Author's Accepted Manuscript

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PII: S1386-4181(16)30337-8
DOI: http://dx.doi.org/10.1016/j.finmar.2017.07.002
Reference: FINMAR438

To appear in: *Journal of Financial Markets*

Received date: 19 December 2016
Revised date: 14 July 2017
Accepted date: 20 July 2017

Cite this article as: Kee H. Chung and Chairat Chuwonganant, Market volatilit and stock returns: the role of liquidity providers, *Journal of Financial Markets* http://dx.doi.org/10.1016/j.finmar.2017.07.002

Market volatility and stock returns: the role of liquidity providers☆

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Abstract

This study shows that market volatility affects stock returns both directly and indirectly through its impact on liquidity provision. The negative relation between market volatility and stock returns arises not only from greater risk premiums but also greater illiquidity premiums that are associated with higher market volatility. Consistent with our expectation, we also find that stock returns are more sensitive to volatility shocks in the high-frequency trading era, and after the regulatory changes in the U.S. markets that increased competition between public traders and market makers, reduced the tick size, and decreased the role of market makers.

JEL classification: G01, G02, G10, G18

Keywords: Risk premium, Illiquidity premium, VIX, Market structure

1. Introduction

Market volatility, liquidity, and stock returns are all variables of significant interest to financial economists, market regulators, and investors.[2] However, why and how these variables

☆The authors thank Gideon Saar (the editor) and an anonymous referee for valuable suggestions. The authors also thank Hank Bessembinder, Changhui Choi, Jong Yeon Choi, Karl Diether, Chanyoung Eom, Terrence Hendershott, Bong-Gyu Jang, Hyoung-Goo Kang, Andy Kim, Changki Kim, Ho-Seok Lee, Ji Yeol Oh, Hong Liu, Stefan Nagel, Dominik Roesch, Roy Song, Raluca Stan, Inho Suk, session participants at the 2016 Financial Management Association Annual Meetings, and seminar participants at Ewha Womans University, Hanyang University, Pohang University of Science and Technology (POSTECH), Seoul National University (SNU), and Sungkyungkwan University (SKKU) for useful discussions and comments. The usual disclaimer applies. This work was supported by the National Research Foundation of Korea Grant funded by the Korean Government (NRF-2014S1A3A2036037) and the Investment Research and Education Center (IREC) in the Institute of Finance and Banking at Seoul National University.

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[2] These variables are of particular interest to market participants in times of high uncertainty; for example, during the 2007-2009 financial crisis and the 2010 Flash Crash when market volatility exploded, liquidity disappeared, and share prices plummeted. Prior research attributes disappearing liquidity during financial crises to at least two factors. Gorton and Metrick (2010) suggest that liquidity is lower during financial crises because they aggravate adverse selection problems. Nagel (2012) suggests an alternative explanation. He shows that financially-constrained

are interrelated has not been fully understood. For example, the literature provides little guidance as to *why* the returns of certain securities are more sensitive to volatility shocks than the returns of other securities. In addition, no previous study explicitly considers the role of liquidity providers in the analysis of the relation between market volatility and stock returns. As a result, prior research attributes the negative relation between market volatility and market returns primarily to greater risk premiums that are associated with higher market volatility.[3]

In this study, we shed additional light on the relation between market volatility and stock returns by examining the cross-section of stock returns that result from volatility shocks using the Chicago Board Options Exchange Market Volatility Index (VIX).[4] Our study shows that the negative relation between market volatility and stock returns arises not only from greater risk premiums but also greater illiquidity premiums that are associated with higher market volatility. We also provide estimates of the direct effect of volatility shock on stock returns, which is driven by greater risk premiums, and the indirect effect of volatility shock on stock returns, which is driven by greater illiquidity premiums associated with higher market volatility.

Ang et al. (2006) analyze the pricing of aggregate volatility risk (e.g., whether stocks with high return sensitivities to changes in market volatility have higher or lower expected returns than stocks with low return sensitivities). In contrast, we examine why some stocks have higher return sensitivities to changes in market volatility than other stocks. Our study also differs from Bali et al. (2014) in that we underscore an important channel (i.e., liquidity) through which

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liquidity providers reduce the supply of liquidity during times of market turmoil because they require higher returns during such periods.

[3] French, Schwert, and Stambaugh (1987) first show that unexpected market returns are negatively related to unexpected increases in market volatility, and interpret the negative relation as indirect evidence of a positive relation between expected risk premiums and volatility. In a similar vein, Haugen, Talmor, and Torous (1991) show that increases in market volatility are associated with a significant subsequent decline in stock prices and higher future returns.

[4] A number of studies have employed VIX as a measure of market volatility (e.g., Bao, Pan, and Wang, 2008; Pan and Singleton, 2008; Graham and Harvey, 2010; Longstaff et al., 2010; Nagel, 2012).

market volatility affects stock returns, while they focus primarily on the effect of liquidity shocks on stock returns without considering the role of market volatility.

We show that unexpected increases (decreases) in market volatility accompany decreases (increases) in both the liquidity and returns of individual stocks after controlling for the effect of idiosyncratic volatilities of individual securities on returns. We measure liquidity shocks by unexpected changes in the bid-ask spread and Amihud's illiquidity measure. More importantly, we also show that the decreases (increases) in individual stock returns associated with increases (decreases) in market volatility are larger for stocks with greater concurrent liquidity shocks.[5] On the whole, our results underscore the important role of liquidity providers in the analysis of the effect of market volatility on individual stock returns.

Chung and Chuwonganant (2014) show that the uncertainty elasticity of liquidity (i.e., percentage change in liquidity given a 1% change in VIX) increased significantly around regulatory changes in the U.S. markets that increased competition between public traders and market makers, reduced the tick size, and decreased or eliminated the role of NASDAQ dealers and NYSE specialists in the price discovery process. We show that the effect of market volatility on individual stock returns has increased in a similar fashion following these regulatory changes. These results support the idea that a direct reflection of expected volatility in prices and quotes, without filtering by market intermediaries, may increase the effect of market volatility on returns. In addition, we show that the sensitivity of stock returns to market volatility in the high-frequency trading era is significantly higher than that in the pre high-frequency trading period.

Our study contributes to the literature by providing an integrated analysis of market volatility, liquidity, and stock returns. Some prior studies relate market volatility to stock returns

[5] The negative relation between volatility shocks and stock returns is consistent with the positive relation between expected risk premiums and volatility (French, Schwert, and Stambaugh, 1987). The positive relation between liquidity shocks and stock returns is consistent with the positive relation between expected returns and illiquidity (i.e., investors demand a premium for less liquid stocks) (Amihud and Mendelson, 1986).

without an explicit recognition of the role of liquidity providers (e.g., French, Schwert, and Stambaugh, 1987). Other studies relate liquidity shocks to stock returns without considering how volatility shocks could affect both liquidity and stock returns (e.g., Bali et al., 2014). Our study helps better understand the effect of market volatility on stock returns by underscoring the concurrent effect of market volatility on stock liquidity and showing how the latter effect (through illiquidity premiums) could magnify the effect of market volatility on stock returns.

Many prior studies have documented the positive ramifications of the four regulatory changes analyzed in Chung and Chuwonganant (2014) for market quality. Our study suggests another possible ramification of these rule changes that has not been addressed in the literature: the higher sensitivity of stock returns to market volatility after these rule changes may imply a market-wide increase in the equity investment risk and risk premiums. A number of recent papers show that high-frequency trading has generally improved liquidity and lowered trading costs.[6] Our finding of a greater effect of volatility shocks on stock returns in the high-frequency trading era suggests that high-frequency trading may have also increased the aggregate equity investment risk and risk premiums.

2. Data sources, variable measurement, and descriptive statistics

Our study sample consists of NYSE, AMEX, and NASDAQ stocks from January 1990 to December 2012. We obtain daily and monthly stock returns, trading volume, and the number of shares outstanding from the Center for Research in Security Prices (CRSP). We retrieve the book value of equity from the Compustat database and analyst coverage data from the Institutional Brokers' Estimate System (I/B/E/S). We include stocks that have at least 15 daily observations

[6] See O'Hara (2015) for an excellent review of this literature and other related issues.

for the month in our sample. Stocks with a price lower than $5 or higher than $1,000 are excluded from the sample. Our study sample contains 4,939 NYSE/AMEX stocks and 5,155 NASDAQ stocks.

We measure unexpected changes in market volatility ($VIXSHOCK_t$) and unexpected changes in individual stock liquidity ($AMISHOCK_{i,t}$ and $SPRSHOCK_{i,t}$) as follows:[7]

$$VIXSHOCK_t = \frac{VIX_t - AVGVIX_{t-12,t-1}}{AVGVIX_{t-12,t-1}}, \tag{1}$$

$$AMISHOCK_{i,t} = -\frac{ILLIQ_{i,t} - AVGILLIQ_{i|t-12,t-1}}{AVGILLIQ_{i|t-12,t-1}}, \tag{2}$$

$$SPRSHOCK_{i,t} = -\frac{SP_{i,t} - AVGSP_{i|t-12,t-1}}{AVGSP_{i|t-12,t-1}}; \tag{3}$$

where subscript i denotes stock i and subscript t denotes month t. VIX_t is the mean daily CBOE VIX Index for month t and $AVGVIX_{t-12,t-1}$ is the mean of VIX in the past 12 months.[8] A negative *VIXSHOCK* means a decline in VIX index relative to the past 12-month average. $ILLIQ_{i,t}$ is Amihud's illiquidity (price impact) measure for stock i in month t defined as $ILLIQ_{i,t} = Average\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right]$, where $|R_{i,d}|$ and $VOLD_{i,d}$ are the absolute daily stock return and dollar trading volume of stock i on day d in month t (Amihud, 2002). $AVGILLIQ_{i|t-12,t-1}$ is the mean of *ILLIQ* in the past 12 months. A negative *AMISHOCK* means a decline in liquidity relative to the past 12-month average. $SP_{i,t}$ is the mean value of the daily quoted percentage spread $\left\{\frac{Ask_{i,d}-Bid_{i,d}}{\left(\left[\frac{Ask_{i,d}+Bid_{i,d}}{2}\right]\right)}\right\}$ for stock i in month t, where $Ask_{i,d}$ and $Bid_{i,d}$ are the ask and bid prices of stock i on day d reported in

[7] We also measure unexpected changes in market volatility and individual stock liquidity using the autoregressive moving average (ARMA) model, as discussed later in Subsection 3.3.

[8] We obtain daily observations of the VIX from Yahoo Finance (http://finance.yahoo.com/q/hp?s=^VIX+Historical+Prices). VIX measures the expected (annualized) movement in the S&P 500 Index over the following 30-day period. Although VIX is a measure of the implied volatility of S&P 500 Index options, we use it as an empirical proxy for market-wide volatility.

the CRSP database.[9] $AVGSP_{i|t\text{-}12,t\text{-}1}$ is the mean of *SP* in the past 12 months. A negative *SPRSHOCK* means an increase in *SP* (a decrease in liquidity) relative to the past 12-month average.

Table 1 shows summary statistics for NYSE/AMEX and NASDAQ stocks in our study sample. We measure return volatility of each stock by the standard deviation of daily returns in each month. The mean values of volatility shock, liquidity shock, monthly return, share price, daily dollar trading volume, and return volatility for the NYSE/AMEX stocks are 0.0178, 0.0481, 0.0383, 0.0110, $26.92, $4.60 million, and 0.0203. The corresponding values for the NASDAQ stocks are 0.0214, 0.0429, 0.0530, 0.0147, $19.22, $1.97 million, and 0.0326, respectively.

As the first step in our analysis of the impact of market volatility shocks (*VIXSHOCK*) on the liquidity and returns of individual stocks, we sort our sample stocks into ten portfolios according to volatility shock in each month and calculate the average return and liquidity shock for each portfolio during the entire study period. Table 2 shows that the average monthly return declines monotonically from 0.0322 for the lowest volatility shock portfolio (Decile 1) to -0.0181 for the highest volatility shock portfolio (Decile 10). The difference (-0.0503) in returns between the highest and lowest volatility shock portfolios is statistically (and economically) significant at the 1% level. Similarly, both measures of liquidity shock (*AMISHOCK* and *SPRSHOCK*) decline monotonically from the lowest to highest volatility shock portfolios and the differences (-0.4316 and -0.4067) in liquidity shock between the two portfolios are statistically

[9] We obtain qualitatively similar results when we use the quoted dollar spread ($Ask_{i,d} – Bid_{i,d}$) instead of the quoted percentage spread. Chung and Zhang (2014) show that the CRSP-based spread is highly correlated with the TAQ-based spread across stocks, providing a better approximation of the TAQ-based spread than all other low-frequency liquidity measures in cross-sectional settings. Fong, Holden, and Trzcinka (2014) show that the simple bid-ask spread measure suggested by Chung and Zhang (2014) has much higher correlations with intraday effective, quoted, and realized spreads than any other low-frequency measures.

significant at the 1% level.[10] Overall, these results indicate that as market volatility increases, both liquidity and stock returns decline.

3. Regression models and empirical results

The main premise of our study is that market volatility affects stock returns both directly and indirectly through its impact on liquidity. That is, $R = R(U, L)$, where R denotes stock return, U denotes volatility shock, L denotes liquidity shock, and $L = L(U)$. Applying the chain rule to $R = R(U, L)$ yields:

$$\frac{dR(U,L)}{dU} = \frac{\partial R(U,L)}{\partial U} + \left(\frac{\partial R(U,L)}{\partial L}\right)\left(\frac{dL(U)}{dU}\right); \tag{4}$$

where $\frac{\partial R(U,L)}{\partial U}$ is the direct effect of the volatility shock on stock returns and $(\frac{\partial R(U,L)}{\partial L})(\frac{dL(U)}{dU})$ is the indirect effect of the volatility shock on stock returns that operates through its impact on liquidity (L). We expect $\frac{\partial R(U,L)}{\partial U} < 0$, given the positive relation between expected risk premiums and volatility (French, Schwert, and Stambaugh, 1987). We expect $\frac{\partial R(U,L)}{\partial L} > 0$, given the positive relation between expected returns and illiquidity (Amihud and Mendelson, 1986). We also expect $\frac{dL(U)}{dU} < 0$ based on the findings of Gorton and Metrick (2010), Nagel (2012), and Chung and Chuwonganant (2014).

Now consider the following parsimonious model of stock returns:

$$R = \beta_0 + \beta_1 U + \beta_2 L + \beta_3 U * L, \tag{5}$$

where R, U, and L are the same as defined above. Differentiating equation (5) with respect to U, we obtain:

$$\frac{dR}{dU} = \beta_1 + \beta_3 L + (\beta_2 + \beta_3 U)(\frac{dL}{dU}), \tag{6}$$

[10] This result is consistent with the prediction of Brunnermeier and Pedersen (2009) that market liquidity decreases with VIX because higher volatility reduces market makers' liquidity provision capacity.

Note that the first two terms (i.e., $\beta_1 + \beta_3 L$) in equation (6) measure the effect of volatility shock on stock returns [i.e., $\frac{\partial R(U,L)}{\partial U}$] in equation (4)] if L were independent of U (i.e., $\frac{dL}{dU} = 0$). The remaining term [i.e., $(\beta_2 + \beta_3 U)(\frac{dL}{dU})$] in equation (6) measures the additional effect of volatility shock on stock returns that operates through its effect on liquidity [i.e., $(\frac{\partial R(U,L)}{\partial L})(\frac{dL(U)}{dU})$ in equation (4)] since $\frac{dR(U,L)}{dL} = \beta_2 + \beta_3 U$ given the assumption that *U* is independent of *L*. In what follows, we use equation (5) as the basis of our empirical models of stock returns and interpret the regression results accordingly.

3.1. Regression results for the effects of volatility and liquidity shocks on stock returns

To examine the effects of volatility and liquidity shocks on stock returns after controlling for the effects of other variables, we estimate the following regression models using the pooled time series and cross-sectional data for the combined sample of NYSE, AMEX, and NASDAQ stocks from January 1990 to December 2012:

$$\begin{aligned} RET_{i,t} \text{ or } ALPHA_{i,t} = {} & \beta_0 + \beta_1 VIXSHOCK_t + \beta_2 \left(AMISHOCK_{i,t} \text{ or } SPRSHOCK_{i,t}\right) \\ & + \beta_3 VIXSHOCK_t * \left(AMISHOCK_{i,t} \text{ or } SPRSHOCK_{i,t}\right) \\ & + \beta_4 IVOLASHOCK_{i,t} + \beta_5 MKTRET_t \\ & + \beta_6 (MKTAMISHOCK_t \text{ or } MKTSPRSHOCK_t) \\ & + \beta_7 DVOLSHOCK_{i,t} + \beta_8 BETA_{i,t} + \beta_9 Log\left(MVE_{i,t}\right) + \beta_{10} CVILLIQ_{i,t} \\ & + \beta_{11} MAXRET_{i,t} + \beta_{12} REVISE_{i,t} + \beta_{13} MOMENT_{i,t} + \beta_{14} STDTO_{i,t} \\ & + \beta_{15} BVTOMV_{i,t} + \beta_{16} SUE_{i,t} + \beta_{17} SKEW_{i,t} + \beta_{18} NAF_{i,t} + \varepsilon_{i,t}; \qquad (7) \end{aligned}$$

where subscripts *i* and *t* denote stock *i* and month *t*, respectively, and $\varepsilon_{i,t}$ is the error term. To determine whether the results are sensitive to different measures of stock returns, we employ both the raw monthly return ($RET_{i,t}$) and the three-factor Fama-French alpha ($ALPHA_{i,t}$) as dependent variables. $VIXSHOCK_t$, $AMISHOCK_{i,t}$, and $SPRSHOCK_{i,t}$ denote unexpected changes in market volatility, Amihud illiquidity measure, and the bid-ask spread, respectively. Note that $RET_{i,t}$ and $ALPHA_{i,t}$ correspond to R, $VIXSHOCK_t$ corresponds to U, and $AMISHOCK_{i,t}$, and $SPRSHOCK_{i,t}$ corresponds to L, respectively, in equation (5).

To assess whether unexpected changes in market volatility exert an impact on stock returns that is beyond the effect on the stock returns of unexpected changes in the idiosyncratic volatility and trading volume of individual securities, we include unexpected changes in idiosyncratic volatility and dollar trading volume ($IVOLASHOCK_{i,t}$ and $DVOLSHOCK_{i,t}$) in the regression. We include a number of additional control variables in the regression. $MKTRET_t$ is the market return, $MKTAMISHOCK_t$ is the market Amihud illiquidity shock, $MKTSPRSHOCK_t$ is the market spread shock, $BETA_{i,t}$ is the systematic risk, $MVE_{i,t}$ is the market value of equity, $CVILLIQ_{i,t}$ is the coefficient of variation of the Amihud illiquidity measure, $MAXRET_{i,t}$ is the maximum daily return, $REVISE_{i,t}$ is the return in the previous month, $MOMENT_{i,t}$ is the cumulative return during month t-12 and month t-1, $STDTO_{i,t}$ is the standard deviation of monthly volume turnover during the last 12 months, $BVTOMV_{i,t}$ is the book-to-market value of equity ratio, $SUE_{i,t}$ is the standardized unexpected earnings, $SKEW_{i,t}$ is the co-skewness measure, and $NAF_{i,t}$ is the number of analysts. We exclude stock i when we compute the market return, market illiquidity shock, and market spread shock. The Appendix provides the detailed descriptions of these variables.

We estimate regression model (7) with clustered standard errors by firm and time because the residuals of a given firm may be correlated across months and/or the residuals of a given month may be correlated across different firms [see Petersen (2009) for a detailed description of the method]. For a robustness check, we also employ the following three methods: (1) add an intercept for each month (θ_t) and use standard errors clustered by time; (2) add an intercept for each stock (λ_i) and use standard errors clustered by firm; and (3) add both θ_t and λ_i and use no error clustering. The results from these alternative models are qualitatively similar to those from regression model (7). Thus, for brevity, we report only the results of regression model (7).

Table 3 shows the regression results. The first two columns show the results when the dependent variable is the raw return and the next two columns show the results when the dependent variable is the three-factor Fama-French alpha. The first and third columns show the results when we measure liquidity shock by the change in the Amihud price impact (*AMISHOCK*) and the second and fourth columns show the results when we measure liquidity shock by the change in the bid-ask spread (*SPRSHOCK*).

The results in Table 3 show that both the raw return and the Fama-French alpha are significantly and negatively related to volatility shock, indicating that an increase in market volatility results in a decrease in stock returns. Both the raw return and the Fama-French alpha are significantly and positively related to liquidity shock, regardless of whether we measure liquidity shock by *AMISHOCK* or *SPRSHOCK*, indicating that an increase in liquidity results in an increase in stock returns. Most importantly, we find that the regression coefficients on the interaction term between volatility shock and liquidity shock are positive and significant in all four regressions, indicating that the negative effect of an increase in market volatility on stock returns is greater (smaller) for stocks with a larger concurrent decrease (increase) in liquidity.

The results in Table 3 also show that the coefficients on idiosyncratic volatility shock (*IVOLASHOCK*) (i.e., unexpected change in the idiosyncratic volatility of individual securities) are negative and significant in all four regressions, indicating that both the raw and abnormal stock returns decrease with unexpected increases in the idiosyncratic volatility of individual securities. In addition, the results show that both the raw return and the three-factor Fama-French alpha are positively and significantly related to *BETA*, *CVILLIQUID*, *MOMENT*, *BVTOMV*, *SUE*, and *SKEW*, but negatively and significantly related to *MVE*, *MAXRET*, *REVISE*, *STDTO* and *NAF*. These results are qualitatively similar to those reported in prior studies (e.g., Bali, Peng, Shen, and Tang, 2014).

3.2. Economic significance

Note that the discrete version of equation (6) could be written as $\frac{\Delta R}{\Delta U} = \beta_1 + \beta_3 L + (\beta_2 + \beta_3 U)(\frac{\Delta L}{\Delta U})$, where Δ represents the difference. Multiplying both sides by ΔU yields $\Delta R = (\beta_1 + \beta_3 L)\Delta U + (\beta_2 + \beta_3 U)\Delta L$, where the first term [i.e., $(\beta_1 + \beta_3 L)\Delta U$] represents the direct effect of volatility shock on stock returns and the second term [i.e., $(\beta_2 + \beta_3 U)\Delta L$] represents the indirect effect of volatility shock on stock returns that operates through its effect on liquidity.

To assess the economic significance of the indirect effect of volatility shock on stock returns, we estimate the difference in returns (or excess returns) associated with the median volatility shock between stocks with the 75th percentile value of *AMISHOCK* and stocks with the 25th percentile value of *AMISHOCK* by $(\beta_2 + \beta_3 VIXSHOCK_{50})(AMISHOCK_{75} - AMISHOCK_{25})$, where $VIXSHOCK_{50}$ is the 50th percentile value of *VIXSHOCK* in Table 1, β_2 and β_3 are corresponding regression coefficients in Table 3, and $AMISHOCK_{75}$ and $AMISHOCK_{25}$ are the 75th and 25th percentile values of *AMISHOCK* in Table 1.

The results show that for NASDAQ stocks the difference in monthly returns between the two *AMISHOCK* percentile groups is 0.20% (which is equivalent to 2.40% per annum) and the difference in monthly *excess* returns (i.e., alphas) between the two groups is 0.17% (which is equivalent to 2.04% per annum). For NYSE/AMEX stocks, the corresponding figures are 0.13% (1.56% per annum) and 0.11% (1.32% per annum). When we repeat the above calculations for

NASDAQ stocks using the other measure of liquidity shock (i.e., *SPRSHOCK*), the difference in monthly returns between the two *SPRSHOCK* percentile groups is 0.12% (1.44% per annum) and the difference in monthly *excess* returns between the two groups is 0.10% (1.20% per annum). For NYSE/AMEX stocks, the corresponding figures are 0.09% (1.08% per annum) and 0.08% (0.96% per annum). On the whole, these results indicate that liquidity plays a significant role in how volatility shocks affect stock returns.

Similarly, we measure the direct effect of volatility shock on stock returns by $(\beta_1 + \beta_3 AMISHOCK_{50})(VIXSHOCK_{75} - VIXSHOCK_{25}$ and $(\beta_1 + \beta_3 SPRSHOCK_{50})(VIXSHOCK_{75} - VIXSHOCK_{25})$, where β_1 and β_3 are corresponding regression coefficients in Table 3, $AMISHOCK_{50}$ and $SPRSHOCK_{50}$ are the 50th percentile values of *AMISHOCK* and *SPRSHOCK* in Table 1, and $VIXSHOCK_{75}$ and $VIXSHOCK_{25}$ are the 75th and 25th percentile values of *VIXSHOCK* in Table 1. The results show that the direct effect of volatility shock on stock returns is between -0.16% (-1.92% per annum) and -0.21% (-2.52% per annum), depending on whether we measure liquidity shock by *AMISHOCK* or *SPRSHOCK*. The direct effect of volatility shock on excess returns (i.e. alphas) is between -0.10% (-1.20% per annum) and -0.15% (-1.80% per annum), depending on whether we measure liquidity shock by *AMISHOCK* or *SPRSHOCK*.

3.3. Regression results with alternative measures of volatility and liquidity shocks

To assess the robustness of our main results with respect to how we measure volatility and liquidity shocks, we also estimate *AMISHOCK* and *SPRSHOCK* using the ARMA(1,1) model:

$ILLIQ_{i,t} = \alpha_0 + \alpha_1 ILLIQ_{i,t-1} + \alpha_2 \varepsilon_{i,t-1} + \varepsilon_{i,t}$ and $SP_{i,t} = \gamma_0 + \gamma_1 SP_{i,t-1} + \gamma_2 \varepsilon_{i,t-1} + \varepsilon_{i,t}$. We run the regressions for each stock using a 60-month rolling sample. The liquidity shock is defined as the negative difference between the realized *ILLIQ* (or *SP*) of stock *i* and its conditional mean estimated from the ARMA(1,1) model in month *t*. Similarly, we estimate the *VIXSHOCK* using the following regression model: $VIX_t = \lambda_0 + \lambda_1 VIX_{t-1} + \lambda_2 \varepsilon_{t-1} + \epsilon_t$.[11] We measure the VIX shock as the difference between the realized VIX and its conditional mean in month *t*. We then estimate regression model (7) using these alternative measures of liquidity and VIX shocks. The results are qualitatively similar to those reported in Table 3.

4. Market structure and the effect of VIX and liquidity on stock returns

Chung and Chuwonganant (2014) show that the uncertainty elasticity of liquidity increased significantly after the following regulatory changes in market structure: (1) the implementation of the new order handling rules on NASDAQ in 1997; (2) the reduction of tick size from \$1/8 to \$1/16 in 1997 and from \$1/16 to \$0.01 (decimalization) in 2001; (3) the amendment of NASDAQ Rule 4613(c) in 2007 that dealer quotes must be reasonably related to the prevailing market; and (4) the replacement of the specialist system with the designated market maker system on the NYSE in 2008. These findings suggest an important implication for our study: to the extent that these regulatory changes increase the sensitivity of stock liquidity to market volatility and the magnitude of this increase differs across stocks (as shown in Chung and Chuwonganant, 2014), they are also likely to increase the sensitivity of stock *returns* to market volatility, with the magnitude of the increase differing across stocks. In this section, we examine how these regulatory changes affect the sensitivity of stock returns to volatility shocks.

4.1. Order handling rules and tick size

[11] We use this simple model because Ahoniemi (2008) shows that it provides reasonably good forecasts. The author shows that adding more variables in the model does not materially improve the results.

In 1997, the Securities and Exchange Commission (SEC) changed the order handling rules to increase competition between public traders and NASDAQ dealers in the price discovery process. Prior to the new rules, public traders were unable to compete with dealers because NASDAQ was a pure dealer market. The new limit order handling rule allowed public traders to directly compete with dealers by requiring dealers to display public limit orders in the best bid and offer (BBO). The new quote rule gave the public access to quotes posted by market makers in the electronic communication network. The SEC also decreased the tick size in the U.S. markets from \$1/8 to \$1/16 in 1997 to reduce trading costs, increase the informational efficiency of prices, and make the U.S. markets more competitive in the global market.

The SEC phased in the new order handling rules from January 20, 1997 to October 13, 1997 for different groups of NASDAQ stocks. In addition, NASDAQ began using the smaller tick size on June 2, 1997 while the NYSE began using it on June 24, 1997. Because of the close time proximity of these regulatory changes, it is difficult to disentangle the effect of the order handling rules change from the effect of the tick size change. As a result, we begin our analysis by measuring the aggregate effects of both rule changes on the relation between stock returns and volatility (and liquidity) shocks. We use the six-month period from July 1996 to December 1996 as the pre-rule change period and the six-month period from November 1997 to April 1998 as the post-rule change period. Our sample consists of 1,827 NASDAQ stocks and 2,144 NYSE stocks.

We first estimate the regression model separately for NASDAQ stocks and NYSE stocks using the pooled data of the pre- and post-rule change periods and provide the results in Table 4. The coefficient (β_4) on the interaction term $VIXSHOCK_t * \left(AMISHOCK_{i,t} \text{ or } SPRSHOCK_{i,t}\right) * POST$ in regression model (a) indicates whether these rule changes increase or decrease the effect of volatility shock on stock returns operating through the liquidity shock triggered by volatility shock. For expositional convenience, we use an abbreviated term, "the volatility-liquidity effect on returns" instead of "the effect of volatility shock on stock returns operating through the liquidity shock triggered by volatility shock" in the rest of the paper.

Panel A of Table 4 shows the results when we measure liquidity shock by unexpected changes in the Amihud price impact (*AMISHOCK*) and Panel B shows the results when we measure liquidity shock by unexpected changes in the bid-ask spread (*SPRSHOCK*). The results from both panels show that stock returns are negatively related to volatility shock (*VIXSHOCK*), positively related to liquidity shock (*AMISHOCK* and *SPRSHOCK*), and positively related to the interaction terms between volatility and liquidity shocks for both the NASDAQ and NYSE samples. These results are all consistent with the results in Table 3, which show that an increase in liquidity results in an increase in stock returns, and the negative effect of an increase in market volatility on stock returns is greater for stocks with a larger concurrent decrease in liquidity.

More importantly, the coefficient on *VIXSHOCK**(*AMISHOCK* or *SPRSHOCK*)**POST* is positive and significant for both NASDAQ and NYSE stocks, indicating that the rule changes increased the volatility-liquidity effect on returns in both markets. Overall, these results indicate that the regulatory rule changes that increase the importance of public traders in the price discovery process and reduce the minimum allowable price variation (i.e., tick size) magnify the effect of market volatility on liquidity, and consequently, on stock returns.

We also estimate the regression model using the combined sample of NASDAQ and NYSE stocks to determine whether the rule changes exert different volatility-liquidity effects on returns between NASDAQ and NYSE stocks. The last column in Table 4 shows the regression results. Note that, in regression model (b), β_3 measures the volatility-liquidity effect on returns for NYSE stocks in the pre-event period, β_4 measures the difference in the volatility-liquidity effect on returns between the pre- and post-rule change periods for NYSE stocks, β_5 measures the difference in the volatility-liquidity effect on returns between NASDAQ and NYSE stocks in the pre-rule change period, and β_6 measures whether the difference in the volatility-liquidity effect on returns between the pre- and post-rule change periods is different between NASDAQ and NYSE stocks. We predict $\beta_6 > 0$ based on the fact that NASDAQ stocks are subject to changes in both the order handling rules and the tick size while NYSE stocks are subject to only the tick size reduction.

The results show that β_4 estimates are positive and significant in both panels, indicating that the rule changes result in a significant increase in the volatility-liquidity effect on returns for NYSE stocks. We find that β_5 estimates are positive and significant, indicating that the volatility-liquidity effect on returns is greater for NASDAQ stocks in the pre-rule change period. More importantly and consistent with our conjecture, we find that β_6 estimates are positive and significant, indicating that the rule changes exert a greater impact on the volatility-liquidity effect on returns for NASDAQ stocks than for NYSE stocks.

4.2. Decimal pricing

NASDAQ phased in decimal pricing from March 12, 2001 to April 9, 2001. Hence, we use the six-month period before March 2001 (i.e., September 2000 to February 2001) as the pre-decimal period and the six-month period after April 2001 (i.e., May 2001 to October 2001) as the post-decimal period for NASDAQ stocks. The NYSE phased in decimal pricing from August 29, 2000 to January 29, 2001. Hence, the pre-decimal period for the NYSE stocks is the six-month period before August 2000 (i.e., February 2000 to July 2000) and the post-decimal period is the six-month period after January 29, 2001 (i.e., February 2001 to July 2001). Our study sample consists of 1,809 NASDAQ stocks and 2,223 NYSE stocks.

We show the regression results in Table 5 in the same format used in Table 4. As in Table 4, we find that stock returns are negatively related to volatility shock, positively related to liquidity shock, and positively related to the interaction terms between volatility and liquidity shocks for both the NASDAQ and NYSE samples. As in Table 4, we also find that the coefficient on *VIXSHOCK**(*AMISHOCK* or *SPRSHOCK*)**POST* is positive and significant for both NASDAQ and NYSE stocks, indicating that decimal pricing increased the volatility-liquidity effect on returns in both markets.

The results from the combined sample of NYSE and NASDAQ stocks (see the last column) show that β_4 estimates are positive and significant in both panels, indicating that decimal pricing results in a significant increase in the volatility-liquidity effect on returns for NYSE stocks. We also find that β_5 estimates are positive and significant, indicating that the volatility-liquidity effect on returns is greater for NASDAQ stocks in the pre-decimal period. In addition, β_6 estimates are not significantly different from zero, indicating that decimal pricing exerts a similar impact on the volatility-liquidity effect on the returns for both NASDAQ and NYSE stocks.

4.3. Amendment of NASDAQ Rule 4613(c)

Prior to the amendment of NASDAQ Rule 4613(c), NASDAQ dealers had an obligation to ensure that their quotes reflected the prevailing market when public traders did not provide sufficient liquidity. NASDAQ argued that such an affirmative obligation is unnecessary in highly competitive and automated trading environments and filed a proposed rule change to eliminate the obligation. Subsequently, the SEC approved the proposed rule change and the new rule became effective on November 7, 2007. We use the six-month period from May 2007 to October 2007 as the pre-amendment period and the six-month period from December 2007 to May 2008 as the post-amendment period. Since the amendment applied only to the NASDAQ Stock Market, we use NYSE stocks as a control sample. The sample contains 1,828 NASDAQ stocks and 2,134 NYSE stocks.

We report the regression results in Panels A and B of Table 6. The first two columns in both panels show that stock returns are negatively related to volatility shocks, positively related to liquidity shocks, and positively related to the interaction terms between volatility and liquidity shocks. These results are consistent with the results in Table 4. The regression coefficients on *VIXSHOCK**(*AMISHOCK* or *SPRSHOCK*)**POST* are positive and significant for the NASDAQ sample, while the corresponding coefficients for the NYSE sample are not significantly different from zero. These results are consistent with our expectation, because only NASDAQ stocks are subject to the rule amendment.

We find that β_4 estimates in the third column in both panels are not significantly different from zero, indicating that the amendment did not have an impact on the volatility-liquidity effect on returns for NYSE stocks. We find that β_5 estimates in the third column in both panels are not significantly different from zero, indicating that the volatility-liquidity effect on returns is similar between NASDAQ and NYSE stocks in the pre-amendment period. More importantly and consistent with our expectation, β_6 estimates are positive and significant, indicating that the rule amendment exerts a greater impact on the volatility-liquidity effect on returns for NASDAQ stocks than for NYSE stocks.[12]

4.4. Implementation of the designated market maker system on the NYSE in 2008

[12] To assess the robustness of our results to different study samples, we replicate the above analysis using matching samples of NASDAQ and NYSE stocks that are similar in share price, dollar volume, volatility, and market capitalization. The results are similar to those reported here and available from the authors upon request.

The NYSE replaced the specialist system with the designated market maker system in 2008. This system puts more emphasis on speed and technology and relies less on the human intermediation provided by the specialist. The NYSE implemented the phased introduction of the system from October 27, 2008 through November 13, 2008. To examine the impact of the system on the volatility-liquidity effect on returns, we use the four-month period from June 2008 to September 2008 as the pre-change period and the six-month period from December 2008 to May 2009 as the post-change period. Because the system applies only to the NYSE, we use NASDAQ stocks as a control sample. The sample contains 1,788 NASDAQ securities and 1,896 NYSE stocks.

We report the regression results in Table 7. The first two columns in both panels show that the regression coefficients on *VIXSHOCK**(*AMISHOCK* or *SPRSHOCK*)**POST* are positive and significant for the NYSE sample, while the corresponding coefficients for the NASDAQ sample are not significantly different from zero. These results are consistent with our expectation because only NYSE stocks are subject to the new system. We also estimate the regression model using the combined sample of NYSE and NASDAQ stocks in the pooled pre- and post-event periods and provide the results in the third column of Table 7. Note that β_4 measures the difference in the volatility-liquidity effect on returns between the pre- and post-change period for NASDAQ stocks, β_5 measures the difference in the volatility-liquidity effect on returns between NASDAQ and NYSE stocks in the pre-change period, and β_6 measures whether the difference in the volatility-liquidity effect on returns between the pre- and post- change periods is different between NASDAQ and NYSE stocks.

We find that β_4 estimates are not significantly different from zero, indicating that there is no significant difference in the volatility-liquidity effect on returns between the pre- and post-change period for NASDAQ stocks. We find that β_5 estimates are negative and significant, indicating that the volatility-liquidity effect on returns is smaller for NYSE stocks in the pre-change period. More importantly and consistent with our expectation, β_6 estimates are positive and significant, indicating that the new system exerts a greater impact on the volatility-liquidity effect on returns for NYSE stocks than for NASDAQ stocks.[13]

5. High-frequency trading (HFT) and the effect of VIX and liquidity on stock returns

There has been a dramatic increase in high-frequency trading (HFT) during the last decade. HFT accounted for less than 10% of all US equity trading volume in the early 2000s, but grew by 164% between 2005 and 2009.[14] In 2009, high-frquency trading firms represented only 2% of the about 20,000 firms in the U.S., but HFT accounted for 60%-73% of all U.S. equity trading volume.[15] High-frequency traders use sophisticated technology and computer algorithms to generate, route, and execute orders. They submit a large number of orders and cancel most of them shortly after submission. Many high-frequency firms are market makers and provide liquidity to the market. Some market participants believe that HFT contributed to the Flash Crash of May 6, 2010 as many high-frequency traders stopped providing liquidity at the initial signs of market stress, which led to a dramatic fall in the prices of the affected stocks.

O'Hara (2015, p. 264) observes that "episodic instability is also now characteristic of markets, driven perhaps by the desires of the 'informed' high frequency market makers fleeing when they suspect other 'more informed' traders are present." She also suggests that markets are more tightly interconnected through market making/statistical arbitrage that operates across markets. These considerations suggest that market volatility may have greater effects on stock liquidity and returns when high-frequency traders dominate the market.

[13] We replicate the analysis using matching samples of NYSE and NASDAQ stocks and find similar results.
[14] Source: Charles Duhigg, Stock Traders Find Speed Pays, in Milliseconds. *The New York Times*, July 23, 2009.
[15] Source: Rob Iati, The Real Story of Trading Software Espionage, AdvancedTrading.com, July 10, 2009. Times Topics: High-Frequency Trading, *The New York Times*, December 20, 2012.

To assess the impact of HFT on the volatility-liquidity effect on returns, we estimate the regression model for NASDAQ stocks and NYSE stocks separately, as well as for the combined sample of NASDAQ and NYSE stocks to determine whether HFT exerts different volatility-liquidity effects on the returns for NASDAQ and NYSE stocks. In Table 8, Panels A and B show the regression results when we use January 2005 to December 2005 as the pre-HFT period and January 2009 to December 2009 as the HFT period. Panels C and D show the results when we use January 1999 to December 2005 as the pre-HFT period and January 2006 to December 2012 as the HFT period. Panels A and C show the results when we measure liquidity shocks by unexpected changes in the Amihud price impact (*AMISHOCK*) and Panels B and D show the results when we measure liquidity shocks by unexpected changes in the bid-ask spread (*SPRSHOCK*).

The results in Table 8 show that the estimated coefficients on *VIXSHOCK**(*AMISHOCK* or *SPRSHOCK*)**HFTPRD* are positive and significant for both NASDAQ and NYSE stocks in all four panels, indicating that HFT increased the volatility-liquidity effect on returns in both markets, regardless of how we define the HFT period. The results from the combined sample of NYSE and NASDAQ stocks show that β_4 estimates are positive and significant in all four panels, indicating that HFT resulted in a significant increase in the volatility-liquidity effect on the returns for NYSE stocks. We find that β_5 estimates are positive and significant, indicating that the volatility-liquidity effect on returns is greater for NASDAQ stocks in the pre-HFT period. We find that β_6 estimates are positive and significant, indicating that HFT exerts a greater impact on the volatility-liquidity effect on returns for NASDAQ stocks. On the whole, these results show that stock liquidity and returns have become more sensitive to market volatility as high-frequency traders have become a dominant force in the U.S. stock markets.

Although a number of studies show that HFT has generally improved market quality (e.g., lower spreads and faster execution speed),[16] there are still many unanswered questions regarding the role of high-frequency traders. High-frequency traders are different from traditional market makers in that high-frequency traders do not have an obligation to maintain a fair and orderly market. Consequently, high-frequency traders are likely to provide liquidity opportunistically and stop supplying liquidity when there are large adverse selection risks. This could be another possible reason for why stock liquidity and returns have become more sensitive to market volatility with the proliferation of HFT. For those traders who do not have HFT technology, the market is no longer a level playing field because they cannot compete with high-speed computers. Hence, they might find the market unfair and inequitable and, as a result, shy away from it altogether, especially when investment risks are high. The smaller market trading volume in recent years may be one manifestation of this concern.

6. Summary and concluding remarks

This study provides strong evidence that the effect of market volatility on individual stock returns depends on how the liquidity of individual stocks reacts to unexpected changes in market volatility. Specifically, we show that unexpected changes in market volatility exert a greater impact on a stock's return when its liquidity disappears more sharply in response to volatility shocks, indicating that the inverse relation between market volatility and stock returns is due to not only greater risk premiums but also greater illiquidity premiums associated with higher market volatility.

Prior research shows that market volatility exerts a greater impact on stock liquidity after the regulatory changes that increased the role of public traders, reduced the tick size, and

[16] See O'Hara (2015) and Chung and Lee (2016) for reviews of this literature.

decreased or eliminated the role of market makers. To the extent that stock returns are related to market volatility through their respective link to stock liquidity, these regulatory changes are also expected to increase the sensitivity of stock returns to market volatility. We find evidence that is consistent with this expectation, suggesting that these rule changes may have resulted in a market-wide increase in the equity investment risk and risk premiums. Similarly, we find that stock returns became more sensitive to market volatility with the proliferation of high-frequency trading, suggesting that high-frequency trading may have also increased the aggregate equity investment risk.

Appendix

This appendix describes how we construct our control variables. Unless otherwise indicated, we calculate the monthly data from daily variables with at least 15 observations for the month.

Variable	Definition and Measurement
$IVOLASHOCK_{i,t}$	The idiosyncratic volatility shock of stock *i* in month *t*. We first estimate the following regression model (see Ang etal, 2006): $R_{i,d} - R_{F,d} = \alpha_i + \beta_i\left(R_{M,d} - R_{F,d}\right) + \omega_i SMB_d + \lambda_i HML_d + \epsilon_{i,d}$, (A1) where subscript *d* denotes day *d*, R_i is the return on stock *i*, R_F is the return on the one-month Treasury Bills, and R_M is the return on the CRSP value-weighted index. *SMB* and *HML* are the Fama and French's size and book-to-market factors (see Fama and French,1993). The idiosyncratic volatility of the stock *i* for the month ($IVOLA_{i,t}$) is the standard deviation of the residuals for the above regression. We then calculate the $IVOLASHOCK_{i,t}$ as $\frac{IVOLA_{i,t} - AVGIVOLA_{i\mid t-12,t-1}}{AVGIVOLA_{i\mid t-12,t-1}}$, where $AVGIVOLA_{i\mid t-12,t-1}$ is the mean value of *IVOLA* in the past 12 months.
$DVOLSHOCK_{i,t}$	Dollar trading volume shock for stock *i* in month *t* defined as $\frac{DVOL_{i,t} - AVGDVOL_{i\mid t-12,t-1}}{AVGDVOL_{i\mid t-12,t-1}}$, where $DVOL_{i,t}$ is the dollar trading volume of the stock in month t and $AVGDVOL_{i\mid t-12,t-1}$ is the mean value of stock *i*'s dollar trading volume in the past 12 months.

$MKTRET_t$	The value-weighted average market return in month *t*.
$MKTAMISHOCK_t$	The value-weighted average market *AMISHOCK* in month *t*.
$MKTSPRSHOCK_t$	The value-weighted average market *SPRSHOCK* in month *t*.
$BETA_{i,t}$	The market beta of stock *i* in month *t*. We follow Fama and French (1992) by estimating the beta from the following regression model: $$R_{i,t} - R_{F,t} = \alpha_i + \beta_i(R_{M,t} - R_{F,t}) + \beta_i^2(R_{M,t-1} - R_{F,t-1}) + \varepsilon_{i,t}, \quad \text{(A2)}$$ where subscripts *t* and *t*-1 denote month *t* and month *t*-1, respectively. R_i is the return on stock *i*, R_F is the return on one-month Treasury bills, and R_M is the return on the CRSP value-weighted index. The market beta for stock *i* ($BETA_i$) is the sum of the estimated regression coefficients $\beta_i + \beta_i^2$. We use monthly returns over the prior 60 months in the regression (at least 24 observations required).
$MVE_{i,t}$	The market value of equity of stock *i* in month *t* computed as the product of the share price and number of shares outstanding. *MVE* is expressed in million dollars.
$CVILLIQ_{i,t}$	The coefficient of variation in the Amihud illiquidity of stock *i* in month *t*. Following Petkova, Akbas, and Armstrong (2011), we calculate *CVILLIQ* as the standard deviation of the of the daily Amihud illiquidity measure divided by the average Amihud illiquidity measure for the month.
$MAXRET_{i,t}$	The maximum daily return over the past one month for stock *i* (see Bali, Cakici, and Whitelaw, 2011).
$REVISE_{i,t}$	The return for stock *i* in the prior month.
$MOMENT_{i,t}$	The momentum of stock *i* in month *t* defined as the cumulative return of stock *i* over the previous 11 months ending one month prior to month *t* (see Jegadeesh and Titman (1993)).
$STDTO_{i,t}$	The standard deviation of monthly turnover over the last 12 months for stock *i* in month *t* (see Chordia, Subrahmanyan, and Anshuman, 2001).
$BVTOMV_{i,t}$	The ratio of book value of equity to market value of equity for the stock.
$SUE_{i,t}$	The standardized unexpected earnings for stock *i* in month *t*. Following Ball and Brown (1968) and Bernard and Thomas (1989, 1990), we first compute the unexpected earnings per share (*UEPS*) for the stock in quarter *q* of earnings announcement as: $$UEPS_{i,q} = EPS_{i,q} - EPS_{i,q-4}, \quad \text{(A3)}$$

	where subscripts q and q-4 denote quarter q and quarter q-4, respectively. EPS_i is the earnings per share of stock i. We then calculate SUE for quarter q as $UEPS_q$ divided by its standard deviation over the last eight quarters (with at least four $UEPS$ quarters).
$SKEW_{i,t}$	The co-skewness of stock i in month t. We follow the methodology described in Harvey and Siddique (2000) to estimate co-skewness. We run the following regression model for each stock using the monthly returns over the past 60 months (with at least 24 months available): $$R_{i,t} - R_{F,t} = \alpha_i + \beta_i\left(R_{M,t} - R_{F,t}\right) + \omega_i(R_{M,t} - R_{F,t})^2 + \varepsilon_{i,t}, \quad \text{(A4)}$$ where $R_{i,t}$ is the monthly return for stock i, $R_{F,t}$ is the one-month Treasury bill return for the month, and $R_{M,t}$ is the CRSP value-weighted index return. The estimated regression coefficient ω_i is the co-skewness measure of the stock.
$NAF_{i,t}$	The number of analysts following stock i in month t.

References

Ahoniemi, K., 2008. Modeling and forecasting the VIX index. Available at SSRN: http://ssrn.com/abstract=1033812 or http://dx.doi.org/10.2139/ssrn.1033812.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid-ask spread. Journal of Financial Economics 17, 223–249.

Ang, A. Hodrick, R. J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259-299.

Bali, T. G., Cakici, N., Whitelaw, R., 2011. Maxing out: stocks as lotteries and the cross-section of expected returns. Journal of Financial Economics 99, 427-446.

Bali, T. G., Peng, L., Shen, Y., Tang, Y., 2014. Liquidity shocks and stock market reactions. Review of Financial Studies 27, 1434-1485.

Ball, R., Brown, P., 1968. An empirical evaluation of accounting income numbers. Journal of Accounting Research 6, 159-178.

Bao, J., Pan, J., Wang, J., 2008. Liquidity of corporate bonds. Social Science Research Network, http://ssrn.com/abstract=1106852, http://dx.doi.org/10.2139/ssrn.1106852

Bernard, V. L., Thomas, J. K., 1989. Post-earnings announcement drift: delayed price response or risk premium. Journal of Accounting Research 27, 1-36.

Bernard, V. L., Thomas, J. K., 1990. Evidence that stock prices do not reflect the implications of current earnings for future earnings. Journal of Accounting and Economics 13, 305-340.

Brunnermeier, M. K., Pedersen, L. H., 2009. Market liquidity and funding liquidity. Review of Financial Studies 22, 2201-2238.

Chordia, T., Subrahmanyan, A., Anshuman V. R., 2001. Trading activity and expected stock returns. Journal of Financial Economics 59, 3-32.

Chung, K. H., Chuwonganant, C., 2014. Uncertainty, market structure, and liquidity. Journal of Financial Economics 113, 476-499.

Chung, K. H., Lee, A. J., 2016. High-frequency trading: review of the literature and regulatory initiatives around the world. Asia-Pacific Journal of Financial Studies 45, 7-33.

Chung, K. H., Zhang, H., 2014. A simple approximation of intraday spreads with daily data. Journal of Financial Markets 17, 94-120.

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. Journal of Finance 46, 427-466.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns of stocks and bonds. Journal of Financial Economics 33, 3-56.

Fong, K., Holden, C., Trzcinka, C., 2014. What are the best proxies for global research? Working paper, Indiana University.

French, K. R., Schwert, G. W., Stambaugh, R. F., 1987. Expected stock returns and volatility. Journal of Financial Economics 19, 3–29.

Gorton, G., Metrick, A., 2010. Haircuts, Federal Reserve Bank of St. Louis Review 92, 507–519.

Graham, J. R., Harvey, C. R., 2010. The equity risk premium in 2010. Social Science Research Network, http://ssrn.com/abstract=1654026, http://dx.doi.org/10.2139/ssrn.1654026.

Harvey, C. R., Siddique, A., 2000. Conditional skewness in asset pricing tests. Journal of Finance 55, 1263-1295.

Haugen, R. A., Talmor, E., Torous, W. N., 1991. The effect of volatility changes on the level of stock prices and subsequent expected returns. Journal of Finance 46, 985-1007.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: implications for stock market efficiency. Journal of Finance 48, 65-91.

Longstaff, F., Pan, J., Pedersen, L., Singleton, K., 2010. How sovereign is sovereign credit risk? American Economic Journal: Macroeconomics 3, 75–103.

Nagel, S., 2012. Evaporating liquidity. Review of Financial Studies 25, 2005-2039.

O'Hara, M., 2015. High frequency market microstructure, Journal of Financial Economics 116, 257-270.

Pan, J., Singleton, K., 2008. Default and recovery implicit in the term structure of sovereign CDS spreads. Journal of Finance 63, 2345-2384.

Petersen, M.A., 2009. Estimating standard errors in finance panel data sets: comparing approaches. Review of Financial Studies 22, 435-480.

Petkova, R., Akbas, F., Armstrong, W., 2011. The volatility of liquidity and expected stock returns. Available at SSRN: http://ssrn.com/abstract=1786991.

Table 1. Descriptive statistics

This table shows descriptive statistics of the variables for our sample of 4,939 NYSE/AMEX stocks and 5,155 NASDAQ stocks. We measure unexpected changes in market volatility (*$VIXSHOCK_t$*) and unexpected changes in individual stock liquidity (*$AMISHOCK_{i,t}$* and *$SPRSHOCK_{i,t}$*) for each stock and each month from January 1990 to December 2012 using the following formulas:

$$VIXSHOCK_t = \frac{VIX_t - AVGVIX_{t-12,t-1}}{AVGVIX_{t-12,t-1}},$$

$$AMISHOCK_{i,t} = -\frac{ILLIQ_{i,t} - AVGILLIQ_{i|t-12,t-1}}{AVGILLIQ_{i|t-12,t-1}},$$

$$SPRSHOCK_{i,t} = -\frac{SP_{i,t} - AVGSP_{i|t-12,t-1}}{AVGSP_{i|t-12,t-1}};$$

where VIX_t is the mean daily CBOE VIX Index for month *t*; $AVGVIX_{t-12,t-1}$ is the mean of *VIX* in the past 12 months; $ILLIQ_{i,t;}$ is Amihud's illiquidity measure for stock *i* in month *t* defined as $ILLIQ_{i,t} = Average\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right]$, where $|R_{i,d}|$ and $VOLD_{i,d}$ are the absolute daily stock return and dollar trading volume of stock *i* on day *d* within month *t*; $AVGILLIQ_{i|t-12,t-1}$ is the mean of *ILLIQ* in the past 12 months for stock *i*; $SP_{i,t}$ is the mean daily quoted percentage spread $\left\{\frac{Ask_{i,d}-Bid_{i,d}}{\left[\frac{Ask_{i,d}+Bid_{i,d}}{2}\right]}\right\}$ for stock *i* within month *t*; and $AVGSP_{i|t-12,t-1}$ is the mean of *SP* in the past 12 months for stock *i*. We measure return volatility by the standard deviation of daily returns for the month and trading volume by the dollar trading volume. We show the descriptive statistics for NASDAQ and NYSE/AMEX stocks in Panel A and Panel B, respectively.

			Percentile				
Variable	Mean	Standard deviation	5	25	50	75	95

Panel A: Descriptives statistics for NASDAQ stocks							
VIXSHOCK	0.0214	0.0656	-0.0826	-0.0022	0.0228	0.0519	0.1240
AMISHOCK	0.0429	0.2280	-0.3188	-0.0499	0.0541	0.1469	0.3873
SPRSHOCK	0.0530	0.1157	-0.1213	0.0028	0.0585	0.1071	0.2234
Return	0.0147	0.0246	-0.0193	0.0055	0.0146	0.0244	0.0484
Price	19.22	14.87	7.03	10.59	15.90	23.84	41.32
Volume ($ million)	1.97	19.03	0.01	0.04	0.16	0.72	5.74
Volatility	0.0326	0.0113	0.0171	0.0248	0.0313	0.0386	0.0529
Panel B: Descriptive statistics for NYSE and NASDAQ stocks							
VIXSHOCK	0.0178	0.0487	-0.0727	-0.0015	0.0156	0.0399	0.1053
AMISHOCK	0.0481	0.1729	-0.1887	-0.0145	0.0457	0.1146	0.3050
SPRSHOCK	0.0383	0.1076	-0.1253	0.0038	0.0482	0.0860	0.1763
Return	0.0110	0.0167	-0.0109	0.0056	0.0104	0.0169	0.0337
Price	26.92	23.78	8.25	13.50	20.64	33.82	62.54
Volume ($ million)	4.60	20.99	0.02	0.11	0.59	2.94	18.68
Volatility	0.0203	0.0082	0.0084	0.0144	0.0196	0.0254	0.0344

Table 2. Monthly stock returns and liquidity shocks for volatility shock portfolios

We measure unexpected changes in market volatility ($VIXSHOCK_t$) and unexpected changes in individual stock liquidity ($AMISHOCK_{i,t}$ and $SPRSHOCK_{i,t}$) for each stock and each month from January 1990 to December 2012 using the following formulas:

$$VIXSHOCK_t = \frac{VIX_t - AVGVIX_{t-12,t-1}}{AVGVIX_{t-12,t-1}},$$
$$AMISHOCK_{i,t} = -\frac{ILLIQ_{i,t} - AVGILLIQ_{i|t-12,t-1}}{AVGILLIQ_{i|t-12,t-1}},$$
$$SPRSHOCK_{i,t} = -\frac{SP_{i,t} - AVGSP_{i|t-12,t-1}}{AVGSP_{i|t-12,t-1}};$$

where VIX_t is the mean daily CBOE VIX Index for month t; $AVGVIX_{t-12,t-1}$ is the mean of VIX in the past 12 months; $ILLIQ_{i,t}$ is Amihud's illiquidity measure for stock i in month t defined as $ILLIQ_{i,t} = Average\left[\frac{|R_{i,d}|}{VOLD_{i,d}}\right]$, where $|R_{i,d}|$ and $VOLD_{i,d}$ are the absolute daily stock return and dollar trading volume of stock i on day d within month t; $AVGILLIQ_{i|t-12,t-1}$ is the mean of $ILLIQ$ in the past 12 months for stock i; $SP_{i,t}$ is the mean daily quoted percentage spread $\left\{\frac{Ask_{i,d}-Bid_{i,d}}{\left(\left[\frac{Ask_{i,d}+Bid_{i,d}}{2}\right]\right)}\right\}$ for stock i within month t; and $AVGSP_{i|t-12,t-1}$ is the mean of SP in the past 12 months for stock i. To examine the impact of volatility shock (*VIXSHOCK*) on the liquidity and returns of individual stocks, we sort months for the NYSE, AMEX, and NASDAQ sample stocks into decile portfolios based on volatility shock and compute the average return and liquidity shocks (*AMISHOCK* and *SPRSHOCK*) for each portfolio. Numbers in parentheses are Welch's unequal variances t-statistics. **Significant at the 1% level.

	Volatility Shock (*VIXSHOCK*) Decile										
	1 (Low)	2	3	4	5	6	7	8	9	10 (High)	High - Low
RET	0.0322	0.0283	0.0220	0.0189	0.0178	0.0165	0.0106	0.0090	0.0075	-0.0181	-0.0503**
											(-23.31)
AMISHOCK	0.2752	0.1848	0.1393	0.1280	0.1056	0.0882	0.0463	0.0233	0.0171	-0.1564	-0.4316**
											(-25.24)
SPRSHOCK	0.2424	0.1462	0.1187	0.1042	0.0929	0.0771	0.0381	0.0215	0.0141	-0.1643	-0.4067**

(-28.73)

Table 3. The effects of volatility shock, liquidity shock, and liquidity effect of VIX on stock returns

This table reports the results of the following regression model using the combined sample of NYSE, AMEX, and NASDAQ stocks from January 1990 to December 2012:

$$RET_{i,t}\ or\ ALPHA_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2\left(AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}\right) + \beta_3 VIXSHOCK_t * \left(AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}\right) + \beta_4 IVOLASHOCK_{i,t} + \beta_5 MKTRET_t + \beta_6\left(MKTAMISHOCK_t\ or\ MKTSPRSHOCK_t\right) + \beta_7 DVOLSHOCK_{i,t} + \beta_8 BETA_{i,t} + \beta_9 Log\left(MVE_{i,t}\right) + \beta_{10} CVILLIQ_{i,t} + \beta_{11} MAXRET_{i,t} + \beta_{12} REVISE_{i,t} + \beta_{13} MOMENT_{i,t} + \beta_{14} STDTO_{i,t} + \beta_{15} BVTOMV_{i,t} + \beta_{16} SUE_{i,t} + \beta_{17} SKEW_{i,t} + \beta_{18} NAF_{i,t} + \varepsilon_{i,t};$$

where subscripts *i* and *t* stand for stock *i* and month *t*, respectively; *RET* is the stock return; *ALPHA* is three-factor Fama and French alpha; *VIXSHOCK* is the VIX shock; *AMISHOCK* is the liquidity shock, *SPRSHOCK* is the quoted spread shock; *IVOLASHOCK* is the idiosyncratic volatility shock; *MKTRET* is the market return, *MKTAMISHOCK* is the market Amihud illiquidity shock, *MKTSPRSHOCK* is the market spread shock, *DVOLSHOCK* is the dollar volume shock; *BETA* denotes market beta; *MVE* is the market value of equity; *CVILLIQ* is the coefficient of variation in the Amihud illiquidity measure; *MAXRET* denotes the maximum return; *REVISE* is the return revision; *MOMENT* is the momentum; *STDTO* denotes the standard deviation of volume turnover; *BVTOMV* is the book-to-market ratio; *SUE* denotes standardized unexpected earnings; *SKEW* denotes co-skewness measure; *NAF* is the number of analysts following the firm; and ε_i is the error term. Our sample consists of 10,094 NYSE, AMEX, and NASDAQ stocks. Numbers in parentheses are *t*-statistics based on standard errors clustered by firm and time. **Significant at the 1% level. *Significant at the 5% level.

	RET_t	RET_t	$ALPHA_t$	$ALPHA_t$
VIXSHOCK	-0.0384**	-0.0396**	-0.0253**	-0.0276**
	(-14.01)	(-13.29)	(-11.89)	(-12.34)
AMISHOCK	0.0099**		0.0082**	
	(11.54)		(10.58)	
*VIXSHOCK*AMISHOCK*	0.0156**		0.0118**	
	(9.59)		(8.70)	
SPRSHOCK		0.0105**		0.0098**
		(12.29)		(11.37)
*VIXSHOCK*SPRSHOCK*		0.0183**		0.0154**
		(9.67)		(8.74)
IVOLASHOCK	-0.0030**	-0.0033**	-0.0028**	-0.0026**
	(-6.32)	(-6.20)	(-5.59)	(-5.48)
MKTRET	0.7596**	0.7731**	0.4443**	0.4457**
	(5.29)	(5.97)	(3.79)	(3.85)
MKTAMISHOCK	0.0045**		0.0030**	
	(3.57)		(3.13)	
MKTSPRSHOCK		0.0049**		0.0035**
		(3.75)		(3.25)
DVOLSHOCK	0.0025**	0.0026**	0.0019**	0.0021**
	(7.32)	(7.39)	(6.15)	(6.33)
BETA	0.0007*	0.0008*	0.0005*	0.0006*
	(2.27)	(2.35)	(2.01)	(2.16)
MVE	-0.0042**	-0.0043**	-0.0029**	-0.0031**
	(-4.06)	(-4.21)	(-2.94)	(-2.83)
CVILLIQUID	0.0016**	0.0018**	0.0011**	0.0013**
	(3.74)	(3.99)	(3.18)	(3.93)
MAXRET	-0.0158**	-0.0172**	-0.0125**	-0.0127**
	(-3.49)	(-3.84)	(-3.30)	(-3.41)
REVISE	-0.0379**	-0.0399**	-0.0285**	-0.0289**
	(-4.67)	(-4.88)	(-4.21)	(-4.27)
MOMENT	0.0072**	0.0076**	0.0064**	0.0060**
	(5.07)	(5.20)	(4.84)	(4.45)
STDTO	-0.0028**	-0.0032**	-0.0025**	-0.0027**
	(-2.73)	(-3.13)	(-2.88)	(-3.09)
BVTOMV	0.0017*	0.0018**	0.0020**	0.0021**
	(2.51)	(2.86)	(3.14)	(3.28)
SUE	0.0025**	0.0023**	0.0015**	0.0016**
	(4.67)	(4.56)	(4.08)	(3.79)
SKEW	0.0016*	0.0019*	0.0013**	0.0014**
	(2.32)	(2.37)	(2.73)	(3.01)
NAF	-0.0012**	-0.0013**	-0.0014**	-0.0016**
	(-3.40)	(-3.46)	(-3.45)	(-3.75)
R^2	0.20	0.20	0.17	0.17

Table 4.

The effects of 1997 NASDAQ OHR market reform and 1997 tick size reduction on liquidity effect of VIX

We estimate the following regression model separately for NASDAQ stocks and NYSE stocks using a combined sample before and after the Order Handling Rules (OHR) implementation and tick size reduction in 1997 to examine the effects of the OHR market reform and tick size change on the liquidity effect of VIX:

$$RET_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2 (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_3 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_4 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST + control\ variables + \varepsilon_{i,t}, \quad \text{(a)}$$

where subscripts *i* and *t* stand for stock *i* and month *t*, respectively; *RET* is the stock return; *VIXSHOCK* is the VIX shock; *AMISHOCK* is the liquidity shock, *SPRSHOCK* is the quoted spread shock; *POST* is a dummy variable that equals one for the post-rule change period and zero for the pre-rule change period; and ε_i is the error term. We use the same control variables as in regression model (7). The pre-period is from July 1996 to December 1996 and the post-period is from November 1997 to April 1998. We also estimate the following regression model for combined NASDAQ and NYSE stocks using pooled sample in the pre-event and post-event periods:

$$RET_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2 (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_3 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_4 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST + \beta_5 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * NASDAQ + \beta_6 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST * NASDAQ + control\ variables + \varepsilon_{i,t}, \quad \text{(b)}$$

where NASDAQ is a dummy variable that equals one for NASDAQ stocks and zero for NYSE stocks. The study sample contains 1,827 NASDAQ and 2,144 NYSE stocks. Panel A shows the results for liquidity stock. Panel B reports the results for spread shock. Numbers in parentheses are *t*-statistics based on standard errors clustered by firm and time. **Significnt at the 1% level.

	Results from model (a)		Results from model (b)
	NASDAQ	NYSE	NASDAQ + NYSE
	RET_t	RET_t	RET_t
Panel A: Regression results for *AMISHOCK*			
VIXSHOCK	-0.0137**	-0.0131**	-0.0134**
	(-6.50)	(-5.66)	(-5.99)
AMISHOCK	0.0028**	0.0017**	0.0023**
	(5.33)	(4.70)	(5.13)
*VIXSHOCK*AMISHOCK*	0.0074**	0.0044**	0.0066**
	(5.52)	(4.63)	(5.27)
*VIXSHOCK*AMISHOCK*POST*	0.0085**	0.0057**	0.0077**
	(4.86)	(3.72)	(4.36)
*VIXSHOCK*AMISHOCK*NASDAQ*			0.0068**
			(3.89)
*VIXSHOCK*AMISHOCK*POST*NASDAQ*			0.0084**
			(4.51)
Panel B: Regression results for *SPRSHOCK*			
VIXSHOCK	-0.0143**	-0.0135**	-0.0139**
	(-6.57)	(-5.93)	(-6.14)
SPRSHOCK	0.0033**	0.0019**	0.0025**
	(5.65)	(4.78)	(5.41)
*VIXSHOCK*SPRSHOCK*	0.0086**	0.0047**	0.0067**
	(5.85)	(4.58)	(5.57)
*VIXSHOCK*SPRSHOCK*POST*	0.0090**	0.0059**	0.0077**
	(5.12)	(4.13)	(4.78)
*VIXSHOCK*SPRSHOCK*NASDAQ*			0.0072**
			(4.20)
*VIXSHOCK*SPRSHOCK*POST*NASDAQ*			0.0088**
			(4.74)

Table 5. The effects of NASDAQ and NYSE decimalization on liquidity effect of VIX

We estimate the following regression model separately for NASDAQ stocks and NYSE stocks using a combined sample before and after decimal pricing to examine the effects of decimalization on the liquidity effect of VIX:

$$RET_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2 (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_3 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_4 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST + control\ variables + \varepsilon_{i,t}, \quad \text{(a)}$$

where subscripts *i* and *t* stand for stock *i* and month *t*, respectively; *RET* is the stock return; *VIXSHOCK* is the VIX shock; *AMISHOCK* is the liquidity shock, *SPRSHOCK* is the quoted spread shock; *POST* is a dummy variable that equals one for the post-decimalization period and zero for the pre-decimalization period; and ε_i is the error term. We use the same control variables as in regression model (7). For NASDAQ stocks, the pre-period is from September 2000 to February 2001 and the post-period is from May 2001 to October 2001. For NYSE stocks, the pre-period and post-period are February 2000 to July 2000 and February 2001 to July 2001, respectively. We also estimate the following regression model for combined NASDAQ and NYSE stocks using pooled sample in the pre-and post-decimalization periods:

$$RET_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2 (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_3 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_4 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST + \beta_5 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * NASDAQ + \beta_6 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST * NASDAQ + control\ variables + \varepsilon_{i,t}, \quad \text{(b)}$$

where *NASDAQ* is a dummy variable that equals one for NASDAQ stocks and zero for NYSE stocks. Our study sample consists of 1,809 NASDAQ and 2,223 NYSE stocks. Panel A shows the results for liquidity shock. Panel B reports the results for spread shock. Numbers in parentheses are *t*-statistics based on standard errors clustered by firm and time. **Significant at the 1% level.

	Results from model (a)		Results from model (b)
	NASDAQ	NYSE	NASDAQ + NYSE
	RET_t	RET_t	RET_t
Panel A: Regression results for *AMISHOCK*			
VIXSHOCK	-0.0216**	-0.0203**	-0.0212**
	(-7.46)	(-6.83)	(-7.25)
AMISHOCK	0.0076**	0.0063**	0.0071**
	(6.73)	(6.22)	(6.52)
*VIXSHOCK*AMISHOCK*	0.0148**	0.0124**	0.0134**
	(5.58)	(5.21)	(5.47)
*VIXSHOCK*AMISHOCK*POST*	0.0085**	0.0076**	0.0081**
	(4.87)	(4.65)	(4.78)
*VIXSHOCK*AMISHOCK*NASDAQ*			0.0065**
			(3.97)
*VIXSHOCK*AMISHOCK*POST*NASDAQ*			0.0005
			(0.37)
Panel B: Regression results for *SPRSHOCK*			
VIXSHOCK	-0.0222**	-0.0209**	-0.0216**
	(-7.53)	(-7.34)	(-7.42)
SPRSHOCK	0.0080**	0.0068**	0.0072**
	(6.85)	(6.35)	(6.48)
*VIXSHOCK*SPRSHOCK*	0.0152**	0.0137**	0.0142**
	(6.32)	(5.71)	(5.84)
*VIXSHOCK*SPRSHOCK*POST*	0.0089**	0.0081**	0.0085**
	(5.16)	(4.69)	(4.86)
*VIXSHOCK*SPRSHOCK*NASDAQ*			0.0069**
			(4.34)
*VIXSHOCK*SPRSHOCK*POST*NASDAQ*			0.0006
			(0.47)

Table 6. The effects of amendment of NASDAQ Rule 4613(c) in 2007 on liquidity effect of VIX

We estimate the following regression model separately for NASDAQ stocks and NYSE stocks using a combined sample before and after the amendment of NASDAQ Rule 4613(c) in 2007 to assess the effects of the rule amendment on the liquidity of VIX:

$$RET_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2 (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_3 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_4 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST + control\ variables + \varepsilon_{i,t},$$

(a)

where subscripts *i* and *t* stand for stock *i* and month *t*, respectively; *RET* is the stock return; *VIXSHOCK* is the VIX shock; *AMISHOCK* is the liquidity shock, *SPRSHOCK* is the quoted spread shock; *POST* is a dummy variable that equals one for the post-rule change period and zero for the pre-rule change period; and ε_i is the error term. We use the same control variables as in regression model (7). The pre-period is from May 2007 to October 2007 and the post-period is from December 2007 to May 2008. We also estimate the following regression model for combined NASDAQ and NYSE stocks using pooled sample in the pre-event and post-event periods:

$$RET_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2 (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_3 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_4 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST + \beta_5 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * NASDAQ + \beta_6 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST * NASDAQ + control\ variables + \varepsilon_{i,t},$$

(b)

where *NASDAQ* is a dummy variable that equals one for NASDAQ stocks and zero for NYSE stocks. The sample contains 1,828 NASDAQ and 2,134 NYSE stocks. Panel A shows the results for liquidity shock. Panel B reports the results for spread shock. Numbers in parentheses are *t*-statistics based on standard errors clustered by firm and time. **Significant at the 1% level.

	Results from model (a)		Results from model (b)
	NASDAQ	NYSE	NASDAQ + NYSE
	RET_t	RET_t	RET_t
Panel A: Regression results for *AMISHOCK*			
VIXSHOCK	-0.0305**	-0.0251**	-0.0284**
	(-8.89)	(-7.82)	(-8.44)
AMISHOCK	0.0128**	0.0097**	0.0117**
	(7.43)	(6.58)	(6.80)
*VIXSHOCK*AMISHOCK*	0.0237**	0.0192**	0.0218**
	(7.17)	(6.82)	(6.91)
*VIXSHOCK*AMISHOCK*POST*	0.0092**	0.0002**	0.0035
	(4.76)	(0.49)	(1.15)
*VIXSHOCK*AMISHOCK*NASDAQ*			0.0013
			(0.73)
*VIXSHOCK*AMISHOCK*POST*NASDAQ*			0.0102**
			(6.36)
Panel B: Regression results for *SPRSHOCK*			
VIXSHOCK	-0.0308**	-0.0258**	-0.0288**
	(-8.98)	(-8.12)	(-8.84)
SPRSHOCK	0.0134**	0.0093**	0.0113**
	(7.53)	(6.37)	(6.84)
*VIXSHOCK*SPRSHOCK*	0.0249**	0.0199**	0.0223**
	(7.63)	(6.65)	(7.03)
*VIXSHOCK*SPRSHOCK*POST*	0.0098**	0.0003	0.0037
	(5.09)	(0.63)	(1.20)
*VIXSHOCK*SPRSHOCK*NASDAQ*			0.0017
			(0.82)
*VIXSHOCK*SPRSHOCK*POST*NASDAQ*			0.0108**
			(6.47)

Table 7. The effects of the implementation of the designated market maker (DMM) system on the NYSE in 2008 on liquidity effect of VIX

We estimate the following regression model separately for NASDAQ stocks and NYSE stocks using a combined sample before and after the implementation of the designated market maker (DMM) system on the NYSE to assess the effects of the DMM system on the liquidity of VIX:

$$RET_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2 (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_3 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_4 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST + control\ variables + \varepsilon_{i,t},$$

(a)

where subscripts *i* and *t* stand for stock *i* and month *t*, respectively; *RET* is the stock return; *VIXSHOCK* is the VIX shock; *AMISHOCK* is the liquidity shock, *SPRSHOCK* is the quoted spread shock; *POST* is a dummy variable that equals one for the post-DMM period and zero for the pre-DMM period; and ε_i is the error term. We use the same control variables as in regression model (7). The pre-period is from June 2008 to September 2008. The post-period is from December 2008 to December 2009. We also estimate the following regression model for combined NASDAQ and NYSE stocks using pooled sample in the pre-event and post-event periods:

$$RET_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2(AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_3 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_4 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST + \beta_5 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * NYSE + \beta_6 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * POST * NYSE + control\ variables + \varepsilon_{i,t},$$

(b)

where *NYSE* is a dummy variable that equals one for NYSE stocks and zero for NASDAQ stocks. The study sample contains 1,788 NASDAQ and 1,896 NYSE stocks. Panel A shows the results for liquidity shock. Panel B reports the results for spread shock. Numbers in parentheses are *t*-statistics based on standard errors clustered by firm and time. **Significant at the 1% level.

	Results from model (a)		Results from model (b)
	NASDAQ	NYSE	NASDAQ + NYSE
	RET_t	RET_t	RET_t
Panel A: Regression results for *AMISHOCK*			
VIXSHOCK	-0.0377**	-0.0338**	-0.0361**
	(-9.84)	(-9.62)	(-9.76)
AMISHOCK	0.0169**	0.0148**	0.0158**
	(7.50)	(7.27)	(7.48)
*VIXSHOCK*AMISHOCK*	0.0238**	0.0217**	0.0230**
	(6.05)	(6.23)	(6.17)
*VIXSHOCK*AMISHOCK*POST*	0.0003**	0.0098**	0.0027**
	(0.52)	(4.57)	(0.88)
*VIXSHOCK*AMISHOCK*NYSE*			-0.0078**
			(-5.46)
*VIXSHOCK*AMISHOCK*POST*NYSE*			0.0104**
			(5.56)
Panel B: Regression results for *SPRSHOCK*			
VIXSHOCK	-0.0381**	-0.0334**	-0.0367**
	(-9.97)	(-9.49)	(-9.83)
SPRSHOCK	0.0176**	0.0157**	0.0166**
	(7.74)	(7.57)	(7.64)
*VIXSHOCK*SPRSHOCK*	0.0245**	0.0224**	0.0238**
	(6.49)	(6.34)	(6.28)
*VIXSHOCK*SPRSHOCK*POST*	0.0004	0.0107**	0.0030
	(0.63)	(5.08)	(1.09)
*VIXSHOCK*SPRSHOCK*NYSE*			-0.0083**
			(-5.27)
*VIXSHOCK*SPRSHOCK*POST*NYSE*			0.0116**
			(5.70)

Table 8. The effects of high frequency trading (HFT) on liquidity effect of VIX

We estimate the following regression model separately for NASDAQ stocks and NYSE stocks to assess the impact of HFT on the volatility-liquidity effect on returns:

$$RET_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2(AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_3 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_4 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * HFTPRD + control\ variables + \varepsilon_{i,t},$$

(a)

where subscripts *i* and *t* stand for stock *i* and month *t*, respectively; *RET* is the stock return; *VIXSHOCK* is the VIX shock; *AMISHOCK* is the liquidity shock; *SPRSHOCK* is the quoted spread shock; *HFTPRD* is a dummy variable that equals one for the HFT period and zero for the pre-HFT period; and ε_i is the error term. We use the same control variables as in regression model (7). We also estimate the following regression model for combined NASDAQ and NYSE stocks:

$$RET_{i,t} = \beta_0 + \beta_1 VIXSHOCK_t + \beta_2(AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_3 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) + \beta_4 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * HFTPRD + \beta_5 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * NASDAQ + \beta_6 VIXSHOCK_t * (AMISHOCK_{i,t}\ or\ SPRSHOCK_{i,t}) * HFTPRD * NASDAQ + control\ variables + \varepsilon_{i,t},$$

(b)
where *NASDAQ* is a dummy variable that equals one for NASDAQ stocks and zero for NYSE stocks. Panel A and Panel B show the regression results when we use January 2005 to December 2005 as the pre-HFT period and January 2009 to December 2009 as the HFT period and Panels C and D show the results when we use January 1999 to December 2005 as the pre-HFT period and January 2006 to December 2012 as the HFT period. Panels A and C show the results when we measure liquidity shocks by unexpected changes in the Amihud price impact (*AMISHOCK*) and Panels B and D show the results when we measure liquidity shocks by unexpected changes in the bid-ask spread (*SPRSHOCK*). Numbers in parentheses are *t*-statistics based on standard errors clustered by firm and time. **Significant at the 1% level.

	Results from model (a)		Results from model (b)
	NASDAQ	NYSE	NASDAQ + NYSE
	RET_t	RET_t	RET_t
Panel A: Regression results for *AMISHOCK* when we use January 2005 to December 2005 as the pre-HFT period and January 2009 to December 2009 as the HFT period			
VIXSHOCK	-0.0367**	-0.0342**	-0.0356**
	(-9.75)	(-9.17)	(-9.54)
AMISHOCK	0.0166**	0.0140**	0.0147**
	(7.60)	(6.96)	(7.27)
*VIXSHOCK*AMISHOCK*	0.0236**	0.0221**	0.0228**
	(6.28)	(5.83)	(6.05)
*VIXSHOCK*AMISHOCK*HFTPRD*	0.0104**	0.0131**	0.0113**
	(5.72)	(5.81)	(5.76)
*VIXSHOCK*AMISHOCK*NASDAQ*			0.0093**
			(5.23)
*VIXSHOCK*AMISHOCK*HFTPRD*NASDAQ*			0.0104**
			(5.36)
Panel B: Regression results for *SPRSHOCK* when we use January 2005 to December 2005 as the pre-HFT period and January 2009 to December 2009 as the HFT period			
VIXSHOCK	-0.0371**	-0.0351**	-0.0363**
	(-9.96)	(-9.33)	(-9.65)
SPRSHOCK	0.0173**	0.0145**	0.0155**
	(7.85)	(7.14)	(7.58)
*VIXSHOCK*SPRSHOCK*	0.0248**	0.0228**	0.0241**
	(6.50)	(6.09)	(6.38)
*VIXSHOCK*SPRSHOCK*HFTPRD*	0.0110**	0.0140**	0.0128**
	(5.89)	(5.97)	(5.90)
*VIXSHOCK*SPRSHOCK*NASDAQ*			0.0102**
			(5.42)
*VIXSHOCK*SPRSHOCK*HFTPRD*NASDAQ*			0.0111**
			(5.70)

Table 8 (continued)
The effects of high frequency trading (HFT) on liquidity effect of VIX

	Results from model (a)		Results from model (b)
	NASDAQ	NYSE	NASDAQ + NYSE
	RET_t	RET_t	RET_t
Panel C: Regression results for *AMISHOCK* when we use January 1999 to December 2005 as the pre-HFT period and January 2006 to December 2012 as the HFT period			
VIXSHOCK	-0.0327**	-0.0317**	-0.0321**
	(-9.41)	(-9.09)	(-9.25)
AMISHOCK	0.0118**	0.0102**	0.0112**
	(6.93)	(6.34)	(6.68)
*VIXSHOCK*AMISHOCK*	0.0165**	0.0143**	0.0151**
	(7.65)	(6.94)	(7.35)
*VIXSHOCK*AMISHOCK*HFTPRD*	0.0106**	0.0114**	0.0110**
	(4.32)	(4.67)	(4.49)
*VIXSHOCK*AMISHOCK*NASDAQ*			0.0113**
			(5.54)
*VIXSHOCK*AMISHOCK*HFTPRD*NASDAQ*			0.0106**

			(5.60)
Panel D: Regression results for *SPRSHOCK* when we use January 1999 to December 2005 as the pre-HFT period and January 2006 to December 2012 as the HFT period			
VIXSHOCK	-0.0335**	-0.0322**	-0.0329**
	(-9.75)	(-9.21)	(-9.41)
SPRSHOCK	0.0131**	0.0115**	0.0122**
	(7.29)	(6.69)	(7.18)
*VIXSHOCK*SPRSHOCK*	0.0175**	0.0164**	0.0170**
	(7.75)	(7.49)	(7.62)
*VIXSHOCK*SPRSHOCK*HFTPRD*	0.0115**	0.0123**	0.0118**
	(4.48)	(4.81)	(4.56)
*VIXSHOCK*SPRSHOCK*NASDAQ*			0.0121**
			(5.63)
*VIXSHOCK*SPRSHOCK*HFTPRD*NASDAQ*			0.0115**
			(5.72)

Highlights

- Market volatility affects stock returns both directly and indirectly through its impact on liquidity provision.
- The negative relation between market volatility and stock returns arises not only from greater risk premiums but also greater illiquidity premiums.
- Stock returns are more sensitive to volatility shocks in the high-frequency trading era.
- Stock returns are more sensitive to volatility shocks after the regulatory changes that increased competition between public traders and market makers, reduced the tick size, and decreased the role of market makers.