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CYCLES OF DECLINES AND REVERSALS FOLLOWING OVERNIGHT MARKET DECLINES

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WORKING PAPERS ON FINANCE NO. 2018/29

SWISS INSTITUTE OF BANKING AND FINANCE (S/BF – HSG)

SEPTEMBER 2018

Cycles of Declines and Reversals following Overnight Market Declines*

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This version: September 2018
Latest version available at farshidabdi.net/jmp

ABSTRACT

This paper uncovers and explains the emergence of cycles of intraday declines and overnight reversals in the U.S. stock market in the 21st century. Using quote midpoints for the past 24 years of common stocks traded in the three main exchanges, I show that the cross-sectional association between average intraday and overnight returns has steadily shifted from a direct association into a strong inverse association over the years. I explain this shift by showing that after 2001, consistent with theoretical models in which binding capital constraints lead to liquidity dry-ups, an overnight decline in the stock market is followed by a further intraday decline for volatile stocks and their reversal over the next overnight period. Moreover, I show that market liquidity of volatile stocks further deteriorates following an overnight market decline, which confirms my proposed explanation. Finally, I show that idiosyncratic volatility, compared with systematic risk, better explains the cross section of the documented systematic intraday declines and overnight reversals.

JEL Classification: G10, G12, G15, G20
Keywords: Market Liquidity, Funding Liquidity, Reversals, Effective Spread, TAQ

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* I am especially grateful to Joel Hasbrouck, Loriano Mancini, and Angelo Ranaldo. I also thank Yakov Amihud, Robert Engle, Kose John, Fahad Saleh, Alexi Savov, Paul Söderlind, Marti Subrahmanyam, Davide Tomio, Robert Whitelaw, and Botao Wu, and the seminar participants at NYU Stern (October 2017, September 2018) and University of St. Gallen (March 2018) for comments and suggestions. All remaining errors are my own.

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Introduction

This paper documents the emergence of an inverse association between *average* intraday and overnight returns in the cross section of stocks over the past two decades, and explains it by finding directional declines and reversals cycles between intraday and overnight returns, that are driven by overnight wealth shocks. Overnight stock market declines are followed by intraday declines and next day overnight reversals. Declines and reversals are stronger for more volatile stocks.

The reversals that I document in this paper resemble Nagel's (2012) illiquidity-driven reversals, but depart from Nagel (2012) along three important aspects. First, the scope of this study is between intraday and overnight returns rather than daily and weekly returns. Second, I document reversals in annually rebalanced volatility quintiles portfolios, whereas Nagel (2012) constructs portfolios from stocks that have already declined. Third, and finally, I not only predict overnight reversals, but also predict intraday declines prior to overnight reversals, because the entire decline and reversal cycle is preceded by overnight market declines.

Because intraday declines are (1) followed by reversals, and (2) are preceded by overnight *market* declines, they express an important link between market and funding liquidity (Brunnermeier and Pedersen, 2009), where wealth shocks can lead to deteriorating market liquidity in the next period. I corroborate the significance of this link by extending Hameed, Kang and Viswanathan (2010), and empirically document that overnight market declines predict deteriorating market liquidity in the next trading session.

By looking at intraday and overnight periods, I separate trading and nontrading periods, and provide better identification for the interaction of market and funding liquidity (Brunnermeier and Pedersen, 2009; Hameed, Kang and Viswanathan, 2010), where two channels of wealth shocks and margin adjustments can lead to liquidity spirals. I show that overnight market declines, not intraday market declines, mainly drive the cycles of declines and reversals. This provides further emphasis on the importance of wealth shocks in market liquidity deterioration.

My findings are also consistent with Adrian and Shin's (2010) argument on the adjustment of leverage to wealth, with the key distinction that wealth shocks at overly short periods, which are overnight, can lead to such adjustments. I argue that it is the increasing dominance of overly short-term debt that makes rolling over debt a day-to-day task.

I discuss five main findings in this paper. First, I document the emergence of an inverse association between *average* intraday and overnight returns. I show that the cross-sectional association between average intraday and overnight returns, calculated every calendar year, starts from values around 0.2 in 1993 and steadily decreases throughout the years to levels as low as –0.9 in 2016. This finding is not driven by outliers, because I obtain similar results using Spearman's rank correlations, or bid-ask bounces (Roll 1984), because I use quote midpoints to calculate returns, following Nagel (2012), among others. To further elaborate this finding, I take several steps, including running cross-sectional regressions between average intraday and overnight returns for every year and showing that the sign of coefficient shift from positive to negative and remains negative until the end of the sample. Furthermore, to show the economic significance of the inverse association, I split the sample period into two subsamples —1993–2000 and 2001–2016— and sort stocks into quintile portfolios by their average realized intraday returns for every subsample. By doing so, I provide clear demonstration that for the second part of the sample, stocks that have lower average intraday returns have higher overnight returns. Average intraday returns for the low-intraday returns quintile portfolio is −18 basis points (bps) per day, which is met with average overnight returns of +16 bps. Consistent with the fact that the declines-and-reversals have recently emerged, no inverse association is discernible for the first part of the sample.

Second, I document that the inverse association between intraday and overnight returns mainly follows overnight *market* declines. I sort stocks into five quintile portfolios based on their previous calendar-year volatility and calculate the average intraday and overnight returns of the portfolios following overnight market surges and declines. In the more recent part of the sample, that is 2001-2016 period, overnight market declines are followed by intraday declines, and then overnight reversals. Intraday declines and following overnight reversals are stronger for more volatile stocks. Moreover, that I do not find the same results for the earlier part of the sample is in line with the recent emergence of decline and reversal cycles. I empirically test these observations, by employing a regression framework in which intraday and overnight returns of quintile portfolios are predicted by their past intraday and overnight returns and the market return and include dummy variables for negative past market and portfolio returns. By doing so, I document an asymmetric effect for the past overnight *market* decline, which predicts further intraday decline and overnight reversal for the next periods. By using volatility quintile portfolios, I show that the decline-and-reversal cycles following overnight market declines are stronger for higher volatility quintile portfolios.

Third, I corroborate that declines are driven by deteriorating liquidity due to the wealth shock, by empirically showing that market illiquidity, measured by Trades and Quotes (TAQ) effective spreads, increases following overnight market declines. By documenting this effect between overnight and intraday periods, I extend the findings of Hameed, Kang and Viswanathan (2010), provided in weekly horizons. I argue that market liquidity has started responding to funding liquidity constraints more rapidly, because of the increasing role of overly short-term debt in the financial market, which requires daily rollover.

Fourth, by analyzing the order flows following overnight declines, I show that investors on average are contrarian and provide liquidity after market declines, consistent with findings of Chordia, Roll, and Subrahmanyam (2001) for the daily horizon. The price declines on the same day that average investors are contrarian, is in line with Dow and Han (2018), who argue that, although overall capital might not be scarce in the financial market, capital of informed traders can be scarce, and when informed traders face constrains, the rest of the market can provide liquidity to buy assets, but with a "lemon" discount (Akerlof, 1970).

Fifth, and finally, I document the key cross-sectional role of idiosyncratic volatility in the observed systematic intraday declines and overnight reversals. To do so, I construct nine portfolios double sorted by market beta and idiosyncratic volatility and show that cross-sectional variations in the intraday and the overnight returns following overnight market declines are better explained by the idiosyncratic volatility than by the market beta. This important finding in the cross section of stocks corroborates Nagel's (2012) finding that reversal portfolios are more profitable following episodes of high idiosyncratic volatility in the market.

This paper contributes to at least three streams of literature. First, it contributes to an emerging literature that aims to understand the link between intraday and overnight returns. Lou, Polk, and Skouras (2018) document that momentum strategy is mainly profitable in the overnight period, and Hendershott, Livdan, and Rösch (2018) document that market beta is mainly priced overnight. This paper puts forward deteriorating market liquidity following tighter funding liquidity constraints to explain the way intraday and overnight returns interact. Second, it contributes to the extensive body of literature on the interaction of market and funding liquidity. Brunnermeier and Pedersen (2009) put forward a model to show that funding constraints can lead to market illiquidity, and Hameed, Kang, and Viswanathan (2010) empirically show that stock market declines predict deteriorating market liquidity. Nagel (2012) proposes stock declines as a noisy proxy for tighter market liquidity and takes reversal portfolio returns following declines as liquidity provision profits. This paper studies declines and reversals between intraday and overnight returns and the way overnight wealth shocks contribute to declines and reversals, and to market liquidity. It also builds on the Adrian and Shin (2010) mark-to-market leverage, and on Dow and Han's (2018) argumentation about the adverse selection discount from uninformed traders' liquidity provision following informed traders' tightened liquidity constraints. Third, and finally, this paper contributes to the existing literature on idiosyncratic volatility by showing that it can explain the cross section of intraday and overnight returns following market declines. I show that the cross section of intraday returns decline with idiosyncratic volatility, whereas overnight returns increase. This can explain the mixed results for close-to-close returns. Goyal, and Santa-Clara (2003) document that the cross-section of expected returns are increasing with idiosyncratic volatility, whereas Bali et al. (2004) find contradicting evidence and Ang, et al. (2006, 2009) document decreasing expected returns with idiosyncratic volatility and show that other risk factors cannot explain the results.

The rest of the paper is organized as follows. Section I describes the data used in the analysis. Section II documents the emergence of one-sided reversals between intraday and overnight returns. Section III shows the way overnight wealth shocks lead to intraday declines and following overnight reversals. Section IV documents deteriorating market liquidity following overnight market declines, and Section V explores the order flow following overnight declines. Section VI demonstrates the role of idiosyncratic risk. Section VII discusses alternative explanations, and Section VIII concludes.

I. Data

I merge Trades and Quotes (TAQ) dataset with the Center for Research in Security Prices (CRSP) daily stock files. I rely on the more accurate Daily TAQ files from October 2003 to December 2016 (Holden and Jacobsen 2014), and between January 1993 and September 2003, when Daily TAQ files are not available, I use Monthly TAQ files. The availability of TAQ data from 1993 defines the start of the sample as January 1993. I match TAQ trades and quotes, for both Monthly and Daily TAQ files, following the instructions provided by Holden and Jacobsen (2014).[1] I then

[1] I build on the SAS codes kindly provided by Craig Holden on his Web site. His generosity is gratefully acknowledged. In addition to the filters included in the codes, I discard all trades outside the market opening hours, and the ones with proportional effective spreads above 40%. Moreover, for analyzing Daily TAQ files, I add an additional criterion to only keep the trades/quotes records without symbol suffixes.

match TAQ quotes and trades with the CRSP dataset using CUSIPs.[2] I keep all U.S. common stocks (CRSP share codes of 10 and 11) primarily listed on NYSE, AMEX, and NASDAQ and adjust TAQ prices for dividends and splits using the CRSP cumulative factor to adjust prices (cfacpr). I exclude stock-days that (a) involve no trade, identified by either negative CRSP price or zero volume, or (b) have missing cfacpr. Furthermore, I exclude stock-months that (a) include any daily close prices below \$5, (b) involve a change in primary exchange, or (c) include a dividend distribution or split that make the CRSP cumulative factor to adjust prices (cfacpr) move beyond 1%.

A. Intraday and overnight returns

The intraday and overnight returns are defined as the returns for holding the stock from open to close and from close to the next day open. In line with Nagel (2012), and to avoid the effect of microstructure noise, specifically the bid-ask bounce (Roll, 1984), I use quote midpoints prevailing the trades to calculate the returns. Equation (1) defines the quote midpoint as the average of the bid and ask prices prevailing the trades, and equations (2) and (3), respectively, show the way intraday and overnight returns are defined. Equation (4) shows the combination of intraday and overnight return yields for the close-to-close returns:

$$M_\tau = \frac{A_\tau + B_\tau}{2} \tag{1}$$

$$R_{i,D(t)} \equiv \frac{M_{i,C(t)}}{M_{i,O(t)}} - 1 \,, \tag{2}$$

$$R_{i,N(t)} \equiv \frac{M_{i,O(t)}}{M_{i,C(t-1)}} - 1 \,, \tag{3}$$

$$R_{i,t} \equiv \frac{M_{i,C(t)}}{M_{i,C(t-1)}} - 1 = \left(1 + R_{i,N(t)}\right)\left(1 + R_{i,D(t)}\right) - 1 \,. \tag{4}$$

[2] I use CUSIPs provided in monthly master files from 1993 until 2014, and the ones provided in daily master files between 2015 and 2016. For more details on merging CRSP and TAQ data, see Abdi and Ranaldo (2017).

where $M_{i,O(t)}$ and $M_{i,C(t)}$ respectively, are quote midpoints prevailing the first and last trade during the trading session of day t. $R_{i,D(t)}$ and $R_{i,N(t)}$ are the intraday and overnight returns, respectively, for day t.

To avoid taking any unrepresentative large (small) asks (bids) of the beginning and end of the day, I take the quote midquotes preceding the first and last trades, and not the first and last submitted quote midquotes between 9:30 and 16:00. The prevailing quotes precede trades by a fraction of a second, depending on how recent the trades are. Between January 1993 and September 2003, I use Monthly TAQ data, with the procedure that Holden and Jacobsen (2014) put forward to split every second into fractions using the number of trades and quotes during the second. Starting from October 2003, since the more accurate Daily TAQ dataset becomes available, I use Daily TAQ data and match trades with prevailing quotes one millisecond, microsecond, or nanosecond before them. The two latter granularities became available starting from July 27, 2015, and October 24, 2016, respectively.

B. Market liquidity

To measure market illiquidity during the trading session, I use the effective spread, which measures the distance between trade prices and the prevailing quote midpoints. Equation (5) shows the way the effective spread is calculated for individual trades. I then average the effective spreads for every day using the dollar volume of trades as the weights:

$$ES_t = 2\frac{|P_t - M_t|}{M_t}, \tag{5}$$

$$ES_{D(t)} = \frac{1}{\sum_{t\in D(t)} DV_t}\sum_{t\in D(t)} DV_t ES_t , \tag{6}$$

C. Order imbalances

Following Hasbrouck (1991, 1993) and Lee and Ready (1991), I compare trade prices with the prevailing quote midpoints to discern the trade direction. I then calculate the order imbalance of every stock-day, which is the net order flow as a fraction of the trade volume. Equations (7) and (8) show the way order flows and order imbalances, respectively, are calculated:

$$OF_t = sign\{P_t - M_t\}\, DV_t\,, \tag{7}$$

$$OI_{D(t)} = \frac{\sum_{t \in D(t)} OF_t}{\sum_{t \in D(t)} DV_t}, \tag{8}$$

Table I provides summary statistics for the intraday and overnight returns, as well as effective spreads and order imbalances. For consistency, the summary statistics are provided for the two subsamples of 1993–2000 and 2001–2016.

[Table I about here]

II. Emergence of One-Sided Reversals

To provide the first evidence of the one-sided reversal in the stock market, I sort stocks into five quintile portfolios using their average realized intraday returns during the two subsamples of 1993–2000 and 2001–2016. Figure 1 shows the average intraday and overnight returns for the specified portfolios. The second part of the sample, which is shown in Panel B, clearly demonstrates an inverse association between average intraday and overnight returns. The quintile portfolios with higher (lower) realized intraday returns have lower (higher) overnight returns. Furthermore, in the earlier sample period, shown in Panel A, no inverse association is discernible. In fact, in the earlier sample, a direct association, if any, seems to exist between intraday and overnight returns. I provide a more extensive set of evidences to better understand this observation in the rest of the section.

[Figure 1 about here]

A. Cross-sectional correlations

To better understand how declines and reversals have evolved over the years, I calculate the cross-sectional association between average intraday and overnight returns taken every year. More specifically, for every year, I calculate average time series of intraday and overnight returns for every stock and then calculate the cross-sectional correlation between average intraday and overnight returns. Stocks with fewer than 100 days of observations are excluded.

Figure 2 shows both the linear and the Spearman's rank cross-sectional correlations for every year in the sample. As the figure clearly shows, the cross-sectional association between intraday and overnight returns has steadily shifted from a weak direct association into a strong inverse association throughout the years. Because the Spearman's rank correlation shows a very similar pattern with the linear correlation, it is unlikely that the results are driven by outliers.

[Figure 2 about here]

B. Cross-sectional regressions

To capture the economic magnitude of the association, I employ a cross-sectional regression framework of average overnight returns on average intraday returns, and vice versa. Equations (9) and (10) show the specific regressions framework:

$$\bar{R}_{i,y}^{N} = \beta_{0,y}^{\mathrm{N|D}} + \beta_{1,y}^{\mathrm{N|D}}\,\bar{R}_{i,y}^{D} + \varepsilon_{i,y}\ , \tag{9}$$

$$\bar{R}_{i,y}^{D} = \beta_{0,y}^{\mathrm{D|N}} + \beta_{1,y}^{\mathrm{D|N}}\,\bar{R}_{i,y}^{N} + \epsilon_{i,y}\ , \tag{10}$$

where $\bar{R}_{i,y}^{N}$ and $\bar{R}_{i,y}^{D}$ are the time-series average of overnight and intraday returns of stock i in year y, respectively.

The specified framework is in the same spirit of the Heston, Korajczyk, and Sadka (2010) regression framework, but it serves a different purpose here. Specifically, the framework is different along two key aspects. First, it is a regression that involves overnight returns, whereas the Heston, Korajczyk, and Sadka (2010) regressions solely involve intraday returns. Second, the regression considers *average* returns during a year, whereas the Heston, Korajczyk, and Sadka (2010) regressions consider individual intraday returns. I study average returns, instead of individual returns, because average returns would show a movement that is, on average, directional.

Figure 3 shows the estimated slope coefficients of the two regressions for every year. Consistent with the results shown in Figure 2, the association shifts from positive to negative throughout the years. Besides that, the regression of overnight returns on the intraday returns provides sharper coefficients, hinting that overnight returns follow intraday patterns. I provide clear evidence on this in the following sections.

[Figure 3 about here]

While the focus of the paper is on the time-series average of returns, individual returns tend to show a very similar pattern as well. Figure 4 shows the estimated slope coefficients for the cross-sectional regression of overnight returns on the intraday returns, estimated for every single day in the sample. Consistent with the previous results, the figure suggests that a reversal between intraday and overnight returns has emerged during the years. The cross-sectional associations appear to be more often negative starting from 2001.

[Figure 4 about here]

Following Fama and McBeth (1973), I estimate the mean of the association using the time-series average of the estimates, and use the Newey and West (1987) standard errors with four lags to account for potential heteroskedasticity or autocorrelation. The results in Table II show the average of the inverse associations is negative, and significantly different from zero at 1% level for the 2001-2016 subsample. This is consistently the case for both the cross-sectional correlation coefficients, and for the coefficients of the cross-sectional regressions.

[Table II about here]

Decline and reversal cycles not only are emerging in the cross-sectional correlations but are also discernible in time-series correlations. Figure 5 shows the average time-series correlation between intraday and following overnight returns, calculated for every stock-year and averaged across stocks.

[Figure 5 about here]

III. Overnight Wealth Shocks and the Decline and Reversal Cycles

I measure the average intraday and overnight returns following overnight declines and surges in the market. Any difference in the returns would suggest that the reversals might be liquidity-driven (Nagel 2012), which would become exacerbated following overnight wealth shocks.

I sort stocks into five quintile portfolios using their last calendar-year's volatilities. Because I take quote midpoints to calculate returns, the results are not prone to bid-ask bounces (Roll, 1984). Figure 6 shows the average of intraday and overnight returns for the five quintile portfolios, following a surge or a decline in the stock market during the previous overnight period, for the 2001–2016 sample. Three important findings emerge from the figure, which I will further corroborate in the rest of the section: (1) volatile stocks tend to decline during the trading session following overnight market declines, although they do not tend to surge significantly following overnight market surges, and (2) part of the decline will be reverted over the next overnight period , because returns for all quintiles portfolios are higher after a previous overnight market decline, compared with an overnight surge.

[Figure 6 about here]

I repeat the analysis using the older subsample of 1993–2000, as shown in Figure 7, and for this subsample, (1) the intraday declines following overnight market declines are less pronounced, with a magnitude of about one-third of the recent subsample, and (2) no considerable reversal over the next overnight period is discernible. These observations suggest that the declines and reversals following overnight market declines have emerged throughout the years, consistent with the results of the previous section. The rest of the section provides extensive analysis on intraday declines and overnight reversals.

[Figure 7 about here]

A. Intraday declines

Building on the descriptive Figure 6, I estimate the regression framework specified in equation (11) to test whether intraday returns are lower after overnight declines:

$$R_{i,D(t)} = \gamma_{0,i} + \gamma_{1,i}R_{M,N(t)} + \gamma_{2,i}R_{M,N(t)}\,\mathbb{1}_{\{R_{M,N(t)}<0\}} + \gamma_{3,i}R_{M,D(t-1)} + \gamma_{4,i}R_{M,D(t-1)}\,\mathbb{1}_{\{R_{M,D(t-1)}<0\}}$$
$$+\gamma_{5,i}R_{i,N(t)} + \gamma_{6,i}R_{i,N(t)}\,\mathbb{1}_{\{R_{i,D(t-1)}<0\}} + \gamma_{7,i}R_{i,D(t-1)} + \gamma_{8,i}R_{i,D(t-1)}\,\mathbb{1}_{\{R_{i,D(t-1)}<0\}} + \varepsilon_{i,t}\,, \qquad (11)$$

where $R_{i,N(t)}$ and $R_{M,N(t)}$ are the quintile portfolio and market portfolio returns during the overnight periods, respectively, and $R_{i,D(t)}$ and $R_{M,D(t)}$are the intraday returns for the specified portfolios. $\mathbb{1}_{\{R_{M,N(t)}<0\}}$ ($\mathbb{1}_{\{R_{M,D(t)}<0\}}$) is a dummy variable that takes the value of one when the overnight (intraday) market return of day t is negative, and zero otherwise. Similarly, $\mathbb{1}_{\{R_{i,N(t)}<0\}}$ ($\mathbb{1}_{\{R_{i,D(t)}<0\}}$) is a dummy variable corresponding to the overnight (intraday) returns of the quintile portfolios. I estimate the coefficients for every quintile portfolio, as well as a portfolio that goes long on high-volatility stocks and goes short on low-volatility stocks. I use the Newey and West (1987) standard errors with four lags to account for heteroskedasticity and autocorrelation.

[Table III about here]

Table III shows the regression's estimates. Panel A shows the estimates for the 1993–2000 period and Panel B shows the estimates for the 2001–2016 period. Three clear results emerge from Panel B. First, in the recent part of the sample, an overnight market decline predicts a further decline during the day, especially for the volatile quintiles, where the effect is more statistically and economically significant. This suggests that intraday declines are caused by overnight wealth shocks. Second, the overnight individual portfolio returns do not predict the next intraday returns, further confirming that intraday declines are driven by overnight wealth shocks. Third, and finally, the intraday market return of the day before does not predict the intraday return of volatile groups, or the return of the high-minus-low volatility group. I explain this by arguing that during the trading session, wealth shocks can almost immediately trigger liquidity- driven trades. Therefore, no lead-lag relationship exists for wealth shocks that occur during trading sessions. Liquidity-driven trades triggered by an overnight wealth shock, on the other hand, only can start being executed after the trading session starts.[3]

Comparing Panels A and B of the table shows that the specified pattern does not exist for the older sample period of 1993–2001, a finding consistent with the previous results showing that declines and reversals have emerged recently.

B. Overnight reversals

So far, I have documented intraday declines following wealth shocks, which are larger for volatile stocks. Liquidity-driven declines are expected to be followed by reversals in the periods that follow. (Nagel 2012). To test this, I estimate the regression framework of equation (12) for each quintile portfolio, as well as the high- minus low-volatility portfolio. Consistent with the regression framework in equation (11), I use the Newey and West (1987) standard errors with four lags to account for heteroskedasticity and autocorrelation:

$$R_{i,N(t)} = \delta_{0,i} + \delta_{1,i} R_{M,D(t-1)} + \delta_{2,i} R_{M,D(t-1)}\, \mathbb{1}_{\{R_{M,D(t-1)}<0\}} + \delta_{3,i} R_{M,N(t-1)} + \delta_{4,i} R_{M,N(t-1)}\, \mathbb{1}_{\{R_{M,N(t-1)}<0\}}$$

$$\delta_{5,i} R_{i,D(t-1)} + \delta_{6,i} R_{i,D(t-1)}\, \mathbb{1}_{\{R_{i,D(t-1)}<0\}} + \delta_{7,i} R_{i,N(t-1)} + \delta_{8,i} R_{i,N(t-1)}\, \mathbb{1}_{\{R_{i,N(t-1)}<0\}} + \epsilon_{i,t}\,, \quad (12)$$

Table IV shows the regression’s estimated coefficients. Three clear results emerge from the regression. First, the high- minus low-volatility portfolio tends to further appreciate over the night

[3] Volume and liquidity in the pre-open and after-close markets of individual stocks are substantially lower than theirs during the trading session (Barclay and Hendershott, 2004). Therefore, in line with an extensive body of literature, I exclude trades outside trading hours.

following a previous overnight decline, suggesting an overnight reversal following overnight wealth shocks in the previous period. Second, no asymmetric reversals following previous intraday market declines are discernible for the post-2000 sample, consistent with the cyclicality of reversals in the recent sample. Third, and finally, asymmetric declines and reversals are both followed by overnight market declines, not by intraday market declines.

[Table IV about here]

IV. Overnight Wealth Shocks and Deteriorating Market Liquidity

The intraday declines and overnight reversals following wealth shocks suggest that reversals are driven by a decline in market liquidity, which is a caused by tightened funding constraints after overnight wealth shocks. For longer horizons, Hameed, Kang and Viswanathan (2010) document that a decline in the stock market is followed by deteriorating market liquidity, consistent with theories in which binding funding constraints affect market liquidity (Brunnermeier and Pedersen 2009).

I employ the time-series regression framework specified in equation (13) to test whether overnight market declines are followed by deteriorating market liquidity in the next trading session. This can be seen as not only a fruitful extension of Hameed, Kang and Viswanathan (2010) for shorter horizons, but also better identification. More specifically, because I divide time into trading, and nontrading periods, I can measure the nonsynchronous effect of a past wealth shock, as well as past trading session movements on the next period's market liquidity. This permits a better understanding of the two main triggers of the illiquidity spirals in the setting of Brunnermeier and Pedersen (2009), that is, wealth shocks and margin changes:

$$ES_{i,D(t)} = \eta_{0,i} + \eta_{1,i} R_{M,N(t)} + \eta_{2,i} R_{M,N(t)}\, \mathbb{1}_{\{R_{M,N(t)}<0\}} + \eta_{3,i} R_{M,D(t-1)} + \eta_{4,i} R_{M,D(t-1)}\, \mathbb{1}_{\{R_{M,D(t-1)}<0\}}$$
$$+\eta_{5,i} R_{i,N(t)} + \eta_{6,i} R_{i,N(t)}\, \mathbb{1}_{\{R_{i,N(t-1)}<0\}} + \eta_{7,i} R_{i,D(t-1)} + \eta_{8,i} R_{i,D(t-1)}\, \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$$
$$+\eta_{9,i} ES_{i,D(t-1)} + \eta_{10,i} ES_{i,D(t-1)}\, \mathbb{1}_{\{R_{i,D(t-1)}<0\}} + \xi_{i,t}\,, \tag{13}$$

where $ES_{i,D(t)}$ is the effective spread of the quintile portfolio during the trading session $D(t)$, calculated as the simple average of the effective spreads of individual stocks in the portfolio. For the high- minus low-volatility portfolio, I take the average of the high-volatility portfolio effective spreads and the ones for the low-volatility portfolio. Because liquidity is a persistent process, I included lagged effective spreads in the regression and allowed the autoregressive coefficient to be different for the previous trading sessions with market declines. I use the Newey and West (1987) standard errors with four lags to account for heteroskedasticity and autocorrelation.

[Table V about here]

Table V shows the regression's estimated coefficients. Three important results that further corroborate my previous findings appear. First, in the recent part of the sample, overnight market declines are followed by strong deteriorating intraday market liquidity, consistent with theories of market and funding liquidity. Second, in the same subsample, market liquidity declines are stronger for more volatile stocks, consistent with the findings of Hameed, Kang and Viswanathan (2010) for weekly horizons. Third, and finally, these patterns are not statistically significant for the older sample period of 1993–2001, in line with my previous results showing that one-sided reversals are a recent phenomenon.

That liquidity further deteriorates for the more volatile stocks, even after controlling for lagged liquidity, can be explained by the recent theoretical development around fire sales puzzles. Dow and Han (2018) argue that while total capital in financial market is not scarce, the capital of the better-informed investors on a particular asset might be limited. Consequently, when a wealth shock hits liquidity-constrained investors and makes them sell some of their holdings, other less-informed traders in the market are willing to buy those assets only with a "lemon" discount. Building on this argument of Dow and Han (2018), and given that for a volatile stock it is more difficult to separate information-based price fluctuations with liquidity-driven fluctuations, the price decline and liquidity deterioration due to the "lemon" discount for the volatile stocks shall be more pronounced.

The emergence of reversals over a short period of time agrees with a heavier reliance on overly short-term financing. Marked-to-market leverage is strongly procyclical (Adrian and Shin 2010) because of the adjustment of borrowing positions following market value changes. Consequently, an overnight wealth shock makes rolling over the short-term financing positions more difficult. Therefore, constrained investors might need to liquidate their positions.

Figure 8 provides evidence of the increasing role of overly short-term financing in financial markets. To proxy the dominance of short-term financing, I compare the size of the overnight repo market with the term repo market, for primary dealers of the Federal Reserve Bank of New York. The New York Fed provides weekly details on the positions of its primary dealers, which include the largest financial institutions.[4] Nagel (2012) uses similar data to proxy the Repo growth, because Repo is one of the main funding sources of broker-dealers. As shown in the figure, immediately before the financial crisis, the size of the overnight borrowing market for the primary dealers, reached levels as high as $3 trillion. Interestingly, the size of the overnight borrowing market became larger than term agreements after 2001, kept growing up to the level of around twice that of agreements before the financial crisis, and almost steadily kept twice the size of term agreements until the end of the sample.

[Figure 8 about here]

V. Overnight Wealth Shocks and Intraday Order Flows

In this section, I use a regression framework in the same spirit of the previous section, to understand the order imbalances following overnight market declines. Equation (14) shows the

[4] https://www.newyorkfed.org/markets/primarydealers

specified regression, in which $OI_{i,D(t)}$ is the order imbalance of quintile portfolio i during the trading session $D(t)$. I calculate the portfolio order imbalance as the simple average of individual stocks in the portfolio. For the high- minus low-volatility quintile portfolio, I take the difference of the high-volatility portfolio order imbalance and that for the low-volatility portfolio. I account for heteroskedasticity and autocorrelation using the Newey and West (1987) standard errors with four lags:

$$OI_{i,D(t)} = \theta_{0,i} + \theta_{1,i} R_{M,N(t)} + \theta_{2,i} R_{M,N(t)} \mathbb{1}_{\{R_{M,N(t)}<0\}} + \theta_{3,i} R_{M,D(t-1)} + \theta_{4,i} R_{M,D(t-1)} \mathbb{1}_{\{R_{M,D(t-1)}<0\}}$$
$$+\theta_{5,i} R_{i,N(t)} + \theta_{6,i} R_{i,N(t)} \mathbb{1}_{\{R_{i,N(t-1)}<0\}} + \theta_{7,i} R_{i,D(t-1)} + \theta_{8,i} R_{i,D(t-1)} \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$$
$$\theta_{9,i} + OI_{i,D(t-1)} + \theta_{10,i} OI_{i,D(t-1)} \mathbb{1}_{\{R_{i,D(t-1)}<0\}} + \zeta_{i,t} \,, \tag{14}$$

[Table VI about here]

Table VI shows the regression’s estimated coefficients. Comparing the results for the high- minus low-volatility portfolio for the two subsamples leads to an interesting finding. Consistent with Chordia, Roll, and Subrahmanyam (2001), investors are contrarian following market declines. Interestingly, in the older sample period, they are contrarian with respect to previous intraday decline, whereas, in the recent period, they mainly respond to overnight declines. Comparing this finding with that in Table III shows that investors provide liquidity when they predict that prices will decline because of illiquidity. Comparing Panels A and B of Table III confirms that declines mainly occur after overnight and intraday market declines, respectively, in the more recent and in the older sample periods.

VI. Systematic versus Idiosyncratic Risk

Throughout the paper, I take volatility as the key variable that determines the cross section of intraday and overnight returns. To understand the importance of systematic and idiosyncratic components of volatility in explaining the cross section of declines and reversals, I construct double-sorted portfolios, sorted by market beta and idiosyncratic volatility. I estimate market beta and idiosyncratic volatility for every stock-year using the daily four factors of Fama-French (1993) and momentum (Carhart 1997).[5] To construct the portfolios, I first construct beta terciles by sorting the stocks by the estimated betas of the previous calendar year. Then I construct idiosyncratic volatility terciles within every beta tercile by sorting stocks according to their idiosyncratic volatility of the past calendar year.

Panel A (B) of Figure 9 shows the average intraday and overnight returns for the double-sorted portfolios following overnight market surges (declines). The figure suggests that generally, the cross section of the intraday declines and overnight reversals are better explained by idiosyncratic volatility, whereas systematic risk tends to provide counterintuitive results after overnight market surges. More specifically, the three following results shown in the picture support this line of reasoning. First, the intraday returns following overnight market declines show a stronger difference in declines between different idiosyncratic volatility terciles, within every beta tercile. Second, the overnight reversals following the specified reversals show a similar pattern, that is, larger differences in returns between the idiosyncratic volatility tercile within beta terciles. Third, and finally, the overnight returns following a previous overnight market surge seem to increase in idiosyncratic volatility but, surprisingly, decrease in beta.

[Figure 9 about here]

In sum, the results suggest idiosyncratic volatility as the key determinant in the cross section of reversals. This is consistent with the "lemon" discount that the less-informed liquidity providers consider when they step in and take the role of better-informed but constrained liquidity providers (Dow and Han, 2018). Stocks with higher idiosyncratic volatility will be further discounted by less-informed investors because of information asymmetry.

[5] I downloaded the factors from Kenneth French's website and gratefully acknowledge his generosity.

VII. Alternative Explanations

Here, I discuss a set of alternative explanations, and explain why they are less plausible than the one I suggested in the paper.

A. Exchange traded funds arbitrage

The share of passive investment in the exchange-traded fund (ETF) market has considerably increased during the same sample period that I use for this paper. An overpriced (underpriced) ETF provides an arbitrage opportunity for authorized participants, to create (redeem) funds while buying (selling) the fund constituents. Doing so increases a stock's volatility (Ben-David, Franzoni, and Moussawi, 2018).

However, reconciling ETF arbitrage with the observed evidence for intraday declines following overnight market declines does not seem plausible. A hypothetical overnight market decline due to underpriced index ETFs should be met with buying the constituents during the following trading session and creating ETFs. However, the pattern that I document is the other way around; that is, overnight market declines are met with further intraday declines.

The findings also cannot be reconciled by assuming different buy and sell price impacts for these arbitrage trades. In this case, buy trades should have a higher price impact (Saar, 2001), and on average, the intraday prices should surge instead of decline.

B. High-frequency trading

Another important disruption in the financial market during the 21st century has been the emergence of high-frequency and algorithmic trading (Hendershott, Jones, and Menkveld, 2011, among others). It is not possible to reconcile reversals using high-frequency trades for at least three reasons. First, the reversals I document start emerging before algorithmic trading becomes an important part of the financial market. Second, high-frequency traders do not tend to keep positions overnight and, consequently, do not require rolling over their positions over the days. Therefore, they are not exposed to funding liquidity constraints. Third, and finally, high-frequency traders are mostly active for larger stocks, which tend to be more liquid, whereas I document stronger reversals for volatile stocks.

C. Betting against beta

In a recent working paper, Hendershott, Livdan, and Rösch (2018) sort intraday and overnight returns using market betas and show that overnight returns follow the security market line, whereas intraday returns follow an opposite trend. They suggest that the patterns for intraday returns are due to betting against beta (Frazzini and Pedersen, 2015).

Although the focus of Hendershott, Livdan, and Rösch (2018) is essentially different from that of this paper, and they do not document declines and reversals that mainly occur following overnight market declines, one can try evaluating betting against beta as an alternative explanation for the findings of this paper.

Betting against beta cannot explain the findings of this paper for at least two reasons: First, as shown in the previous section (see Figure 9), the cross section of intraday declines following overnight market declines are better defined with idiosyncratic volatility, compared to beta. Second, in the other days, that is, following overnight surges, intraday returns tend to increase with beta, which does not match the pattern observed by Hendershott, Livdan, and Rösch (2018). They document average intraday returns, that are decreasing in beta.

VIII. Conclusion

This paper has documented an important link between overnight wealth shocks and following intraday and overnight returns, as well as market liquidity. Market declines in periods as short as overnight lead to deteriorating market liquidity and price drops in the following trading session and their reversal during the next overnight period. These directional and cyclical reversals, which are stronger for more volatile stocks, make both the cross section and time series of intraday and overnight returns inversely associated.

I put forward predictions for the time series and the cross section of returns that have important implications for the ongoing research on intraday and overnight returns. Furthermore, the results provide important applications for financial stability and risk management, because I show that deteriorating market liquidity is predicted by overnight market declines.

This paper also helps clarify the mixed evidence around pricing idiosyncratic risk by showing that intraday (overnight) returns are decreasing (increasing) in idiosyncratic risk, mainly after overnight market declines. Therefore, this paper shows that idiosyncratic risk leads to opposing liquidity-driven systematic price movements in intraday and overnight periods.

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Panel A. 1993–2000 **Panel B. 2001–2016**

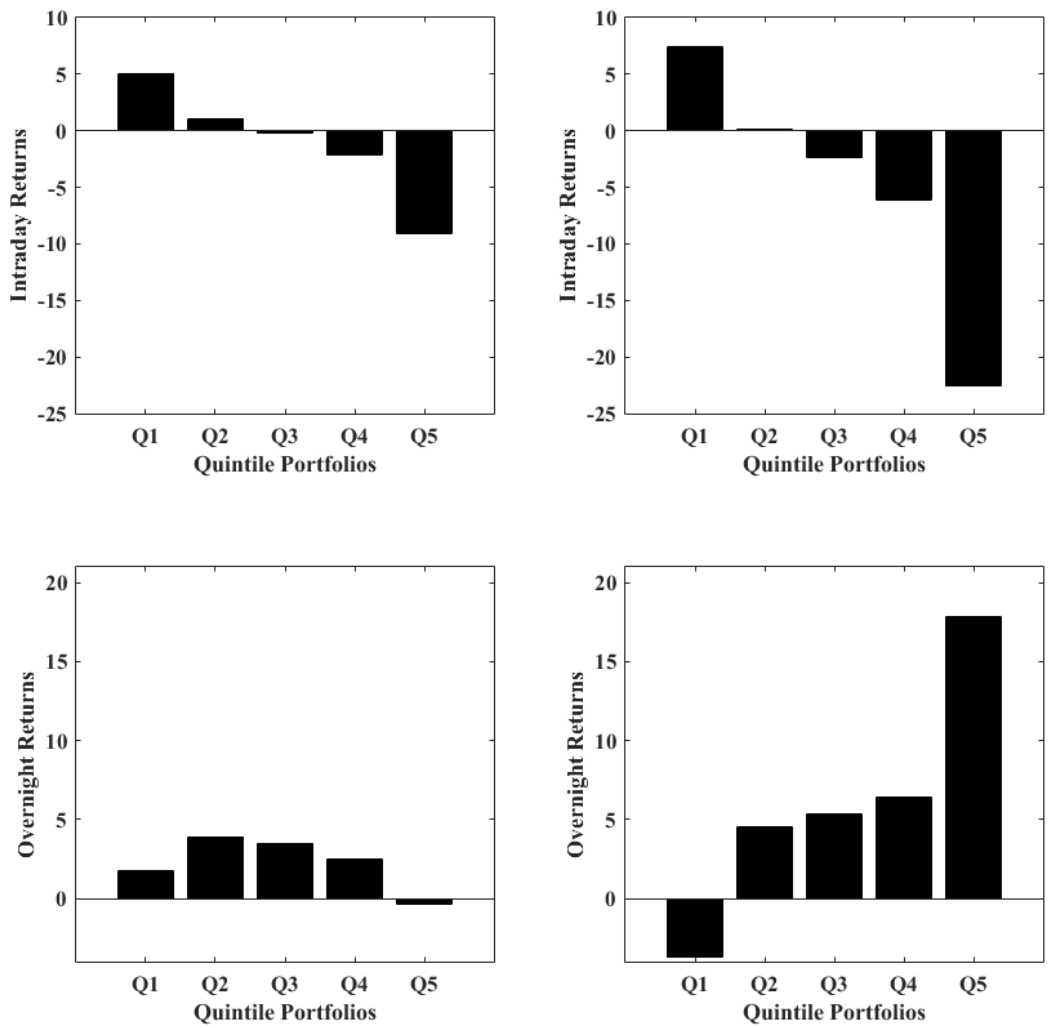


Figure 1. Emergence of the directional reversals between average intraday and overnight returns
In Panel A (B), I group stocks into five quintile portfolios sorted by their average intraday returns for the period of 1993–2000 (2001–2016). Q1 (Q5) corresponds to the quintile portfolio of stocks with highest (lowest) average intraday returns. The bar chart on the top shows the average intraday returns for the quintile portfolios, and the one on the bottom shows the average overnight returns for the same qunitle portfolios during the same time period. Stocks with fewer than 100 days of observations are excluded from the quintile portfolios. To avoid bid-ask bounces affecting the results, I use quote midpoints to calculate returns.

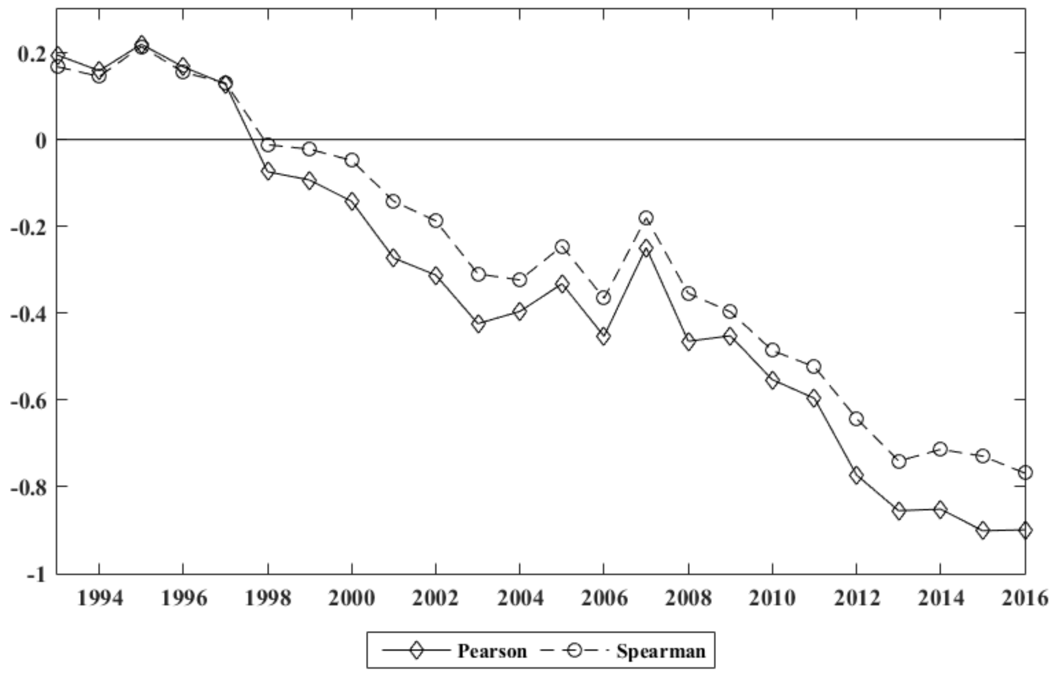


Figure 2. Time-series evolution of the cross-sectional association between average intraday and overnight returns
For every year between 1993 and 2016 and for every U.S. common stock listed in NYSE, AMEX, or NASDAQ, I calculate the time-series average of intraday and overnight returns. Then, for every year, I calcululale the cross-sectional correlations between average intraday and overnight returns. I estimate both Pearson and Spearman's rank correlations for every year. Stock-years with fewer than 100 days of observations are excluded. To avoid bid-ask bounces affecting the results, I use quote midpoints to calculate returns.

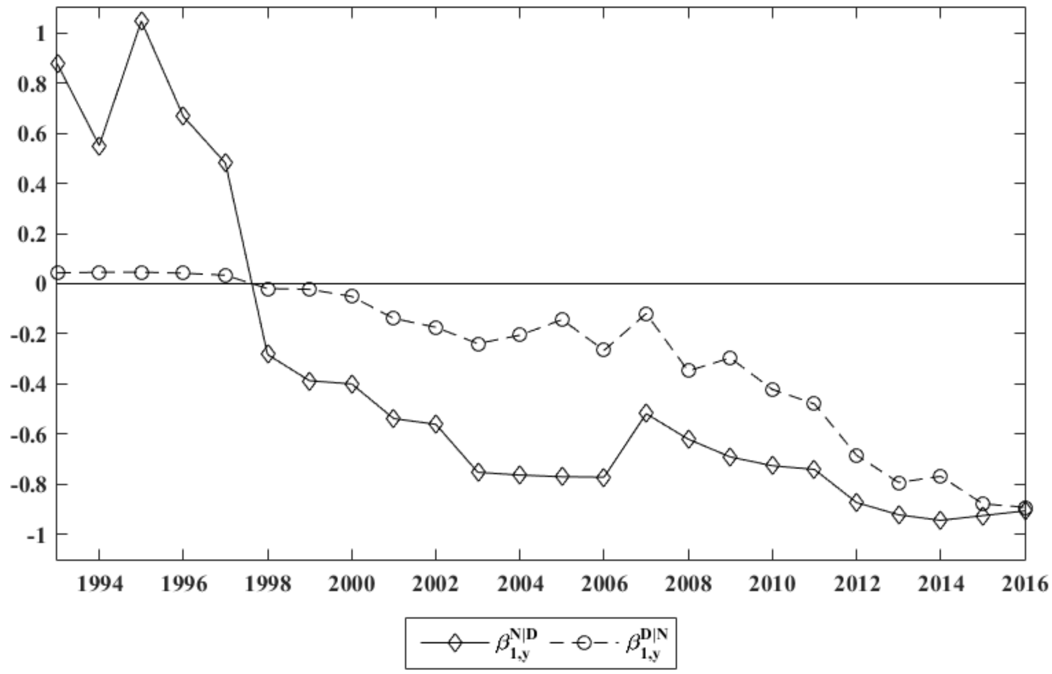


Figure 3. Time-series evolution of the cross-sectional regression between average intraday and overnight returns
For every year between 1993 and 2016 and for every stock, I calculate the annual time-series average of intraday returns and overnight returns. Then, for every year, I run the cross-sectional regressions $\bar{R}_{i,y}^{N} = \beta_{0,y}^{\mathrm{N|D}} + \beta_{1,y}^{\mathrm{N|D}}\, \bar{R}_{i,y}^{D} + \varepsilon_{i,y}$ and $\bar{R}_{i,y}^{D} = \beta_{0,y}^{\mathrm{D|N}} + \beta_{1,y}^{\mathrm{D|N}}\, \bar{R}_{i,y}^{N} + \epsilon_{i,y}$, respectively, to obtain $\beta_{1,y}^{\mathrm{N|D}}$ and $\beta_{1,y}^{\mathrm{D|N}}$. Stock-years with fewer than 100 days of observations are excluded. To avoid bid-ask bounces affecting the results, I use quote midpoints to calculate returns.

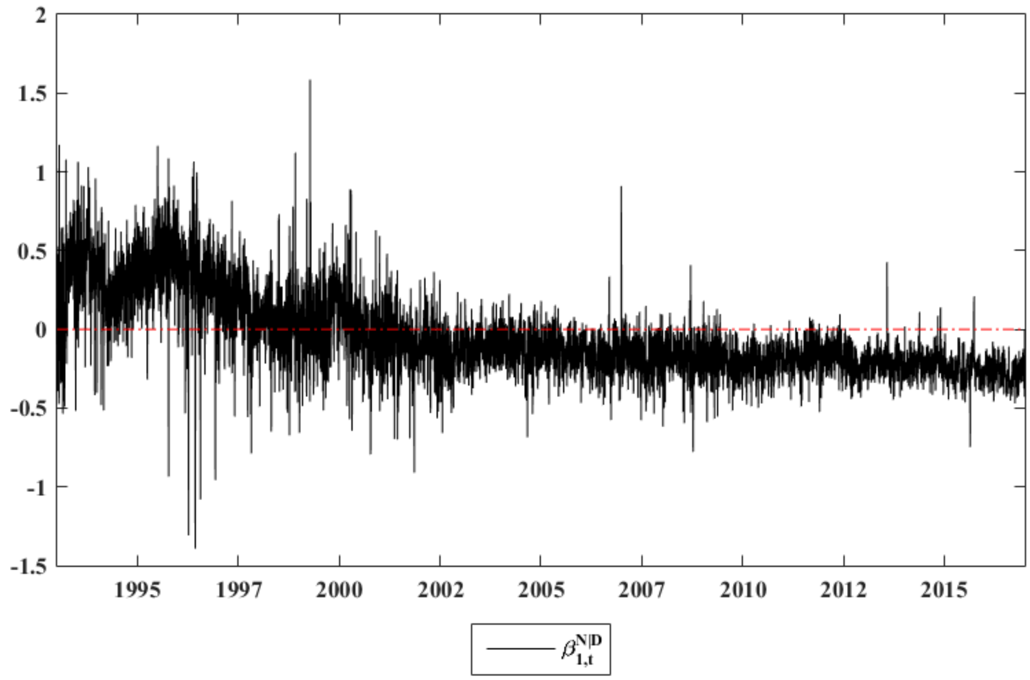


Figure 4. Time-series evolution of the cross-sectional regression between intraday and overnight returns
For every single day between 1993 and 2016, I estimate the following cross-sectional regressions of overnight returns on the intraday returns $R_{i,t}^{N} = \beta_{0,t}^{N|D} + \beta_{1,t}^{N|D} R_{i,t}^{D} + \varepsilon_{i,t}$. To avoid bid-ask bounces affecting the results, I use quote midpoints to calculate returns.

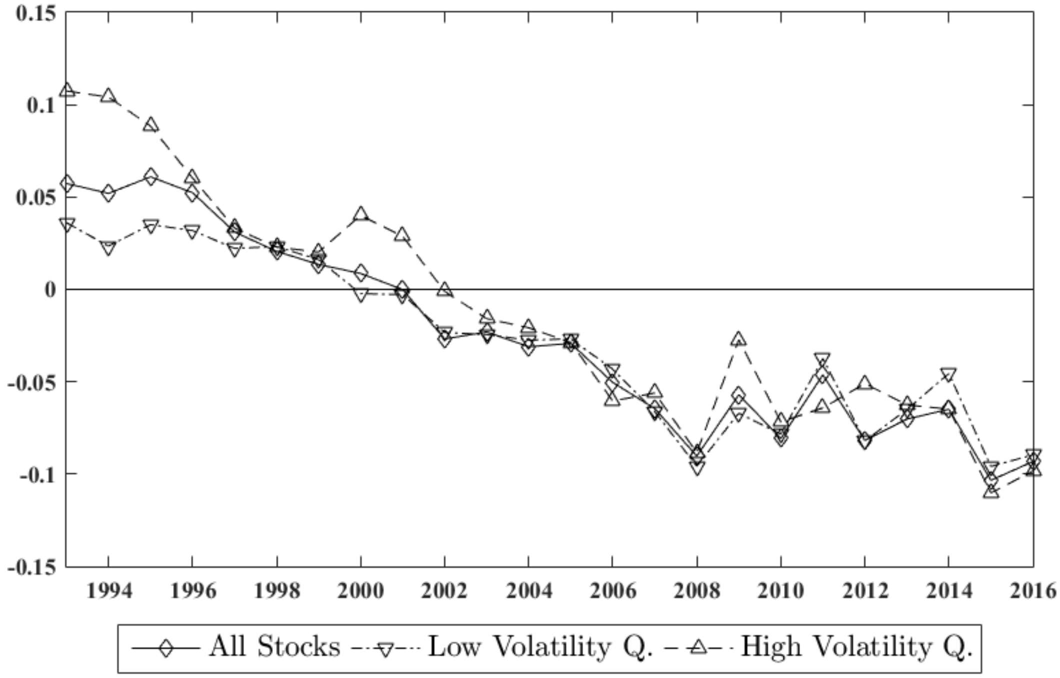


Figure 5. Average time-series correlation between intraday and the following overnight returns
For every year between 1993 and 2016 and for every stock, I calculate the time-series correlation between intraday and following overnight returns and then report the average for the cross section of all stocks, as well as the top and bottom volatility quantile groups of stocks, sorted by the previous calendar-year's volatility. Stock-years with fewer than 100 days of observations are excluded. To avoid bid-ask bounces affecting the results, I use quote midpoints to calculate returns.

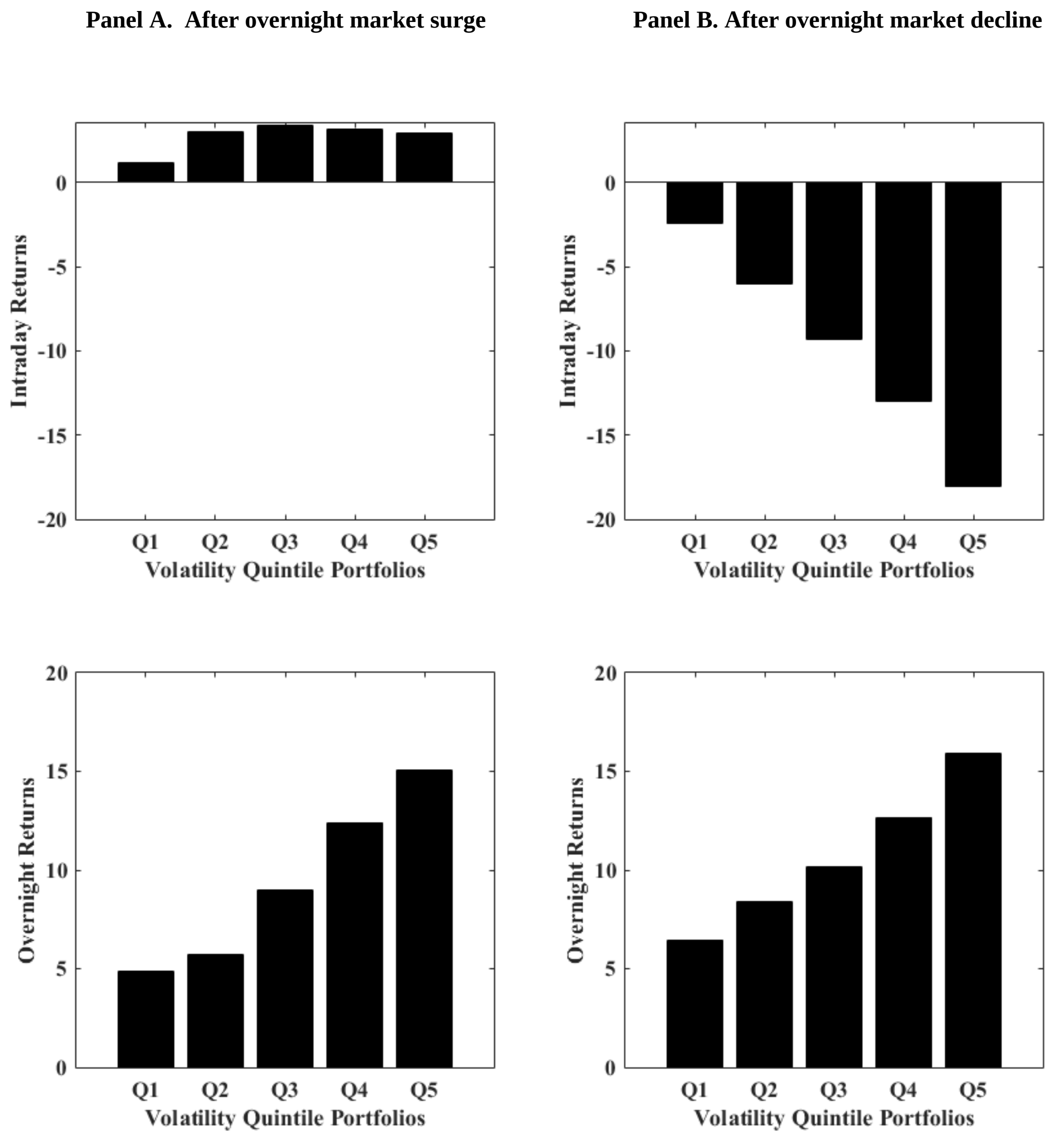


Figure 6. Average returns, following lagged overnight market movements, 2001–2016
For the period of 2001–2016, I sort U.S. common stocks into five quintile portfolios using relized return variances of the past calendar year, from lowest volatility to highest volatility Panel A (B) shows the average intraday and fllowing overnight returns after overnight market surges (declines). Stock-years with fewer than 100 days of observations are excluded. To avoid bid-ask bounces affecting the results, I use quote midpoints to calculate returns.

Panel A. After overnight market surge **Panel B. After overnight market decline**

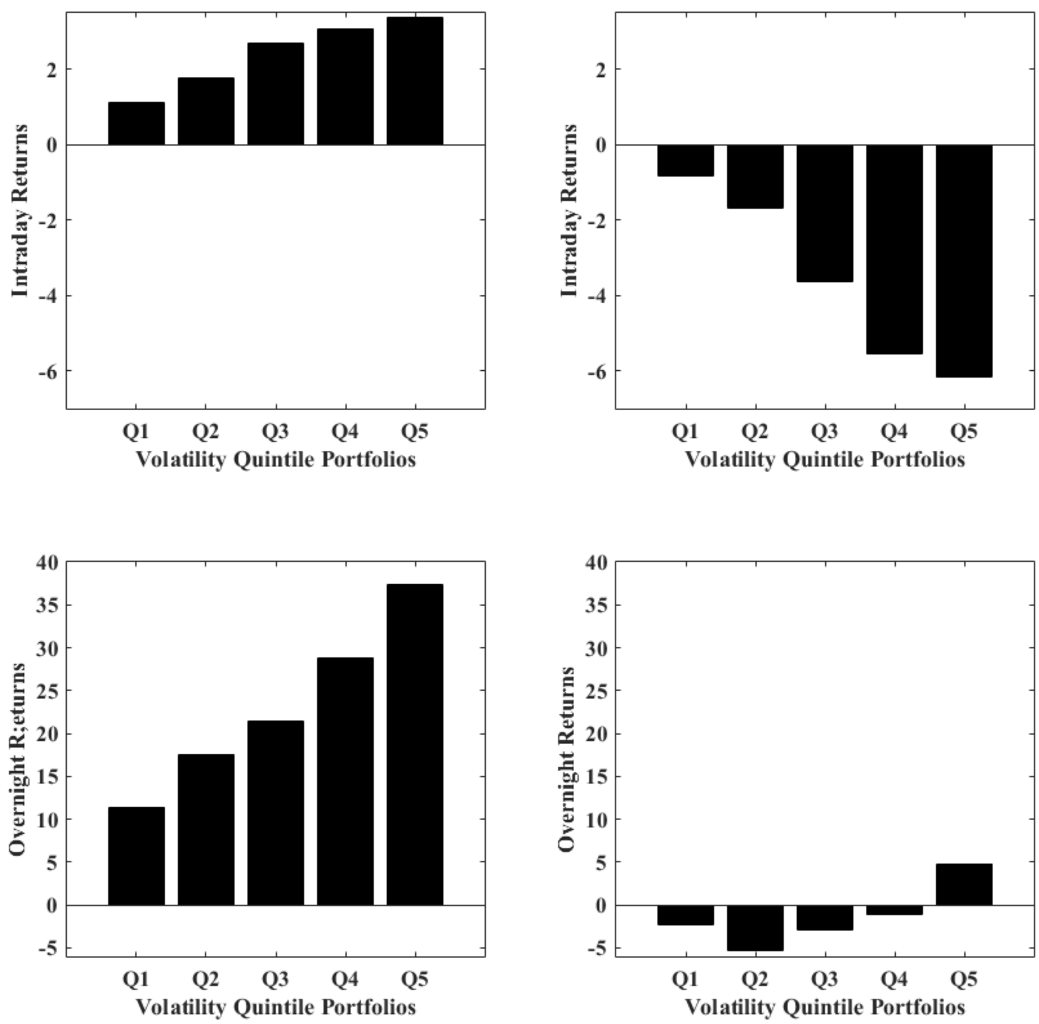
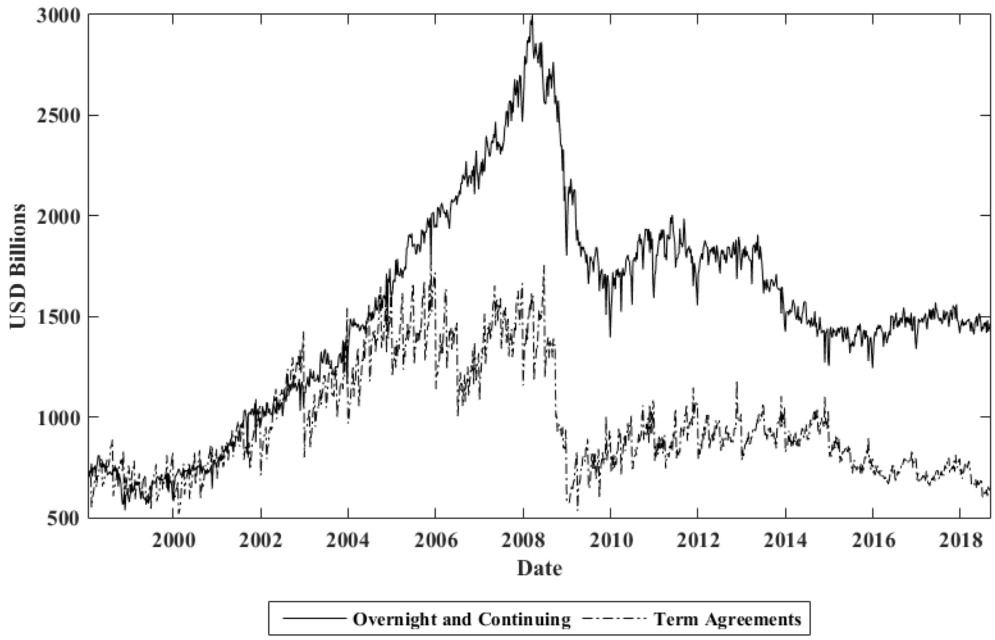


Figure 7. Average returns, following lagged overnight market movements, 1993–2000

For the period of 1993–2000, I sort U.S. common stocks into five quintile portfolios using realized return variances of the past calendar year, from lowest volatility to highest volatility Panel A (B) shows the average intraday and fllowing overnight returns after overnight market surges (declines). Stock-years with fewer than 100 days of observations are excluded. To avoid bid-ask bounces affecting the results, I use quote midpoints to calculate returns.

Panel A. Overnight versus term agreements



Panel B. Volume ratio of overnight over the term agreements

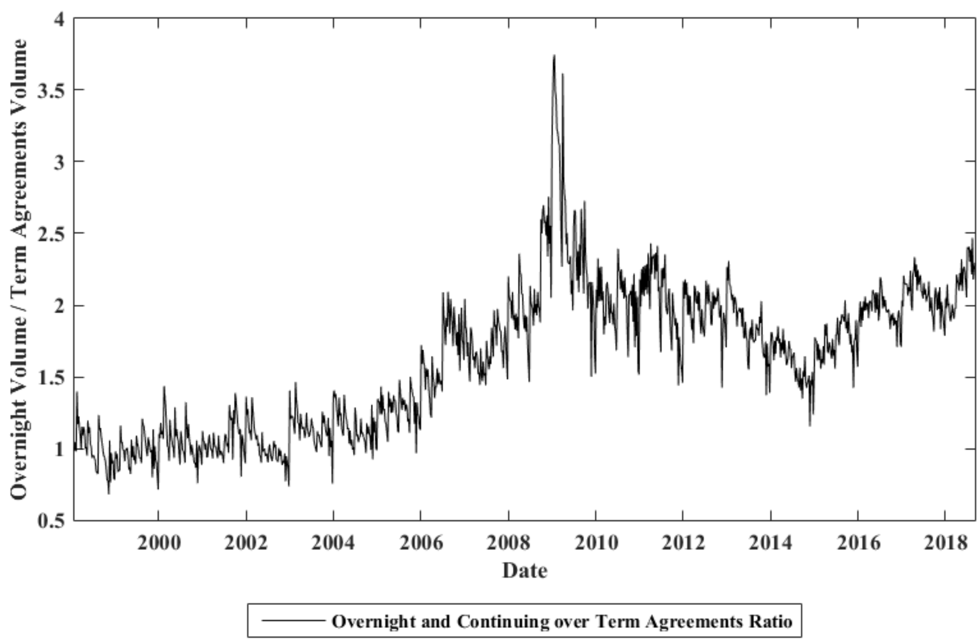


Figure 8. Overly short-term financing

This figure shows the repurchase borrowing volume of primary dealers to the Federal Reserve Bank of New York. Data are downloaded from the New York Fed website. The borrowing volumes are in billions of dollars. Panel A shows the borrowing volumes, and Panel B shows the ratio of overnight borrowing volume to the term agreements volume.

Panel A. After overnight market surge **Panel B. After overnight market decline**

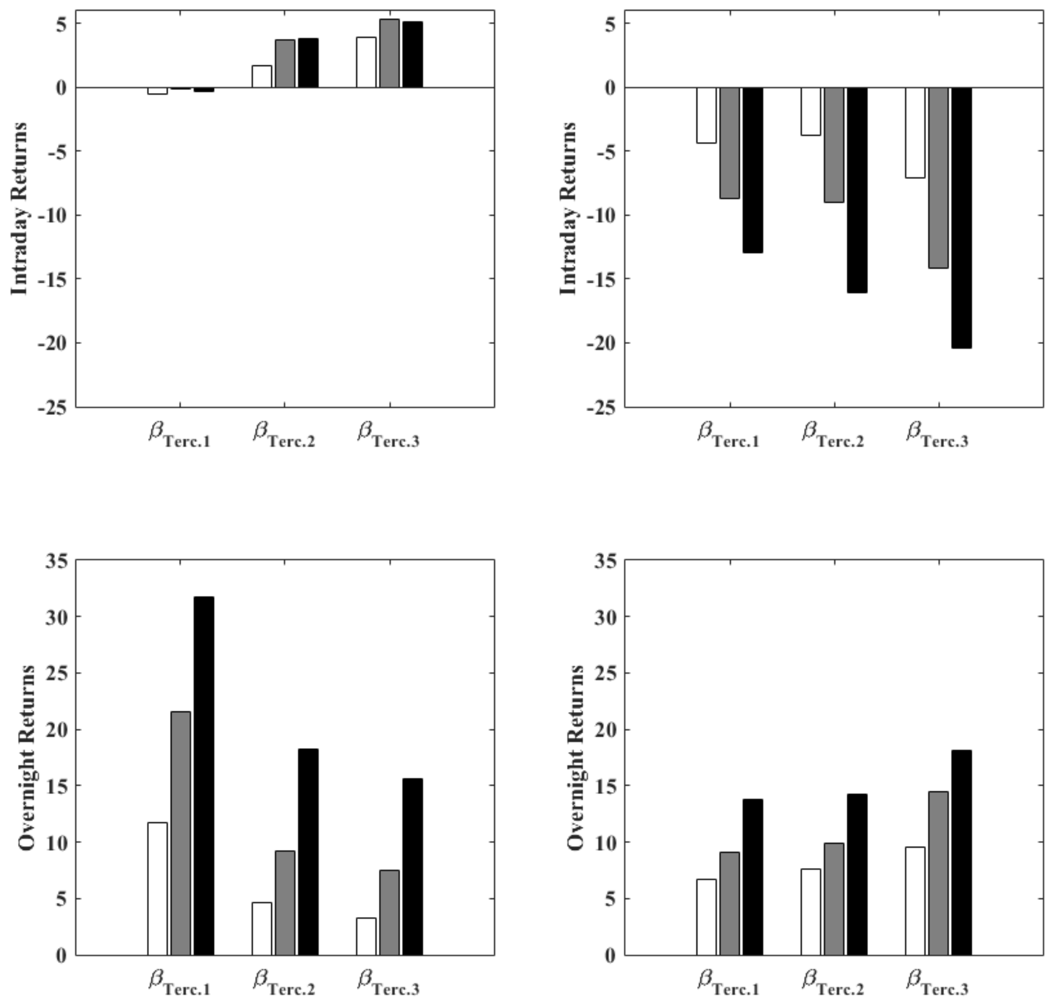


Figure 9. Average returns for double-sorted portfolios

For the period of 2001–2016, I double sort U.S. common stocks into nine (three-by-three) portfolios using market beta and idiosyncratic volatility of the past calendar year. Stocks are first sorted into three tercile groups by the ascending betas, and every beta tercil is sorted into three tercile groups of ascending idiosyncratic volatility. Panel A (B) shows the average intraday and fllowing overnight returns after overnight market surges (declines). Stock-years with fewer than 100 days of observations are excluded. To avoid bid-ask bounces affecting the results, I use quote midpoints to calculate returns.

Table I. Summary statistics

	N	Mean	SD	Quantiles				
				1%	5%	50%	95%	99%
Panel A. 1993–2000								
$R_{D(t),i}$	7,891,196	0.00%	0.70%	-2.17%	-0.69%	0.00%	0.69%	2.12%
$R_{N(t),i}$	7,891,196	0.10%	4.26%	-8.98%	-4.52%	0.00%	5.09%	11.11%
$ES_{D(t),i}$	7,891,196	1.37%	1.48%	0.10%	0.20%	0.92%	4.03%	7.23%
$OI_{D(t),i}$	7,891,196	-5.47%	46.49%	-100.00%	-98.05%	-2.54%	75.33%	100.00%
Panel B. 2001–2016								
$R_{D(t),i}$	12,317,406	-0.03%	1.29%	-4.20%	-1.63%	0.00%	1.49%	4.00%
$R_{N(t),i}$	12,317,406	0.10%	3.00%	-8.00%	-4.12%	0.02%	4.52%	9.08%
$ES_{D(t),i}$	12,317,406	0.51%	1.04%	0.02%	0.04%	0.19%	2.02%	4.89%
$OI_{D(t),i}$	12,317,406	-0.20%	32.62%	-100.00%	-60.78%	0.58%	51.37%	100.00%

This table provides the main summary statistics for the variables. The column labeled "N" refers to the number of observations in the sample. The next columns are the sample's average, the standard deviation, and the specified quantiles of the sample. The row label $R_{D(t),i}$ refers to the intraday open-to-close return of stock i at day t, calculated using midpoint quotes. $R_{N(t),i}$ refers to the overnight close-to-open return between the day $t-1$ close and day t open and is calculated using quote midpoints. $ES_{D(t),i}$ refers to the trade-weighted effective spread of all transactions of stock i at day t during trading hours, and $OI_{D(t),i}$ is the trade-weighted order imbalance of stock i at day t.

Table II. Time-series averages of the cross-sectional association between average intraday and overnight returns

	A. Cross-sectional correlations		B. Cross-sectional regressions	
	Pearson	Spearman	$\beta_{1,y}^{\mathrm{N\|D}}$	$\beta_{1,y}^{\mathrm{D\|N}}$
1993-2016	-0.342**	-0.265**	-0.394	-0.280**
	(-2.35)	(-2.06)	(-1.64)	(-2.24)
1993-2000	0.069	0.091*	0.319	0.014
	(0.94)	(1.79)	(1.09)	(0.75)
2001-2016	-0.549***	-0.444***	-0.751***	-0.427***
	(-5.08)	(-4.43)	(-13.7)	(-3.24)

This table provides the time-series averages for the cross-sectional associations between average intraday and overnight returns, specified in Figures 2 and 3. Panels A (B) provide the time-series average of the estimated cross-sectional correlations (coefficients of the cross-sectional regressions) shown in Figure 2 (3). *t*-statistics are calculated using the Newey and West (1987) estimation errors allowing for four lags of autocorrelation. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table III. Intraday returns $R_{i,D(t)}$

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A. Between 1993 and 2000						
$R_{M,N(t)}$	-0.001	0.003	0.012***	0.02***	0.021**	0.022***
	(-0.24)	(1.2)	(3.24)	(2.94)	(2.51)	(2.97)
$R_{M,N(t)}\ \mathbb{1}_{\{R_{M,N(t)}<0\}}$	0.008**	0.014***	0.007	0.015	0.031*	0.016
	(2.06)	(2.91)	(0.91)	(1.13)	(1.93)	(1.38)
$R_{M,D(t-1)}$	0.002	-0.031	-0.002	-0.011	-0.029	-0.045
	(0.11)	(-1.57)	(-0.09)	(-0.28)	(-0.46)	(-0.78)
$R_{M,D(t-1)}\ \mathbb{1}_{\{R_{M,D(t-1)}<0\}}$	0.025	0.095***	0.074	0.074	0.049	0.023
	(0.7)	(2.78)	(1.49)	(0.91)	(0.41)	(0.19)
$R_{i,N(t)}$	0.022***	0.024***	0.022***	0.026***	0.023***	0.025***
	(3.13)	(5.67)	(4.33)	(4.96)	(4.17)	(4.76)
$R_{i,N(t)}\ \mathbb{1}_{\{R_{i,N(t)}<0\}}$	-0.001	0.001	0.016*	0.004	-0.008	-0.007
	(-0.07)	(0.08)	(1.71)	(0.33)	(-0.61)	(-0.54)
$R_{i,D(t-1)}$	-0.01	-0.037	-0.04	-0.048	-0.003	0.005
	(-0.21)	(-0.66)	(-0.75)	(-0.94)	(-0.06)	(0.1)
$R_{i,D(t-1)}\ \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$	-0.119	-0.116	-0.158*	-0.149*	-0.164*	-0.131*
	(-1.51)	(-1.32)	(-1.95)	(-1.87)	(-1.96)	(-1.65)
c	0***	0.0001***	0	-0.0001**	-0.0002**	-0.0002***
	(2.77)	(3.7)	(0.26)	(-2.18)	(-2.26)	(-2.85)
R^2_{Adj}	20.4%	32.8%	37.3%	36.8%	21.2%	17.4%
Panel B. Between 2001 and 2016						
$R_{M,N(t)}$	0.024***	0.082***	0.141***	0.151***	0.092***	0.075***
	(3.01)	(6.89)	(8.44)	(8.19)	(6.16)	(7.63)
$R_{M,N(t)}\ \mathbb{1}_{\{R_{M,N(t)}<0\}}$	0.025*	0.047**	0.065**	0.076***	0.109***	0.057***
	(1.72)	(2.36)	(2.51)	(2.85)	(3.75)	(3.28)
$R_{M,D(t-1)}$	-0.164***	-0.094*	-0.047	-0.058	-0.121	-0.039
	(-4.08)	(-1.86)	(-0.72)	(-0.74)	(-1.42)	(-0.61)
$R_{M,D(t-1)}\ \mathbb{1}_{\{R_{M,D(t-1)}<0\}}$	0.122**	0.155*	0.111	0.036	0.002	-0.089
	(2.19)	(1.95)	(1.13)	(0.29)	(0.01)	(-0.85)
$R_{i,N(t)}$	-0.015	-0.047***	-0.078***	-0.056***	0.002	0.011
	(-1.35)	(-3.69)	(-6.18)	(-5)	(0.28)	(1.33)
$R_{i,N(t)}\ \mathbb{1}_{\{R_{i,N(t)}<0\}}$	0.02	0.01	0.01	0.011	-0.005	0.01
	(1.06)	(0.46)	(0.5)	(0.69)	(-0.36)	(0.74)
$R_{i,D(t-1)}$	0.241***	0.099**	0.073*	0.018	0.04	0.036
	(4.1)	(2.2)	(1.84)	(0.42)	(0.93)	(0.74)
$R_{i,D(t-1)}\ \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$	0.037	0.035	0.054	0.117**	0.159**	0.162**
	(0.41)	(0.57)	(1)	(2.04)	(2.24)	(2.18)
c	0.0002***	0.0002**	0.0001	0.0001	-0.0002	-0.0003***
	(2.9)	(2.12)	(1.14)	(0.68)	(-1.49)	(-2.99)
R^2_{Adj}	15.2%	23.3%	32.4%	31.7%	28.5%	23.4%

This table reports the estimated coefficients for the regression framework specified in equation (11). Columns labeled "Q1 to Q5" refer to the annually rebalanced volatility quintile porfolios, sorted from the lowest to the highest volatility, and the column labeled "Q5-Q1" corresponds to the high- minus low-volatility portfolio. *t*-statistics account for heteroskedasticity and autocorrelation using the Newey and West (1987) standard errors with four lags. Panel A (B) shows the estimates for the 1993–2000 (2001–2016) period. $^*p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Table IV. Overnight returns $R_{i,N(t)}$

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A. Between 1993 and 2000						
$R_{M,D(t-1)}$	-0.079	-0.191	-0.601	-0.541	-0.274	-0.481
	(-0.24)	(-0.56)	(-1.29)	(-0.71)	(-0.26)	(-0.53)
$R_{M,D(t-1)}\ \mathbb{1}_{\{R_{M,D(t-1)}<0\}}$	-1.27**	-1.398**	-0.966	-0.029	0.256	0.233
	(-2.22)	(-2.15)	(-1.02)	(-0.02)	(0.12)	(0.12)
$R_{M,N(t-1)}$	-0.068**	-0.075*	-0.079	-0.008	0.094	0.061
	(-2.27)	(-1.89)	(-1.5)	(-0.11)	(0.92)	(0.75)
$R_{M,N(t-1)}\ \mathbb{1}_{\{R_{M,N(t-1)}<0\}}$	-0.068	-0.166**	-0.311***	-0.711***	-0.643***	-0.56***
	(-1.05)	(-2.19)	(-2.74)	(-4.29)	(-3.11)	(-3.48)
$R_{i,D(t-1)}$	4.713***	7.239***	6.794***	5.804***	3.488***	2.793***
	(4.71)	(8.27)	(8.63)	(7.12)	(4.12)	(3.33)
$R_{i,D(t-1)}\ \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$	3.434*	0.169	-1.304	-3.516**	-2.584**	-2.247**
	(1.85)	(0.11)	(-0.93)	(-2.47)	(-2.12)	(-1.98)
$R_{i,N(t-1)}$	0.308***	0.322***	0.178***	0.093	0.058	0.095
	(5.02)	(4.61)	(2.64)	(1.42)	(0.8)	(1.4)
$R_{i,N(t-1)}\ \mathbb{1}_{\{R_{i,N(t-1)}<0\}}$	-0.177	-0.193	-0.124	0.22*	0.098	0.1
	(-1.06)	(-1.33)	(-0.78)	(1.67)	(0.74)	(0.75)
c	-0.0002	-0.0008***	-0.0009**	-0.0009	-0.0005	-0.0006
	(-0.79)	(-2.83)	(-2.11)	(-1.6)	(-0.59)	(-0.76)
R^2_{Adj}	12.5%	17.6%	13.7%	9.5%	4.6%	4.8%
Panel B. Between 2001 and 2016						
$R_{M,D(t-1)}$	0.323	0.352	0.547	0.451	0.662	0.678**
	(1.42)	(1.06)	(1.52)	(1.05)	(1.44)	(2.3)
$R_{M,D(t-1)}\ \mathbb{1}_{\{R_{M,D(t-1)}<0\}}$	0.175	0.416	0.208	0.077	-0.364	-0.709
	(0.48)	(0.76)	(0.34)	(0.11)	(-0.49)	(-1.47)
$R_{M,N(t-1)}$	0.001	-0.054	-0.122	-0.16	-0.064	0.008
	(0.03)	(-0.58)	(-1.26)	(-1.6)	(-0.71)	(0.19)
$R_{M,N(t-1)}\ \mathbb{1}_{\{R_{M,N(t-1)}<0\}}$	-0.12	-0.213	-0.231	-0.306*	-0.261	-0.151**
	(-1.44)	(-1.38)	(-1.42)	(-1.71)	(-1.59)	(-2.17)
$R_{i,D(t-1)}$	-0.203	0.254	0.285	0.461*	0.328	-0.031
	(-0.76)	(0.86)	(1.05)	(1.75)	(1.21)	(-0.14)
$R_{i,D(t-1)}\ \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$	-0.002	-0.376	-0.246	-0.203	-0.173	0.194
	(0)	(-0.69)	(-0.55)	(-0.52)	(-0.46)	(0.62)
$R_{i,N(t-1)}$	0.102	0.169	0.234**	0.231***	0.141**	0.103*
	(1.24)	(1.61)	(2.55)	(2.9)	(2.15)	(1.81)
$R_{i,N(t-1)}\ \mathbb{1}_{\{R_{i,N(t-1)}<0\}}$	-0.071	-0.073	-0.111	-0.084	-0.084	-0.091
	(-0.51)	(-0.39)	(-0.71)	(-0.6)	(-0.75)	(-0.95)
c	0.0001	-0.0002	-0.0003	-0.0003	0.0002	0.0003
	(0.19)	(-0.45)	(-0.5)	(-0.54)	(0.38)	(0.7)
R^2_{Adj}	0.9%	1.9%	2.3%	2.4%	1.4%	0.9%

This table reports the estimated coefficients for the regression framework specified in equation (12). Columns labeled "Q1 to Q5" refer to the annually rebalanced volatility quintile porfolios, sorted from the lowest to the highest volatility, and the column labeled "Q5-Q1" corresponds to the high- minus low-volatility portfolio. *t*-statistics account for heteroskedasticity and autocorrelation using the Newey and West (1987) standard errors with four lags. Panel A (B) shows the estimates for the 1993–2000 (2001–2016) period. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table V. Effective spreads $ES_{i,D(t)}$

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A. Between 1993 and 2000						
$R_{M,N(t)}$	-0.004	-0.006	-0.003	-0.017**	-0.046***	-0.022***
	(-1.33)	(-1.46)	(-0.69)	(-2.57)	(-3.9)	(-3.69)
$R_{M,N(t)}\ \mathbb{1}_{\{R_{M,N(t)}<0\}}$	0	0.002	0.01	0.001	0.006	-0.007
	(-0.05)	(0.25)	(1.03)	(0.06)	(0.25)	(-0.67)
$R_{M,D(t-1)}$	0.049**	-0.035	-0.138***	-0.148***	-0.259***	-0.133***
	(2.33)	(-1.36)	(-4.11)	(-2.95)	(-2.65)	(-2.67)
$R_{M,D(t-1)}\ \mathbb{1}_{\{R_{M,D(t-1)}<0\}}$	-0.136***	0.014	0.215***	0.342***	0.656***	0.323***
	(-3.61)	(0.31)	(3.36)	(2.9)	(3.71)	(3.54)
$R_{i,N(t)}$	0.009*	0.006	-0.009	-0.008*	0	-0.006*
	(1.69)	(1.07)	(-1.46)	(-1.69)	(-0.06)	(-1.82)
$R_{i,N(t)}\ \mathbb{1}_{\{R_{i,N(t)}<0\}}$	-0.032***	-0.06***	-0.05***	-0.025***	0.001	0.009
	(-3.56)	(-4.65)	(-4.74)	(-3.06)	(0.09)	(1.46)
$R_{i,D(t-1)}$	-0.157*	0.08	0.047	-0.133**	-0.088	-0.042
	(-1.86)	(0.88)	(0.59)	(-2.02)	(-1.16)	(-1.04)
$R_{i,D(t-1)}\ \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$	0.536***	0.348***	0.346***	0.353***	0.266**	0.096*
	(4.63)	(2.75)	(3.52)	(3.73)	(2.48)	(1.66)
$ES_{i,D(t-1)}$	0.934***	0.842***	0.916***	0.964***	0.903***	0.893***
	(101.8)	(50.2)	(74.4)	(157)	(82.2)	(75.4)
$ES_{i,D(t-1)}\ \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$	0.004	0.002	0.001	-0.012**	0.014*	0.006
	(1.12)	(0.61)	(0.25)	(-2.51)	(1.9)	(0.96)
c	0.0004***	0.0019***	0.0014***	0.0011***	0.0027***	0.0019***
	(7.66)	(9.26)	(7.59)	(6.72)	(9.87)	(10.39)
R^2_{Adj}	91.0%	76.3%	87.0%	93.2%	85.6%	83.1%
Panel B. Between 2001 and 2016						
$R_{M,N(t)}$	0.011	0.014	0.017	0.019	0.026	0.018*
	(1.38)	(1.58)	(0.81)	(0.83)	(1.64)	(1.77)
$R_{M,N(t)}\ \mathbb{1}_{\{R_{M,N(t)}<0\}}$	-0.036***	-0.048***	-0.046*	-0.035	-0.07***	-0.053***
	(-3.26)	(-3.3)	(-1.81)	(-1.44)	(-3.91)	(-4.05)
$R_{M,D(t-1)}$	0.065***	0.121***	0.134***	0.086*	0.071*	0.039*
	(2.79)	(3.59)	(2.95)	(1.88)	(1.74)	(1.65)
$R_{M,D(t-1)}\ \mathbb{1}_{\{R_{M,D(t-1)}<0\}}$	-0.108***	-0.224***	-0.212***	-0.181***	-0.149**	-0.087**
	(-3.54)	(-4.7)	(-3.72)	(-2.85)	(-2.39)	(-2.21)
$R_{i,N(t)}$	0.002	0.005	0.006	0.01	-0.001	0.003
	(0.3)	(0.96)	(0.58)	(1.23)	(-0.11)	(1.18)
$R_{i,N(t)}\ \mathbb{1}_{\{R_{i,N(t)}<0\}}$	0.005	0.001	-0.01	-0.037***	-0.007	-0.013***
	(0.57)	(0.11)	(-0.88)	(-4.32)	(-1.19)	(-3.67)
$R_{i,D(t-1)}$	-0.162***	-0.211***	-0.152**	-0.036	-0.024	0.042**
	(-3.43)	(-3.82)	(-2.52)	(-0.82)	(-0.67)	(2.35)
$R_{i,D(t-1)}\ \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$	0.276***	0.339***	0.262***	0.098**	0.079*	-0.002
	(4.26)	(4.68)	(3.5)	(1.99)	(1.91)	(-0.08)
$ES_{i,D(t-1)}$	0.902***	0.829***	0.814***	0.712***	0.741***	0.766***
	(62.1)	(31.0)	(24.5)	(14.4)	(30.7)	(27.0)
$ES_{i,D(t-1)}\ \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$	0.009	-0.012	0.02**	0.02	0.015	0.028***
	(1.27)	(-1.28)	(2.19)	(1.55)	(1.36)	(2.98)
c	0.0003***	0.0007***	0.0008***	0.0013***	0.0017***	0.001***
	(6.13)	(6.82)	(5.48)	(6.15)	(11.14)	(8.8)
R^2_{Adj}	89.5%	78.3%	76.2%	67.1%	65.4%	75.2%

This table reports the estimated coefficients for the regression framework specified in equation (13). Columns labeled "Q1 to Q5" refer to the annually rebalanced volatility quintile porfolios, sorted from the lowest to the highest volatility, and the column labeled "Q5-Q1" corresponds to the high- minus low-volatility portfolio. *t*-statistics account for heteroskedasticity and autocorrelation using the Newey and West (1987) standard errors with four lags. Panel A (B) shows the estimates for the 1993–2000 (2001–2016) period. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table VI. Order imbalances $OI_{i,D(t)}$

	Q1	Q2	Q3	Q4	Q5	Q5-Q1
Panel A. Between 1993 and 2000						
$R_{M,N(t)}$	-0.872***	-1.218***	-0.763***	-0.142	-0.144	-0.274
	(-3.26)	(-4.2)	(-3.1)	(-0.6)	(-0.47)	(-0.85)
$R_{M,N(t)}\ \mathbb{1}_{\{R_{M,N(t)}<0\}}$	1.422***	1.336***	0.824	-0.267	1.617**	0.147
	(2.86)	(2.62)	(1.61)	(-0.59)	(2.23)	(0.26)
$R_{M,D(t-1)}$	-5.987**	-4.631**	-2.077	-1.397	-1.099	5.855*
	(-2.26)	(-2.23)	(-1.11)	(-0.68)	(-0.41)	(1.94)
$R_{M,D(t-1)}\ \mathbb{1}_{\{R_{M,D(t-1)}<0\}}$	16.88***	12.09***	6.593**	3.053	-0.707	-19.03***
	(3.5)	(3.08)	(2.01)	(0.85)	(-0.14)	(-3.81)
$R_{i,N(t)}$	1.698***	4.085***	2.229***	1.079***	1.015***	1.572***
	(2.82)	(6.24)	(6.22)	(4.47)	(4.37)	(5.54)
$R_{i,N(t)}\ \mathbb{1}_{\{R_{i,N(t)}<0\}}$	-2.013*	-2.44**	-0.733	0.086	-0.912**	-1.637***
	(-1.79)	(-2.45)	(-1.12)	(0.24)	(-2.37)	(-4.38)
$R_{i,D(t-1)}$	-1.511	-3.896	-6.244*	-1.068	-3.758	-6.545
	(-0.19)	(-0.61)	(-1.87)	(-0.51)	(-1.23)	(-1.59)
$R_{i,D(t-1)}\ \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$	-26.97**	-14.38	1.237	-3.113	6.241	9.826
	(-2.04)	(-1.5)	(0.26)	(-0.94)	(1.18)	(1.58)
$OI_{i,D(t-1)}$	0.41***	0.196***	0.461***	0.588***	-0.138	0.114
	(7.4)	(2.62)	(4.38)	(4.08)	(-0.85)	(0.87)
$OI_{i,D(t-1)}\ \mathbb{1}_{\{OI_{i,D(t-1)}<0\}}$	0.133*	0.227**	-0.111	-0.232	0.296*	0.098
	(1.69)	(2.49)	(-0.96)	(-1.55)	(1.66)	(0.72)
c	-0.0061***	-0.0274***	-0.0405***	-0.0495***	-0.0636***	-0.0519***
	(-2.63)	(-9.94)	(-14.17)	(-15.63)	(-13.67)	(-11.81)
R^2_{Adj}	29.9%	31.5%	30.3%	27.6%	8.0%	10.4%
Panel B. Between 2001 and 2016						
$R_{M,N(t)}$	0.125	0.886***	1.128***	0.942***	0.726***	0.707***
	(0.5)	(3.75)	(4.26)	(4.11)	(3.25)	(4.16)
$R_{M,N(t)}\ \mathbb{1}_{\{R_{M,N(t)}<0\}}$	-0.052	-0.644*	-0.44	-0.469	-0.013	-0.911***
	(-0.14)	(-1.75)	(-1.09)	(-1.41)	(-0.04)	(-4.36)
$R_{M,D(t-1)}$	2.427**	3.144***	1.143	0.392	0.97	0.187
	(2.29)	(3.26)	(1.14)	(0.39)	(0.89)	(0.19)
$R_{M,D(t-1)}\ \mathbb{1}_{\{R_{M,D(t-1)}<0\}}$	-4.964***	-5.122***	-1.146	-0.45	-1.674	-0.441
	(-3.13)	(-3.5)	(-0.8)	(-0.31)	(-1.13)	(-0.32)
$R_{i,N(t)}$	-0.282	-0.789***	-0.727***	-0.244	0.184	-0.023
	(-0.8)	(-3.1)	(-3.37)	(-1.61)	(1.57)	(-0.2)
$R_{i,N(t)}\ \mathbb{1}_{\{R_{i,N(t)}<0\}}$	0.814	0.951**	0.634*	0.47*	-0.069	0.114
	(1.5)	(2.28)	(1.67)	(1.72)	(-0.36)	(0.65)
$R_{i,D(t-1)}$	-6.713***	-5.298***	-1.726**	-0.36	0.94	0.227
	(-5.71)	(-7.1)	(-2.41)	(-0.61)	(1.4)	(0.37)
$R_{i,D(t-1)}\ \mathbb{1}_{\{R_{i,D(t-1)}<0\}}$	10.40***	7.765***	2.611**	1.46*	-0.652	-1.415*
	(5.77)	(6.69)	(2.55)	(1.74)	(-0.72)	(-1.75)
$OI_{i,D(t-1)}$	0.445***	0.424***	0.333***	0.266***	0.202***	0.321***
	(14.9)	(12.6)	(9.06)	(6.81)	(4.78)	(7.43)
$OI_{i,D(t-1)}\ \mathbb{1}_{\{OI_{i,D(t-1)}<0\}}$	0.083	-0.014	-0.029	-0.043	0.024	0.188***
	(1.43)	(-0.24)	(-0.5)	(-0.74)	(0.41)	(3.27)
c	0.0056***	0.0031**	-0.0011	-0.0066***	-0.0177***	-0.0143***
	(4.16)	(2.23)	(-0.8)	(-5.14)	(-11.63)	(-9.53)
R^2_{Adj}	27.2%	21.5%	14.6%	13.5%	14.2%	23.7%

This table reports the estimated coefficients for the regression framework specified in equation (14). Columns labeled "Q1 to Q5" refer to the annually rebalanced volatility quintile porfolios, sorted from the lowest to the highest volatility, and the column labeled "Q5-Q1" corresponds to the high- minus low-volatility portfolio. *t*-statistics account for heteroskedasticity and autocorrelation using the Newey and West (1987) standard errors with four lags. Panel A (B) shows the estimates for the 1993–2000 (2001–2016) period. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.