
	(1.58)	(0.22)	(1.44)	(1.60)	(2.46)
$\hat{\sigma}^2_{m,t-1}$	-0.002				
	(-0.74)				
$d.L.\hat{\sigma}^2_{m,t-1}$	-0.024				
	(-6.69)				
$Illiq_{m,t-1}$		0.239			
		(0.99)			
$d.L.Illiq_{m,t-1}$		-3.372			
		(-7.21)			
$BS.Vol_{t-1}$			-0.272		
			(-0.59)		
$d.L.BS.Vol_{t-1}$			-3.081		
			(-5.54)		
$DM.Vol_{t-1}$				-0.224	
				(-0.44)	
$d.L.DM.Vol_{t-1}$				-3.828	
				(-6.05)	
$M.Gap_{t-1}$					-0.125
					(-3.08)
$d.L.M.Gap_{t-1}$					-0.151
					(-4.82)
R^2_{adj}	0.117	0.0961	0.0719	0.0839	0.0723

Table 9: Momentum Profits and Exposure to other Risk Factors

This table provides the results of running the regressions of monthly momentum returns $R_{WML,t}$ for the period of 1965:06-2012:12on the set of explanatory and predictive variables. In Panel A, the momentum returns are controlled for Fama and French three factor model. Whereas, in Panel B, the momentum returns are controlled for the dynamic three factor model in which each factor is interacted with the DMS dummy $d=1$, which takes the value of 1 whenever the returns for the last 24 months of the US market is negative and 0 otherwise. The explanatory and predictive variables are, $d.u.R_{ex,t}$ which shows market returns in DMS when market returns contemporaneously increases, the variance of the last 126 days of market returns $\hat{\sigma}^2_{m,t-1}$, these variables are reported Daniel and Moskowitz (2016). Then other predicative variable is lagged level of market illiquidity $Illiq_{m,t-1}$, unconditional volatility $B.Vol_{t-1}$, the conditional volatility $D.Vol_{t-1}$, of momentum strategy for the last 126 days and Momentum Gap, $M.Gap_{t-1}$. These variables are reported in Avramov et al (2016), Barroso and Santa-Clara (2015), Daniel and Moskowitz (2016) and Huang (2015). Lastly, for each regression we have included $d.S\_LIQ_{,t} > 0$ to measure the increase in market liquidity in DMS. All estimated coefficients are shown below, and the t-stats associated with these coefficients are shown in parentheses. The associated R^2_{adj} with each regression is shown in the last row.

Variables	Panel: A FF-3							Panel: B dynamic FF-3						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Const.	0.004	0.008	0.002	0.009	0.010	0.032	0.022	0.003	0.008	0.002	0.009	0.010	0.025	0.016
	(1.25)	(2.24)	(0.50)	(1.89)	(1.91)	(2.37)	(1.47)	(1.19)	(2.26)	(0.72)	(2.06)	(2.17)	(1.94)	(1.07)
d	0.014	0.001	-0.006	0.000	-0.001	0.001	0.019	-0.010	-0.001	-0.008	-0.001	-0.002	-0.003	-0.003
	(1.53)	(0.14)	(-0.78)	(0.04)	(-0.12)	(0.13)	(1.98)	(-1.10)	(-0.11)	(-1.06)	(-0.12)	(-0.27)	(-0.31)	(-0.32)
$d.u.R_{ex,t}$	-0.959						-0.936	0.085						0.102
	(-4.53)						(-4.41)	(0.41)						(0.49)
$\hat{\sigma}^2_{m,t-1}$		-0.005					-0.005		-0.006					-0.005
		(-2.24)					(-1.54)		(-2.36)					(-1.62)
$Illiq_{m,t-1}$			0.218				0.350			0.107				0.181
			(0.95)				(1.51)			(0.48)				(0.79)
$BS.Vol_{t-1}$				-0.591			0.496				-0.665			0.427
				(-1.44)			(0.55)				(-1.69)			(0.49)
$DM.Vol_{t-1}$					-0.676		-0.088					-0.810		-0.330
					(-1.46)		(-0.09)					(-1.83)		(-0.35)
$M.Gap_{t-1}$						-0.084	-0.062						-0.065	-0.031
						(-2.15)	(-1.21)						(-1.72)	(-0.62)
$d.S\_LIQ_{,t} > 0$	-6.805	-7.241	-8.839	-8.029	-7.894	-7.738	-6.158	-6.764	-5.441	-6.831	-6.193	-6.003	-6.102	-5.756
	(-5.90)	(-5.90)	(-7.35)	(-7.01)	(-6.75)	(-6.70)	(-4.61)	(-6.00)	(-4.61)	(-5.90)	(-5.63)	(-5.35)	(-5.49)	(-4.40)
R^2_{adj}	0.131	0.108	0.101	0.103	0.103	0.107	0.136	0.0720	0.0807	0.0721	0.0763	0.0771	0.0765	0.0749

Appendix A

Table A.I Predictive Variables, Down Market States, and Momentum Returns

This table reports the results of running the regression of momentum returns $R_{wml,t}$ for the period of 1965:06-2012:12 on various predictive variables shown as $P\_Variables_{t-1}$ in DMS $d=1$, when market liquidity either increases $S\_LIQ_{,t} > 0$ or decreases $S\_LIQ_{,t} < 0$ contemporaneously. The regression is as follows

$$R_{wml,t} = \beta_0 + \beta_i .d.L.P\_Variables_{t-1} + \beta_j .d.IL.P\_Variables_{t-1} + \varepsilon_t$$

whereas the DMS dummy d takes the value 1 whenever the returns for the last 24 months of the US market is negative and 0 otherwise. $L=1$ is a dummy for the increase in when liquidity such as $S\_LIQ_{,t} > 0$ and 0 otherwise. Whereas, $IL=1$ is a dummy for the increase in market illiquidity such as $S\_LIQ_{,t} < 0$ and 0 otherwise. The predictive variables $P\_Variables_{t-1}$ are $[\hat{\sigma}^2_{m,t-1}$, $Illiq_{m,t-1}$, $B.Vol_{t-1}$, $D.Vol_{t-1}$, $M.Gap_{t-1}]$. The set of coefficients β_i is estimated on variables shown in above equation are the interaction of the dummies of the down market states $d=1$ and increase in market $L=1$ with the predictive variables such as $[d.L.\hat{\sigma}^2_{m,t-1}$, $d.L.Illiq_{m,t-1}$, $B.L.Vol_{t-1}$, $D.L.Vol_{t-1}$, $M.L.Gap_{t-1}]$. The other set of coefficients β_j estimated on the variables shown in above equation are the interaction of the dummies of DMS dummy $d=1$ and decrease in market $IL=1$ with the predictive variables such as $[d.IL.\hat{\sigma}^2_{m,t-1}$, $d.IL.Illiq_{m,t-1}$, $B.IL.Vol_{t-1}$, $D.IL.Vol_{t-1}$, $M.IL.Gap_{t-1}]$. All estimated coefficients are shown below, the t-stats associated with these coefficients are shown in parentheses. The associated R^2_{adj} with each regression is shown in the last row.

Variables	(1)	(2)	(3)	(4)	(5)
Const.	0.017	0.017	0.017	0.017	0.017
	(5.51)	(5.44)	(5.37)	(5.41)	(5.40)
d	0.012	-0.004	0.012	0.011	0.138
	(1.11)	(-0.37)	(0.89)	(0.86)	(4.17)
$d.L.\hat{\sigma}^2_{m,t-1}$	-0.025				
	(-7.92)				
$d.IL.\hat{\sigma}^2_{m,t-1}$	0.001				
	(0.17)				
$d.L.Illiq_{m,t-1}$		-3.052			
		(-6.78)			
$d.IL.Illiq_{m,t-1}$		0.639			
		(0.89)			
$d.L.B.Vol_{t-1}$			-3.188		
			(-5.39)		
$d.IL.B.Vol_{t-1}$			0.055		
			(0.09)		
$d.L.D.Vol_{t-1}$				-3.834	
				(-5.80)	
$d.IL.D.Vol_{t-1}$				0.252	
				(0.34)	
$d.L.M.Gap_{t-1}$					-0.421
					(-5.79)
$d.IL.M.Gap_{t-1}$					-0.298
					(-3.78)
R^2_{adj}	0.116	0.0958	0.0714	0.0838	0.0799