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Shocks to Order Flow Volatility and Stock Returns

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Abstract

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In theoretical models, liquidity and order flow volatility are determined by the same exogenous parameters. Thus, shocks to the variability of order flow proxy for shocks to unobserved (true) liquidity. We show that shocks to order imbalance volatility predict stock returns in the cross-section, even after accounting for risk factors, firm characteristics known to influence returns, and other illiquidity proxies. The evidence indicates that such shocks are absorbed within one month in large, visible stocks, but take six months to be fully reflected in the prices of small, "neglected" stocks.

1 Introduction

The question of whether investors demand higher returns from less liquid securities is important. Following the work of Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Jacoby, Fowler, and Gottesman (2000), Jones (2002), and Amihud (2002) all investigate the role of liquidity as a determinant of expected returns. In addition, Acharya and Pedersen (2005) and Pástor and Stambaugh (2003) explore the relation between unexpected fluctuations in liquidity and expected stock returns.

Many approaches have been used to measure liquidity in the literature. For example, Amihud and Mendelson (1986) use the bid-ask spread as a liquidity measure. Amihud (2002) develops the ratio of absolute return to dollar trading volume as an illiquidity measure, and this measure is also used by Acharya and Pedersen (2005). Brennan and Subrahmanyam (1996) measure illiquidity by the relation between price changes and order flows. Pástor and Stambaugh (2003) measure illiquidity by the extent to which returns reverse upon high volume, an approach based on the notion that such a reversal captures inventory-based price pressures. Hasbrouck (2005) provides a comprehensive set of estimates of these and other measures including the Roll (1984) measure.

We note that the preceding illiquidity measures are not directly derived from theory. For example, the well-known theory of Kyle (1984, 1985) relates the price impact λ to exogenous parameters such as signal volatility, signal noise variance, the number of informed, and the variance of noise or liquidity trading. Chordia, Huh, and Subrahmanyam (2009) use empirical proxies such earnings estimates and associated errors to measure some of these inputs, but private information is not restricted to that surrounding earnings announcements. Thus, the challenge in using theory to estimate illiquidity is that the exogenous parameters are hard to measure. On the other hand, not using theory implies that any illiquidity measure actually used is necessarily imperfect.

Even though measuring the exogenous parameters in illiquidity models is hard, in the celebrated Kyle (1984, 1985) model, order flow from traders who submit market orders plays a key role as a signal from which the market maker attempts to extract information. Indeed, we analytically show that from an ex ante standpoint, the second moment of order flow is directly linked to the exogenous parameters that drive illiquidity. Since the second moment of order flows can be measured through (admittedly imperfect) signing rules, the dynamics of the second moment of order flow can potentially be linked to the dynamics of (unobserved) true illiquidity, and, in turn, to required equity returns, even when the exogenous parameters that drive illiquidity and order flow variability are not observable.

Previous efforts to link liquidity to equity prices in the cross-section mainly focus on the relation between the level of liquidity and future stock returns; see, for example, See Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Jacoby, Fowler, and Gottesman (2000), Jones (2002), and Amihud (2002). In a recent paper, Bali, Peng, Shen and Tang (BPST)(2014) examine the relation between stock returns and *shocks* to illiquidity, where illiquidity is measured by the procedure suggested by Amihud (2002), and by bid-ask spreads. In our paper, we examine the relation between returns and *both* levels of as well as shocks to the variability of order flows. We show that levels and shocks to order flow volatility have an impact on required returns beyond those documented by BPST for their measures of illiquidity, and also find that the pricing of shocks is more robust than that of levels. Our analysis accords with theoretical arguments that link order flow variability to illiquidity, and also unveils a new predictor of stock returns, that is statistically and economically significant.

We sign trades as buys and sells to create two measures of order imbalance (OIB) one based on shares traded and the other based on number of trades. OIB, in terms of shares traded, is denoted OIB_SHR and is constructed each day as number of shares bought less number of shares sold as a fraction of the sum of shares bought and sold. Similarly, OIB, in terms of the number of trades is denoted OIB_NUM and is constructed each day as the number of buy trades less the number of sell trades as a fraction of the sum of the total daily trades. The OIB volatilities are first computed each month as the volatility of the daily OIB_SHR and OIB_NUM. A six month average (in order to obtain a less volatile measure of the steady state volatility of OIB) of the monthly volatilities is used to obtain $VOIB\_SHR$ and $VOIB\_NUM$, the order imbalance volatilities in terms of shares traded and the number of trades, respectively. Consistent with the model, we find that both $VOIB\_SHR$ and $VOIB\_NUM$ are cross-sectionally correlated with different measures of liquidity, including turnover, bid-ask spreads and the Amihud measure of illiquidity. Univariate sorts of $VOIB\_SHR$ and $VOIB\_NUM$ into quintile portfolios shows that a portfolio that is long the high OIB volatilities and short the low OIB volatilities yields a monthly return in excess of 50 basis points as does the long-short portfolio formed by sorting on the Amihud illiquidity measure. Fama-MacBeth (1973) regressions reveal that lagged values of $VOIB\_SHR$ and $VOIB\_NUM$ are both positively related to risk-adjusted returns even after controlling for a number of characteristics including the Amihud illiquidity measure and turnover. This is consistent with our theoretical model in that the OIB volatilities are proxying for illiquidity. A one standard deviation change in $VOIB\_SHR$ ($VOIB\_NUM$) results in an annual increase of 2.6% (1.7%) in risk adjusted returns.

Shocks to $VOIB\_SHR$ and $VOIB\_NUM$ in month t, (denoted $SVOIB\_SHR_t$ and $SVOIB\_NUM_t$) are computed by subtracting the lagged $VOIB\_SHR$ and $VOIB\_NUM$ from the OIB volatilities in month t. These shocks are highly positively correlated with shocks to the bid-ask spread and shocks to the Amihud measure of illiquidity and negatively correlated with shocks to turnover. $SVOIB\_SHR_t$ and $SVOIB\_NUM_t$ have a contemporaneous as well as delayed impact on returns and illiquidity. Specifically, a positive shock reduces the contemporaneous and next month's return. Quintile portfolios with the largest shocks to volatility of OIB underperform those with the smallest shocks by about 2.7% in the current month and by 0.52% (0.33%) for $SVOIB\_NUM_t$ ($SVOIB\_SHR_t$) in the following month. A positive shock to volatility of order flow also reduces both contemporaneous and future liquidity measured by the turnover ratio, bid-ask spread, and the Amihud (2002) illiquidity proxy. Thus, shocks to volatility of order flow have a contemporaneous as well as a delayed impact on illiquidity and required rates of return.

The effect of shocks to volatility of order flow on next month's returns survives a long list of control variables including firm characteristics such as momentum, monthly reversals, idiosyncratic volatility, profitability, analyst forecast dispersion, asset growth, accruals, new issues and levels as well as shocks to turnover and the Amihud measure of liquidity. The impact of lagged shocks to the volatility of OIB are robust to different return definitions including risk-adjusted returns, raw returns, and open-to-close mid-quote returns. The impact is not driven by the recent financial crisis and it is robust to alternative order flow calculation based on number of shares, number of trades and also based on dollars traded. The results for $SVOIB\_NUM_t$ also survive in different subperiods although in the more recent years there is no impact on returns due to shocks to $VOIB\_SHR_t$. The impact of shocks to volatility of OIB is stronger for firms with small market capitalization, low analyst coverage, low institutional holdings and high idiosyncratic volatility.

A shock that makes markets illiquid should result in lower contemporaneous prices such that the expected return increases. However, due to trading frictions, prices may not decrease instantaneously. An important question in the study of the return dynamics in response to liquidity shocks is how long does it take for liquidity shocks to be absorbed into prices. We find that even for small stocks, stocks with low analyst coverage, low institutional holdings and high idiosyncratic volatility it takes at most six months for impact of liquidity shocks, as measured by $SVOIB\_NUM_t$ and $SVOIB\_SHR_t$, to be incorporated into prices. The negative cross-sectional effect of liquidity shocks on returns turns positive in six months even for the above stocks that have high trading frictions and a poor informational environment.

The rest of the paper is organized as follows. Section 2 shows the theoretical link between order flow volatility and liquidity in a model. Section 3 describes the sample selection and variable construction in empirical analysis. Section 4 examines the pricing effect of the proposed volatility of order flow as a measure of illiquidity and Section 5 examines the pricing effects of the shocks to the volatility of order flow. Section 6 studies the return dynamics of the liquidity shocks. Section 7 concludes.

2 Illiquidity and Order Imbalance Volatility: The Theory

In this section, we provide a brief theoretical motivation for our study. We use ω to denote order flow and v_ω to denote volatility of order flow.

2.1 The Link between Illiquidity and Asset Prices

We first briefly discuss a link between illiquidity and asset prices. Consider an asset that is traded at date 1, and pays off $F = \bar{F} + \delta$ at date 2, where δ is normally distributed with mean zero and $\bar{F}$ is non-stochastic. At date 1 the price is set according to the familiar Kyle (1984) setting as $P = \bar{F} + \lambda\omega$ where ω is the net order flow.

Ex ante, if a liquidity trader (who we assume is the marginal investor) considers purchasing one share of the asset at date 1, then he would be willing to pay a maximum of $\bar{F} - \lambda$ because given a date 1 price P, the expected liquidity cost of trading Y shares is given by $E[(P-F)Y] = \lambda Y^2$, which equals λ for a trade of one share. We would therefore expect a positive shock to illiquidity to lower the price of the asset, and vice versa.

2.2 A Model of Illiquidity with Many Informed Traders

Assume that there are N informed traders, and that each receives a signal $\delta + \epsilon_i$, where the ϵ_i's are i.i.d., and mean zero with variance v_ϵ. The total noise trade is $z \sim N(0, v_z)$, and z, ϵ_i, and δ are each independent of all other random variables. The competitive market maker observes the net order flow and sets prices to earn zero expected profits and, so that the date 1 price equals $P = E(F|\omega) = \bar{F} + \lambda\omega$.

Suppose informed trader i conjectures that others use strategies of the form $\bar{\beta}(\delta+\epsilon_j)$. The trader maximizes

$$E(x_i(\delta - \lambda(x_i + (N-1)\bar{\beta}\delta + \bar{\beta}\sum_{j\neq i}\epsilon_j + z)|\delta + \epsilon_i)$$

$$= -\lambda x_i^2 + x_i E(\delta|\delta+\epsilon_i)[1-(N-1)\lambda\bar{\beta}]$$

implying that

$$x_i = \frac{k(\delta+\epsilon_i)(1-\lambda(N-1)\bar{\beta})}{2\lambda} \tag{1}$$

where

$$k \equiv \frac{v_\delta}{v_\delta + v_\epsilon}$$

so that the informed strategy is of the form $\beta(\delta+\epsilon_i)$. In a symmetric Nash equilibrium $\bar{\beta} = \beta$. From (1) we then have

$$\beta = \frac{k}{\lambda([2+k(N-1)]}$$

Now, λ is given by

$$\lambda = \frac{\mathrm{cov}(\delta, N\beta\delta + \beta\sum\epsilon_i + z)}{\mathrm{var}(N\beta\delta + \beta\sum\epsilon_i + z)}$$

implying

$$\lambda = \frac{v_\delta}{(N+1)v_\delta + 2v_\epsilon}\sqrt{\frac{N(v_\delta + v_\epsilon)}{v_z}}. \tag{2}$$

Note that this measure of λ requires a proxy for the variance of the signal noise as well as that of the signal itself. It is difficult to obtain such proxies, which, in turn, implies it is challenging to directly measure the equilibrium λ. However, since the market maker sets prices based on the total order flow, we instead turn to the volatility of the order flow. The closed-form expression for variance of the order flow is:

$$\text{var}(\omega) \equiv v_\omega = N^2\beta^2 v_\delta + N\beta^2 v_\epsilon + v_z = \frac{v_z[(N+1)v_\delta + 2v_\epsilon]}{v_\delta + v_\epsilon}. \tag{3}$$

Thus, shocks to any of the exogenous parameters will affect v_ω. Not all the effects of exogenous parameters on v_ω and λ are monotonic. For example, let us consider the effect of the signal noise v_ϵ. It follows from (3) that as long as $N > 1$, a decrease in v_ϵ increases v_ω. The intuition is that a high v_ϵ causes more trading *between* the informed agents, causing a drop in the variance of the net order flow presented to the market maker. If we view v_ϵ as a measure of disagreement or dispersion of opinion, it is worth noting that our measure is inversely related to dispersion under the reasonable assumption that $N > 1$, i.e., there is at least one informed trader in the market.

Also note from (2) that an decrease in v_ϵ increases λ if and only if

$$v_\epsilon > 0.5(N-3)v_\delta. \tag{4}$$

A decrease in v_ϵ reduces signal noise and increases information asymmetry, but also makes the signals more strongly correlated, reducing the monopoly power of each informed agent. The net impact of a change in v_ϵ balances out these effects. Turning now to the impact of the variance of noise trading, it has opposite effects on v_ω and λ, as is evident from examining (2) and (3).

We now turn to N. As long as

$$v_\epsilon > 0.5(N-1)v_\delta, \tag{5}$$

an increase in N increases λ. The intuition is as follows. When v_ϵ is high, signals are very diverse, and adding another informed agent increases information asymmetry and thus λ. If v_ϵ is small, however, adding another informed trader simply means more competition between them, thus decreasing λ. Of course, from (3), an increase in N always increases v_ω. Note that since the bound in (5) is stronger than that in (4), as long as $N > 1$, an increase in N or a decrease in v_ϵ will increase both v_ω and λ.

Finally, as long as $N > 1$, an increase in v_δ increases λ as well as v_ω. From (3), v_ω is insensitive to v_δ, if and only if $N = 1$. The intuition is that an increase in v_δ increases the profit potential of informed agents and increases their trading aggressiveness, thus increasing λ as well as the variability of the order flow.

All of the preceding observations immediately lead us to the following proposition, stated without proof.

Proposition 1 *Suppose that $N > 1$ and $v_\epsilon > 0.5(N-1)v_\delta$. Then, a decrease in the variance of the signal error, v_ϵ, an increase in the variance of the fundamental value, v_δ, and an increase in the number of informed agents, N, all increase market illiquidity λ as well as the variance of the order flow, v_ω.*

However, an increase in v_z, increases v_ω and decreases λ. Thus, in our regression analysis we will control for volatility of noise trading by using volatility of share turnover as a proxy (as in Chordia, Huh, and Subrahmanyam, 2009).

While identifying the exogenous parameters of the theoretical model is beyond the scope of our work, the implicit notion is that illiquidity proxies are imperfect, so that v_ω (which is driven by the same exogenous parameters that drive illiquidity) can supplement our understanding of how illiquidity affects asset returns. In the remainder of the paper, we will first examine the impact of the volatility of order imbalance, v_ω, on expected returns and then consider how shocks to v_ω affect expected returns.

3 Sample Selection

Our sample includes common stocks listed on the NYSE/AMEX in the period from January 1993 to December 2012. To be included in the monthly analysis, a stock must have the following data available: (i) its returns in the current month and the past twelve months from CRSP, (ii) sufficient data to calculate market capitalization and turnover, (iii) data on the Compustat tapes to calculate the book-to-market ratio as of December of the previous year, and (iv) data in the NYSE Trade and Quote (TAQ) database to calculate the order imbalance. To avoid extremely illiquid stocks, we eliminate from the sample, stock-month observations with month-end stock prices below one dollar. The following securities are also eliminated from the sample since their trading characteristics can differ from ordinary equities: ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks and REITs.

Transactions data are obtained from TAQ (1993-2012). To eliminate data errors, we exclude trades and quotes with nonpositive bid or ask prices and those with the bid prices above the ask prices. We also exclude trades in the first fifteen minutes and the last five minutes of trading on each day to increase the accuracy of the trade signing algorithm.[1] We require that all stock-month observations have at least 14 daily trading records in a month.

TAQ data does not contain information on whether a trade is initiated by the buyer or

[1]The empirical results are largely the same when these trades are not excluded.

the seller. We use the Lee and Ready (1991) algorithm to classify transactions as either a buy or a sell. Briefly, we implement the Lee and Ready algorithm as follows: if a trade is executed at a price above (below) the quote midpoint, we classify it as a buy (sell); if a trade occurs exactly at the quote mid-point, we sign it using the previous transaction price according to the tick test (i.e., a buy if the sign of the last nonzero price change is positive and vice versa). The Lee and Ready algorithm uses the fact that seller-initiated trades tend to execute at a lower price than buyer-initiated trades. We apply the tick test up to the past five price changes. If the past five price changes are zero then we do not use it in the computation of buys or sells. As Lee and Ready (1991) note, the timestamps on quotes are not always correctly synchronized with those for trades and hence they recommend that the quotes be matched to trades with a five-second delay. We follow this five-second delay rule until 1998. Since such recording errors are not observed in the more recent data (see, for example, Madhavan et al., 2002 as well as Chordia, Roll, and Subrahmanayam, 2005) we do not impose any delays after 1998.

One concern with the Lee and Ready (1991) algorithm is that it may misclassify the side that initiated a particular trade, even if the trade initiator places a market order. Lee and Radhakrishna (2000) and Odders-White (2000) examine the trade-level accuracy of the Lee and Ready algorithm for NYSE traded stocks and report accuracy rates of 93% and 85%, respectively. Both Lee and Radhakrishna and Odders-White use data from the pre-decimalization era, and it is important to assess the reliability of the Lee and Ready algorithm in the post-decimalization era as well. The most recent study that examines this issue is Chakrabarty, Moulton, and Shkilko (2012). They find that the transaction level accuracy of the Lee and Ready algorithm during the June to December 2005 period is about 68%. The study by Chakrabarty, Moulton, and Shkilko, however, is not directly comparable to Lee and Radhakrishna and Odders-White because it examines Nasdaq stocks, and focuses solely on short sales. Ellis, Michaely, and O'Hara (2000) is more directly comparable to Chakrabarty, Moulton, and Shkilko because the former also examine the pre-decimalization period accuracy of the Lee and Ready algorithm with Nasdaq stocks. Ellis, Michaely, and O?Hara find an accuracy rate of 81%. Although the lower accuracy rate in Chakrabarty, Moulton, and Shkilko may be partly due to the fact that it focuses only on short sales, it is quite likely that decimalization contributed to this phenomenon as well.

What is important from the perspective of our study, however, is not the trade-level accuracy, but the accuracy when trade-level classifications are aggregated. For example, even if a fraction of seller-initiated trades on a particular day is misclassified as buyer-initiated trades and a similar fraction of buyer-initiated trades is also misclassified, then daily-level accuracy would be much greater than trade-level accuracy. In fact, Chakrabarty, Moulton, and Shkilko (2012) find that daily-level error rate is close to zero, and statistically insignificant. Since the error rate for NYSE stocks were lower than the error rates for Nasdaq stocks in the pre-decimalization period, it is quite likely that the error rates in the post-decimalization period would be no worse for NYSE stocks than those for Nasdaq stocks. Therefore, any trade-level misclassification is unlikely to meaningfully impact our tests based on aggregated data.

3.1 Measures of Order Imbalance, Order Imbalance Volatility and Shocks to Order Imbalance Volatility

We define order imbalance, order imbalance volatility and shocks to order imbalance volatility as follows:[2]

OIB (order imbalance): We create two measures of order imbalance (OIB) one based on shares traded and the other based on number of trades. OIB, in terms of shares traded, is denoted OIB_SHR and is constructed each day as number of shares bought

[2]Henceforth the terms "order imbalance" and "order flow" are used interchangeably.

less number of shares sold as a fraction of the sum of shares bought and sold. Similarly, OIB, in terms of the number of trades is denoted OIB_NUM and is constructed each day as the number of buy trades less the number of sell trades as a fraction of the sum of the total daily trades. Order imbalance is scaled by the total number of trades or the total number of shares traded so as to eliminate the impact of total trading activity. Actively traded stocks are likely to have higher order imbalances. The scaling standardizes the order imbalance measure.

$VOIB$ (volatility of order imbalance): The OIB volatilities are first computed each month as the volatility of the daily OIB_SHR and OIB_NUM. A six month moving average[3] of the monthly volatilities is used to obtain $VOIB\_SHR$ and $VOIB\_NUM$, the order imbalance volatilities in terms of shares traded and the number of trades, respectively. The six-month moving average of the monthly standard deviation of daily OIB results in a less volatile measure of the steady state volatility of OIB. Based on the paired t-test or the non-parametric ranks test, we find that the standard deviation of the monthly order imbalance volatility is significantly higher that the six month average of the monthly order imbalance volatility.

$SVOIB$ (shocks to volatility of order imbalance): We compute shocks to $VOIB\_SHR$ and $VOIB\_NUM$ in month t, (denoted $SVOIB\_SHR_t$ and $SVOIB\_NUM_t$) by subtracting lagged $VOIB\_SHR$ and $VOIB\_NUM$ from the corresponding month t OIB volatilities.

3.2 Summary Statistics

Panel A of Table 1 provides the summary statistics (computed as the time series averages of the monthly cross-sectional statistics) of the above variables. All variables other than

[3] A three month or a twelve month moving average of the monthly volatilities gives similar results.

realized returns are cross-sectionally winsorized at the 0.5% and 99.5% levels.

(Table 1 about here)

There are about 1600 stocks per month in our sample. Both OIB_SHR and OIB_NUM have positive means and medians indicating that, in general, there is more buying pressure than selling pressure. The mean (median) of $VOIB\_NUM$ is 0.239 (0.186) and for $VOIB\_SHR$ it is 0.303 (0.258) suggesting that OIB_SHR is more volatile. $SVOIB\_NUM$ and $SVOIB\_SHR$ are both close to zero, albeit negative suggesting that on average there are more or larger declines in the volatility of order imbalance.

Panel B reports the time-series averages of the cross-sectional correlations between the volatility of OIB and shocks to these volatilities and the well-known liquidity measures and stock returns (RET). The liquidity measures include the Amihud illiquidity measure ($ILLIQ$, calculated as the monthly average of the ratio of the daily absolute return to daily dollar volume), proportional quoted spread ($SPRD$, defined as monthly averages of bid-ask spread divided by bid-ask midpoint for each stock, extracted from the transactions data) and stock share turnover ($TURN$, calculated as the logarithm of the monthly average ratio of the stock's trading volume to the total number of shares outstanding). The liquidity shocks are computed similarly to shocks to the volatility of order imbalance. For example, the Amihud illiquidity shock ($SILLIQ$) is defined as $ILLIQ$ in the current month minus the moving average of $ILLIQ$ in the previous six months.

$VOIB\_NUM$ ($VOIB\_SHR$) has a correlation of 0.39 (0.38) with $ILLIQ$; a correlation of -0.64 (-0.64) with turnover and a correlation of 0.63 (0.63) with the proportional quoted spread. This suggests that stocks with a higher volatility of order imbalance have lower share turnovers, larger price impacts, and wider bid-ask spreads. The fact that the order imbalance volatilities behave in a manner similar to the traditional illiquidity measures supports the notion that the volatility of OIB at least partially captures the liquidity dynamics, as suggested by Proposition 1. Concurrent and lagged values of $VOIB\_NUM$ and $VOIB\_SHR$ are positively correlated with RET suggesting that more illiquid stocks (as measured by the volatility of OIB) have higher expected returns in the cross-section. Given that the order imbalance volatilities are obtained as the six month moving averages of monthly order imbalance volatilities, it is not surprising to find that the correlations between the lagged values of the volatility of OIB and the traditional (il)liquidity measures are almost the same as that between the concurrent values of the OIB volatilities and the (il)liquidity measures.

Lagged and concurrent values of $SVOIB\_NUM$ and $SVOIB\_SHR$ positively correlated with $SILLIQ$ and $SSPRD$, and negatively correlated with $STURN$, indicating that positive shocks to the volatility of order imbalance is associated with a deterioration in liquidity. However, the correlations are low. For instance, the correlation between $SVOIB\_NUM$ and SILLIQ is 0.17 while the correlation between $VOIB\_NUM$ and $ILLIQ$ is 0.393. The difference in the dynamics between the volatility of order imbalance and $ILLIQ$ indicates that the time-series variation of the order imbalance volatility can capture some information not contained in the variation of $ILLIQ$. The last column shows that both $SVOIB\_NUM$ and $SVOIB\_SHR$ have a negative and significant correlation with stock returns, suggesting that a deterioration in liquidity is accompanied with lower prices and negative returns.

4 Volatility of OIB and stock returns

In this section, we provide evidence that order imbalance volatility is priced in the cross-section. The pricing effect of shocks to order imbalance volatility will be discussed later in section 5.

4.1 Portfolio Sorts

This subsection reports the results from portfolio sorts. We first present univariate portfolio sort results for order imbalances, volatility of order imbalances and other liquidity measures. At the end of each month, we sort stocks into quintile portfolios based on OIB_NUM and OIB_SHR, $SVOIB\_NUM$, $SVOIB\_SHR$, $ILLIQ$, $TURN$, and $SPRD$, respectively. Panel A of Table 2 shows the average raw returns of the quintile portfolios in the next month. Also reported are the raw returns and Fama and French (1993) (FF) alphas for the portfolios that are long in stocks in the highest quintile and short in stocks in the lowest quintile. The associated Newey-West adjusted t-statistics are in parentheses.

(Table 2 about here)

For order imbalances, the return differences between the top and bottom quintiles and the FF alpha are negative and significant. The high minus low, long-short portfolio return amounts to -0.33% (-0.49%) per month when sorting on OIB_NUM (OIB_SHR). This negative relation suggests that the price pressure from order imbalances in the current month reverses in the next month.

For $VOIB\_NUM$ and $VOIB\_SHR$ the Fama-French three factor alpha between the top and bottom quintiles are 0.54% and 0.62% per month, respectively. The raw return (FF aplha) differential for quintile portfolios sorted on ILLIQ at 0.51% (0.33%) is also significantly and positively related to future returns. But for TURN (SPRD), only the FF alpha (the raw return differential) is marginally significant with the expected sign. The results suggest that illiquid stocks are associated with high future returns, consistent with the consensus in the literature.

To examine whether the order imbalance volatility contains information in addition to the traditional liquidity measures, we double sort stocks first on the basis of the traditional liquidity measures and then we sort on $VOIB\_NUM$ or $VOIB\_SHR$. More specifically, at the end of each month t, we first sort stocks into high and low groups based on $ILLIQ$, $TURN$, or $SPRD$, and then sort stocks based on $VOIB\_NUM$ or $VOIB\_SHR$ into quintile portfolios within each group. Portfolio returns at month t+1 are reported. Across all the columns, for $VOIB\_NUM$ and $VOIB\_SHR$, the return differences between the top and bottom quintiles and the FF alpha are larger for stocks with higher $ILLIQ$, higher turnover and higher spreads. Even after controlling for the traditional illiquidity measures, all the return differentials are generally significant at the 5% level or better. This suggests that the volatility of order imbalances provides additional information about the illiquidity of a stock that is not captured by the effect of the traditional liquidity measures.

4.2 Asset Pricing Regressions

4.2.1 Methodology

Our cross-sectional asset pricing tests follow Brennan, Chordia and Subrahmanyam (1998) and Avramov and Chordia (2006), who test factor models by regressing risk-adjusted returns on firm-level attributes such as size, book-to-market, turnover and past returns. Under the null of exact pricing, such attributes should be statistically and economically insignificant in the cross section. The use of individual stocks as test assets avoids the possibility that tests may be sensitive to the portfolio grouping procedure (Lo and MacKinlay (1990)).

We first regress the excess return of stock j, (j=1,..,N) on asset pricing factors, F_{kt}, (k=1,..,K), allowing the factor loadings, β_{jkt}, to vary over time as a function of firm size and book-to-market ratio. The conditional factor loadings of security are modeled as:

$$\beta_{jkt-1} = \beta_{jk1} + \beta_{jk2}Size_{jt-1} + \beta_{jk3}BM_{jt-1}, \tag{6}$$

where $Size_{jt-1}$ and BM_{jt-1} are the market capitalization and the book-to-market ratio at time t−1.[4]

The dependence of factor loadings on size and book-to-market is motivated by the general equilibrium model of Gomes, Kogan, and Zhang (2003), who justify separate roles for size and book-to-market as determinants of beta. In particular, firm size captures the component of a firm's systematic risk attributable to growth options, and the book-to-market ratio serves as a proxy for the risk of existing projects.

Subtracting the component of the excess returns associated with the factor realizations generates the risk-adjusted returns, R^*_{jt}:

$$R^*_{jt} = R_{jt} - R_{Ft} - \sum_{k=1}^{K} \beta_{jkt-1} F_{jk}, \tag{7}$$

where R_{Ft} is the risk-free rate, β_{jkt-1} is the conditional beta estimated by a first-pass time-series regression over the entire sample period.[5]

The risk-adjusted returns are then regressed on the equity characteristics:

$$R^*_{jt} = c_{0t} + \sum_{m=1}^{M} c_{mt} Z_{mjt} + e_{jt}, \tag{8}$$

where Z_{mjt} is the lagged one month value of the characteristic m for security j at time t, and M is the total number of characteristics. This procedure ensures unbiased estimates of the coefficients, c_{mt}, without the need to form portfolios, because the errors in estimation of the factor loadings are included in the dependent variable. The standard

[4]We also check the unconditional specification in which $\beta_{jk}(t) = \beta_{jk}$ (constant betas). The results are unaltered.

[5]Fama and French (1992) and Avramov and Chordia (2006) show that using the entire time series to compute the factor loadings generates qualitatively similar results to those obtained from using rolling regressions. The results are quite similar when we use rolling regressions to estimate the factor betas.

Fama-MacBeth (1973) estimators are the time-series averages of the regression coefficients, $\hat{c}_t$. While we use the risk-adjusted returns to estimate the regression coefficients for the main part of the paper, the results are substantially similar when we use alternative return definitions. These results are reported in section 5.3.

4.2.2 Regression Results

To examine the pricing effect of VOIB, we present the results considering order-imbalance-related control variables and other standard, well-known control variables in the literature. These control variables are:

1. OIB: Order imbalance, defined as in Section 3.1.
2. $POIB$: Positive order imbalance, the logistic transform of the ratio of number of days with positive OIB to the total number of trading days in a month.
3. $SIZE$: Measured as the natural logarithm of the market value of the firm's common equity (Banz (1981)).
4. BM: Book equity for the fiscal year-end in a calendar year divided by market equity at the end of December of that year, as in Fama and French (1992).
5. $R1$: The lagged one month return (Jegadeesh (1990)).
6. $R212$: The cumulative return on the stock over the eleven months ending at the beginning of the previous month (Jegadeesh and Titman (1993)).
7. $ILLIQ$: The Amihud illiquidity measure, defined as in Section 3.2.
8. $TURN$: Turnover ratio, defined as in Section 3.2.
9. $StdTURN$: Standard deviation of the monthly turnover over the past 36 months (Chordia, Subrahmanyam, and Anshuman (2001)).

All control variables are cross-sectionally winsorized at the 0.5% and 99.5% levels.

Table 3 presents the time-series averages of coefficient estimates in the monthly cross-sectional regressions and the associated Newey-West adjusted t-statistics. Different specifications are used. Columns 1 and 5 show the univariate regression result using either $VOIB\_NUM$ or $VOIB\_SHR$. In Columns 2 and 6, SIZE, BM, R212 and R1 are added as control variables. These characteristics are well known to impact returns and the idea behind including them in the Fama-MacBeth regressions is to check whether the impact of the OIB volatilites on returns survives after controlling for the above variables. In Columns 3 and 7, OIB and $POIB$ are also included to control for the reversal effect of the order imbalance. Columns 4 and 8 add $ILLIQ$, $TURN$ and $StdTURN$ as additional control variables. $ILLIQ$ and $TURN$ have been used as measures of (il)liquidity and by including them in the regressions, we want to check whether $VOIB\_NUM$ and $VOIB\_SHR$ provide additional information about the cross-section of returns. Recall that the model shows that the impact of noise trader volatility on order imbalance volatility is the opposite of that on lambda. Thus, we want to control for noise trader volatility. Since the amount of informed trading depends on noise trading, we use $StdTURN$ as a proxy for noise trader volatility.

The main takeaway from Table 3 is that the coefficient estimates of $VOIB\_NUM$ and $VOIB\_SHR$ are always positive and significant regardless of the control variables and even in the presence of the Amihud illiquidity measure as well as turnover. A one-standard deviation change in $VOIB\_NUM$ ($VOIB\_SHR$) is associated with an increase of about 14 (22) basis points in the next month's return, amounting to 1.7% (2.6%) per year.

(Table 3 about here)

5 Shocks to volatility of OIB and stock returns

Having documented the pricing effect of the proposed liqudity measure, $VOIB$, we turn to the shock to this liquidity measure in this section. We first present the portfolio sort results and then show the Fama-MacBeth regressions results.

5.1 Portfolio Sorts

At the end of each month t, we sort stocks into quintile portfolios based on $SVOIB\_NUM$, $SVOIB\_SHR$, $SILLIQ$, $STURN$, and $SSPRD$, respectively. Panel A in Table 4 shows the average raw returns of the quintile portfolios, the return differences, and FF alphas in the current and the following month.

(Table 4 about here)

Shocks to volatility of order imbalance are negatively correlated with the contemporaneous returns. The return difference between the high and low shocks to OIB volatility is over 2.5% per month with a t-statistic of over 12 for both $SVOIB\_NUM$ and $SVOIB\_SHR$. Consistent with Bali, Peng, Shen, and Tang (2014), we find that all of the other liquidity shocks measured using traditional methods also have large and significant impact on the contemporaneous stock prices. A decrease in liquidity is negatively correlated with returns.

All of the liquidity shocks predict the next month's returns too. The raw return differential between stocks in the highest and the lowest $SVOIB\_NUM$ ($SVOIB\_SHR$) quintile is -0.52% (-0.33%) in the following month. The raw return differential between stocks in the highest and the lowest $SILLIQ$ ($STURN$) quintile is -1.16% (0.98%) in the following month. These return differentials and the FF alphas in the last row are all statistically significant at the 5% level.

In order to ascertain whether $SVOIB\_NUM$ and $SVOIB\_SHR$ have any information over and above that contained in $SILLIQ$, $STURN$ and $SSPRD$, in Table 5 we provide results from bivariate sorts. We first sort stocks into high and low groups in month t based on $SILLIQ$, $STURN$, and $SSPRD$, respectively. Then within each group, we sort stocks based on $SVOIB\_NUM$ and $SVOIB\_SHR$ into quintile portfolios. Returns in month t+1 are reported. Similar to the bivariate sort results for $VOIB$, the predictive ability of SVOIB is not captured by shocks to the traditional liquidity measures. For $SVOIB\_NUM$ the return differentials and the Fama-French alphas across the quintile porfolios for high and low values of $SILLIQ$, $STURN$ and $SSPRD$ are all significant at the 5% level. In the case of $SVOIB\_SHR$ all the return differentials and the Fama-French alphas are also significant at the 5% level. The only exceptions are the return differential and the Fama-French alpha for the high $SILLIQ$ portfolio which are significant at the 10% level.

While the bivariate sorts do provide support for the idea that $SVOIB\_NUM$ and $SVOIB\_SHR$ capture shocks to liquidity that are not contained in the traditional measures of liquidity, we now explore this idea in more detail in a regression framework.

5.2 Regression Results

This subsection examines the impact of the shocks to OIB volatility on the cross-section of returns from the Fama-MacBeth regressions. Table 6 presents the time-series averages of the cross-sectional coefficient estimates from the regressions. We consider a long list of controls beyond those listed in Section 4.2.2.

1. $IVOL$: Idiosyncratic volatility, as in Ang, Hodrick, Xing, and Zhang (2006), computed as the standard deviation of the regression residual of the Fama and French (1993) three-factor model using daily data within a month.

2. $SStdTURN$: Shocks to $StdTURN$, defined as the difference between $StdTURN$ in the current month and its moving average in the previous six months.

3. ACC: Accounting accruals, defined as the change in non-cash current assets, less the change in current liabilities (exclusive of short-term debt and taxes payable), less depreciation expense, all divided by average total assets (Sloan (1996)).

4. AG: Asset growth, as in Cooper, Gulen, and Schill (2008), computed as the year-on-year percentage change in total assets.

5. $ISSUE$: New issues, as in Pontiff and Woodgate (2008), measured as the change in shares outstanding from the eleven months ago.

6. $PROFIT$: Profitability, as in Fama and French (2006), calculated as earnings divided by book equity, where earnings is defined as income before extraordinary items.

7. SUE: Standardized unexpected earnings, computed as the most recently announced quarterly earnings less the earnings four quarters ago, standardized by its standard deviation estimated over the prior eight quarters. This is used to proxy for earnings surprises, in order to analyze post-earnings-announcement-drift (PEAD) as in Bernard and Thomas (1989, 1990), and Ball and Brown (1968).

8. MAX: The maximum daily return in the last month, as in Bali, Cakici, and Whitelaw (2011). This variable is included to capture the notion that large returns may be associated with extreme order imbalance.

9. $DISP$: Analyst earnings forecast dispersion, as in Diether, Malloy, and Scherbina (2002), computed as the standard deviation of annual earnings-per-share forecasts scaled by the absolute value of the average outstanding forecast. This variable is

included to address the concern that VOIB can also capture the divergent opinions among investors.

10. $DISPD$: Dummy variable which equals to one if the stock is covered by less than two analysts and zero otherwise.[6]

11. $SSTT$: defined as the small-trade buy-initiated turnover minus the small-trade sell-initiated turnover, measured over the previous six months. Hvidkjaer (2008) suggests that this measure proxies for trading by individual investors.

Again, we winsorize all of the above controls at the 0.5% and 99.5% levels.

We include either $SVOIB\_NUM$ or $SVOIB\_SHR$ in all the regressions, but selectively add firm-level characteristics to the cross-sectional regressions. As we add variables to the cross-sectional regressions, due to the additional data requirements, the sample size decreases from an average of 1595 firms to 1129 firms per month.

Quite a few firm-level characteristics have significant coefficients. The negative coefficient on the one month lagged return is consistent with the reversal effect documented by Jegadeesh (1990). The negative coefficient on analyst forecast dispersion is consistent with Diether, Malloy and Scherbina (2002). Inclusion of analyst forecast dispersion, $DISP$, and shocks to $DISP$ serves to allay that order imbalance volatility is related to disagreement among investors. The negative coefficient on $SSTT$ is consistent with the reversal of returns in response to retail order flow as documented by Barber, Odean, and Zhu (2009) and Hvidkjaer (2008). Stocks heavily bought by retail investors significantly underperform stocks heavily sold by retail investors. The positive coefficient on turnover is consistent with Gervais, Kaniel and Mingelgrin (2002). The negative coefficients on

[6] If there is no or only one analyst forecast in I/B/E/S database, then DISP is missing. The missing DISP reduces the sample by 25%. We include this dummy variable to prevent losing more stocks from the sample.

$StdTURN$, $ISSUE$, and $PROFIT$ are also consistent with prior research. In our sample, we do not find any cross-sectional impact on returns due to accruals, asset growth, earnings and price momentum, book-to-market ratio, the past month's maximum return, order imbalances or shocks to order imbalances, turnover and the volatility of turnover. Note also that in the presence of $SVOIB\_NUM$ or $SVOIB\_SHR$ and $SILLIQ$, the impact of the volatility of OIB and of $ILLIQ$ on stock returns is also not robust.

The main result from this table is the highly significant and robust impact of $SVOIB\_NUM$ and $SVOIB\_SHR$ on the cross-section of returns. The negative coefficient on the shocks to OIB volatilities suggests that a shock that increases illiquidity is accompanied by negative returns in the cross-section. In economic terms, a one-standard deviation increase in $SVOIB\_NUM$ ($SVOIB\_SHR$) this month leads to a 19.04 (8.44) basis points decrease in next month's return. In annual terms a one-standard deviation increase in $SVOIB\_NUM$ ($SVOIB\_SHR$) reduces stock returns by 2.28% (1.01%).

(Table 6 about here)

Overall, we also observe that many firm-level characteristics have an insignificant or weak impact on returns in our sample period. This is consistent with the notion that anomalies documented in the earlier studies have attenuated due to increased arbitrage in the recent era of high liquidity and trading activity (Chordia, Subrahmanyam, and Tong (2014)). However, $SVOIB\_NUM$ and $SVOIB\_SHR$ have a very strong effect on stock returns during this sample period.

5.3 Robustness Checks

In this subsection, we show that the pricing effect from $SVOIB\_NUM$ and $SVOIB\_SHR$ is robust by experimenting with different return definitions, different order imbalance definitions, and different subsample periods. Tables 7 and 8 present the results. The control variables are the same as in Columns 3 and 6 of Table 6.

(Tables 7 and 8 about here)

In the first column of Table 7 we use raw returns instead of the risk adjusted returns as the dependent variable. To avoid the effect of the bid-ask bounce, in the second column, we use open-to-close mid-quote returns as the dependent variable. The open-to-close mid-quote returns are computed using the opening bid-ask midpoint price on the first trading day of the month and the closing bid-ask midpoint price on the last trading day of the month, adjusted for dividends and stock splits. In Column 3, we use dollar trading volume to compute the order imbalance variables. We define OIB as estimated buyer-initiated minus seller-initiated dollar volume scaled by the total dollar volume during the month. Then volatility of OIB and shocks to volatility of OIB are computed as before.[7] In Column 4, volatility of OIB is calculated as the three-month moving average of the standard deviation of daily OIB and all shock variables are calculated using three-month moving averages accordingly. In Column 5, we exclude the financial crisis years of 2008 and 2009. Column 6 uses data after January 2001 only (post-decimalization period) and Column 7 presents results for the period before January 2001 (pre-decimalization period).

In Table 7, the coefficient estimates for $SVOIB\_NUM$ are about the same as those in Table 6. The only exception is in Model 3 when order imbalances are computed using dollars traded. Note that if, during any given day, the prices of buys and sells are about the same then OIB based on dollars traded will the same as that with shares traded. Thus, it is not surprising that the coefficient estimate of the shock to volatility of OIB with OIB computed using dollars traded is close to the coefficient estimate of the shock to volatility of OIB with OIB computed using shares traded.

[7] Table 8 does not repeat the analysis with order imbalance defined in terms of dollars and thus has one fewer column than Table 7.

In Table 8, the coefficient estimates for $SVOIB\_SHR$ are also about the same as those in Table 6. The only exception is the lower and statistically insignificant coefficient in the post-decimalization period. The coefficient in the pre-decimalization period is consequently higher than that in Table 6.

Overall, the negative impact of $SVOIB\_NUM$ and $SVOIB\_SHR$ on the cross-section of returns is robust to a number of different specifications. Any shock that increases illiquidity is accompanied by negative returns.

5.4 Absorption of Order Imbalance Volatility Shocks in the Cross-Section

Thus far we have presented robust evidence of the negative impact of shocks order flow volatility on the cross-section of returns. Could it be the case that these shocks are stronger for stocks that have a poor informational environment, such as small stocks, stocks with small or no analyst coverage ($ANALYST$), stocks which have low institutional holding ($INST$) or stocks with high idiosyncratic volatility (IVOL)? These stocks are generally considered difficult to trade with high transactions costs and are likely to have less arbitrage activity. In other words these stocks are those that are likely to run into limits of arbitrage.

We obtain institutional holding and the number of analysts making one-year forecasts from Thomson Reuters. In Table 9, we first sort stocks by the arbitrage variables (firm size, analyst coverage, institutional holding, and idiosyncratic volatility) into high and low categories and then within each category we sort by $SVOIB\_NUM$ and $SVOIB\_SHR$ into quintiles. Table 9 presents the long-short quintile portfolio return and the long-short Fama-French three factor alpha.

(Table 9 about here)

Panel A shows that for small firms, the long-short differential return (Fama-French alpha) between the high and low $SVOIB\_SHR$ portfolio is -0.53% (-0.47%) both significant at the 1% level. For large firms, the differential return and the Fama-French alpha at -0.02% (-0.06%) is statistically and economically insignificant. Similar results hold for $SVOIB\_NUM$. Thus, the impact of a shock to liquidity is prevalent only in the small stocks probably because in the case of large stocks, liquidity suppliers are more willing to step in to provide liquidity and absorb the shocks.

Panels B and C present the results for analyst coverage and institutional holding. Once again, the impact of a liquidity shock is orders of magnitude larger and statistically significant only for stocks followed by fewer analysts and with low institutional holding. Panel D presents the results sorted on $IVOL$. Even though the long-short differential return and the Fama-French alpha is statistically and economically significant for both the high and low $IVOL$ stocks, the differential return and the Fama-French alpha is more than twice as large for the high $IVOL$ stocks.

Overall, the results are consistent with shocks to liquidity being more easily absorbed by arbitrageurs / liquidity suppliers in the case of large stocks, stocks followed by more analysts, stocks with higher institutional holding and stocks with lower $IVOL$, possibly because these stocks have lower trading costs and a position in these stocks is easier to liquidate at lower cost and lower price impact.

6 Dynamics of Shocks to Order Flow Volatility

The central prediction of the illiquidity premium hypothesis on asset prices is that investors would like to pay lower prices for illiquid stocks. Therefore, a shock that lowers liquidity (proxied here by a positive shock to order flow volatility) should lower the spot price of the asset and thus increase the expected return. Thus far, we have documented that $SVOIB\_NUM$ and $SVOIB\_SHR$ negatively impact the contemporaneous and the following month's stock price. Also, $VOIB\_NUM$ and $VOIB\_SHR$ are positively related to returns in the cross-section. So liquidity shocks do result in lower concurrent prices and more illiquid stocks do earn a premium. A question is how long does it take for the impact of $SVOIB\_NUM$ and $SVOIB\_SHR$ on returns to turn positive, as predicted by the illiquidity premium argument. This subsection examines the return dynamics of the shocks to liquidity.

Panel A of Table 10 reports the univariate portfolio results as well as the Fama-MacBeth coefficients. For the univariate portfolio results we sort stocks into quintile portfolios based on one of $SVOIB\_NUM$, $SVOIB\_SHR$ and $SILLIQ$ and report the Fama-French alphas of the long-short portfolio over time. We report the results over months 2-3, 4-6, and 7-12. When sorting on $SVOIB\_NUM$ and $SVOIB\_SHR$ the long-short Fama-French alphas are essentially zero over months 2-3 and over months 4-6 but they are positive and statistically significant over months 7-12. This suggests that it takes about six months for the liquidity shock to be absorbed into prices and for investors to start earning the illiquidity premium. The overall illiquidity premium due to the liquidity shocks amounts to about 0.27% (0.29%) for shocks measured as $SVOIB\_NUM$ ($SVOIB\_SHR$).

When sorting on $SILLIQ$ the negative impact of the initial shock is felt in months 2-3 (Fama-French alpha=-0.176% with t-statistic=-1.80) as well after which the Fama-French alphas are indistinguishable from zero. This result for $SILLIQ$, while consistent with Bali, Peng, Shen and Tang (2014),[8] suggests that liquidity shocks as measured by $SILLIQ$ do not cause a sufficient drop in prices such that eventually the illiquidity premium obtains. Thus, the illiquidity premium due to ILLIQ in Tables 2 and 3, does not result from stocks that receive the liquidity shocks but is an outcome of the liquidity

[8]See Figure 1 and Table 9 for predicting long-term stock returns in Bali, Peng, Shen, and Tang (2014).

differences between stocks that do not receive the liquidity shock.

Panel A of Table 10 also reports the Fama-MacBeth (FM) coefficients with future returns as the dependent variables and when all the control variables are included as in Table 6 but with only one of $SVOIB\_NUM$, $SVOIB\_SHR$ and $SILLIQ$ as a measure of the shock to liquidity. The FM coefficients for $SVOIB\_NUM$ and $SVOIB\_SHR$ are positive for the future risk adjusted returns over months 7-12. Interestingly, after including all the control variables in Table 6 (except for $SVOIB\_NUM$ and $SVOIB\_SHR$) the coefficients of SILLIQ are negative for all future risk adjusted returns and are statistically significant over months 4-6.

(Table 10 about here)

Panels B, C, D and E of Table 10 present the Fama-MacBeth (FM) coefficients when the dependent variable is future returns and when all the control variables are included as in Table 6. Recall that either $SVOIB\_NUM$ or $SVOIB\_SHR$ is included along with $SILLIQ$ in Table 6. Also, we sort on the variables from Table 9 that proxy for the limits to arbitrage. In Panel B we examine the dynamic impact of the liquidity shocks to small and large firms; in Panel C we examine the impact on firms with high and low analyst coverage; in Panel D we sort on institutional ownership and in Panel E we sort on idiosyncratic volatility.

Consider first the small stocks, stocks with low analyst coverage, low institutional holdings and high idiosyncratic volatility. These are the stocks with higher transactions costs, a poor informational environment and, thus, lower arbitrage activity. For these stocks there is some evidence that the liquidity shock is not immediately impounded into prices but persists for a few months. For instance, in the case of small stocks the coefficient of the regression of future returns in months 2-3 (4-6) on $SVOIB\_SHR$ is -2.09 (-1.16) with a t-statistic of -3.51 (-2.23). Similarly, for high IVOL stocks the regression coefficient in months 2-3 on $SVOIB\_NUM$ ($SVOIB\_SHR$) is -1.47 (-1.55) with a t-statistic of -1.78 (-2.09). More importantly in all these cases, the coefficient estimates in months 7-12 are positive and significant suggesting that, for these stocks, shocks to liquidity eventually result in a positive illiquidity premium in the cross-section.

Turning now to large stocks, stocks with high analyst coverage, high institutional holdings and low idiosyncratic volatility, we see that there is no spillover of the negative impact of the shock to liquidity on future returns. There is some evidence of a positive coefficient for future returns but this is not robust across the different sorts. Thus, for the low trading cost stocks that are likely to be subject to more arbitrage activity, the impact of a liquidity shock is quickly impounded into prices and there is weak evidence that the liquidity shocks eventually lead to a positive illiquidity premium. It is not surprising to find that shocks to liquidity are absorbed more easily in the case of large stocks, stocks with high analyst coverage, high institutional holdings and low idiosyncratic volatility.

It is puzzling that the coefficient on $SILLIQ$ surprisingly does not turn positive even after 12 months. This finding suggests that shocks to $SILLIQ$ have an initial negative impact on future returns, but the effect does not convert to a standard liquidity premium in the longer term, unlike our $SVOIB$ coefficients. The discrepancy between $SILLIQ$ and $SVOIB$ deserves attention in future research.

7 Conclusion

Both liquidity and the volatility of order flow are driven by the same exogenous parameters in models of illiquidity such as that of Kyle (1984, 1985). Since illiquidity proxies are necessarily imperfect, we instead consider the dynamics of order flow volatility and relate it to illiquidity metrics and the cross-section of expected stock returns.

Interestingly, we find that shocks to order flow volatility are strongly and negatively related to current and future illiquidity, and are also negatively related to both current and next month's returns. This finding is consistent with the notion that positive shocks to order flow increase true (unobserved) illiquidity which translates to a drop in current prices.

Markets are resilient in the sense that shocks to order imbalance volatility are quickly absorbed into prices. Even for small stocks, stocks with low analyst coverage, low institutional holdings and high idiosyncratic volatility it takes at most six months for the impact of these shocks to be incorporated into prices.

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Table 1: Summary statistics of order imbalance variables

Panel A presents the time-series averages of the cross-sectional statistics for common stocks listed on NYSE and AMEX from January 1993 to December 2012. The stock-month observation must have valid information to calculate the return, market capitalization, book-to-market ratio, and order imbalance, and has the month-end prices above one dollar. OIB_NUM is the monthly order imbalance defined as $(B - S)/(B + S)$, where B (S) is the number of trades initiated by buyers (sellers). $VOIB\_NUM$ is the six-month moving average of the standard deviation of daily OIB_NUM in a month. $SVOIB\_NUM$ is the difference between the standard deviation of daily OIB_NUM in a month and $VOIB\_NUM$ in the previous month. The variables calculated using the number of shares traded are termed as OIB_SHR, $VOIB\_SHR$, and $SVOIB\_SHR$. Panel B presents the time-series averages of the monthly cross-sectional correlations. The Amihud illiquidity ($ILLIQ$) is calculated as the monthly average of the ratio of the daily absolute return to daily dollar volume. Turnover ($TURN$) is the logarithm of the monthly share trading volume divided by shares outstanding. Spread ($SPRD$) is the proportional quoted spread, calculated as the monthly averages of all observations for each stock. The shocks to the Amihud illiquidity ($SILLIQ$), turnover ($STURN$), and spread ($SSPRD$) are computed similarly to $SVOIB$. RET is the monthly stock return. The corresponding z-statistics are reported in parentheses.

Panel A: Descriptive statistics

Statistics	N	Mean	St. dev.	Median	Minimum	Maximum
OIB_NUM	1645	0.015	0.120	0.027	-0.490	0.375
$VOIB\_NUM$	1614	0.239	0.155	0.186	0.059	0.798
$SVOIB\_NUM$	1595	-0.003	0.058	-0.004	-0.357	0.284
OIB_SHR	1645	0.014	0.151	0.031	-0.617	0.460
$VOIB\_SHR$	1614	0.303	0.156	0.258	0.092	0.826
$SVOIB\_SHR$	1595	-0.005	0.062	-0.006	-0.363	0.270

Panel B: Correlations

	$ILLIQ$	$TURN$	$SPRD$	$SILLIQ$	$STURN$	$SSPRD$	RET
$VOIB\_NUM$	0.393	-0.639	0.634	-0.045	0.005	-0.040	0.023
	(67.95)	(-71.39)	(43.40)	(-4.32)	(0.77)	(-2.43)	(4.24)
lag($VOIB\_NUM$)	0.383	-0.626	0.628	-0.050	0.017	-0.051	0.028
	(65.10)	(-69.03)	(43.21)	(-4.76)	(2.70)	(-3.09)	(5.15)
$SVOIB\_NUM$	0.088	-0.133	0.044	0.173	-0.169	0.158	-0.094
	(14.62)	(-19.76)	(4.33)	(33.90)	(-42.94)	(22.06)	(-20.73)
lag($SVOIB\_NUM$)	0.050	-0.069	0.043	0.105	-0.075	0.138	-0.019
	(8.53)	(-10.11)	(4.22)	(20.38)	(-25.92)	(20.51)	(-5.66)
$VOIB\_SHR$	0.382	-0.641	0.627	-0.046	0.007	-0.045	0.024
	(58.97)	(-73.98)	(39.81)	(-4.51)	(1.07)	(-2.75)	(4.36)
lag($VOIB\_SHR$)	0.374	-0.630	0.622	-0.049	0.018	-0.054	0.030
	(56.36)	(-71.49)	(39.36)	(-4.75)	(2.80)	(-3.25)	(5.30)
$SVOIB\_SHR$	0.080	-0.106	0.045	0.155	-0.158	0.155	-0.094
	(15.08)	(-17.81)	(4.61)	(33.03)	(-40.98)	(21.61)	(-21.05)
lag($SVOIB\_SHR$)	0.048	-0.066	0.045	0.097	-0.077	0.137	-0.011
	(8.73)	(-10.78)	(4.57)	(19.63)	(-26.98)	(19.82)	(-3.12)

Table 2: Portfolio sorts for VOIB

In Panel A, for each month from January 1993 to December 2012, we sort all stocks in the sample into five quintile portfolios based on *OIB_NUM*, *OIB_SHR*, *VOIB_NUM*, *VOIB_SHR*, *ILLIQ*, *TURN* and *SPRD* at month t and report the equally-weighted portfolio returns in month t+1. *OIB_NUM* is the monthly order imbalance defined as $(B - S)/(B + S)$, where B (S) is the number of trades initiated by buyers (sellers). *VOIB_NUM* is the six-month moving average of the standard deviation of daily *OIB_NUM* in a month. Variables calculated using the number of shares traded are termed *OIB_SHR* and *VOIB_SHR*. *ILLIQ* represents Amihud measure of illiquidity. Turnover (*TURN*) is the logarithm of the monthly share trading volume divided by shares outstanding. Spread (*SPRD*) is the proportional quoted spread, calculated as the monthly averages of all observations for each stock. The return difference between the high and low quintiles and the alpha with respect to the Fama-French (1993) factors are also reported with Newey-West t-statistics in parentheses. In Panel B, we first sort stocks into high and low groups based on *ILLIQ*, *TURN*, and *SPRD* separately and then sort on *VOIB_NUM* into quintile portfolios in each group at month t. Portfolio returns and return differences in month t+1 are reported. In Panel C, we perform the double sorting analysis using *VOIB_SHR*. All returns are reported in percent. *,**, and *** denote statistical significant at the 10%, 5%, and 1% level, respectively.

Panel A: Univariate sorts

Quintile	OIB_NUM	OIB_SHR	VOIB_NUM	VOIB_SHR	ILLIQ	TURN	SPRD
Low-1	1.414	1.449	0.917	0.866	0.869	1.070	0.887
2	1.136	1.245	0.983	0.970	1.003	1.077	1.033
3	1.041	1.073	0.980	0.998	1.189	1.149	1.074
4	0.970	0.914	1.223	1.276	1.204	1.193	1.101
High-5	1.083	0.964	1.441	1.431	1.379	1.173	1.457
High−Low	-0.331**	-0.485***	0.524**	0.565***	0.510*	0.103	0.570*
	(-2.19)	(-4.64)	(2.35)	(2.70)	(1.86)	(0.49)	(1.82)
FF	-0.385***	-0.539***	0.540***	0.620***	0.329**	-0.299*	0.276
	(-2.77)	(-5.33)	(3.43)	(4.10)	(1.99)	(-1.83)	(1.55)

Panel B: Bivariate sorts on VOIB_NUM

	ILLIQ		TURN		SPRD	
Quintile	Low	High	Low	High	Low	High
Low-1	0.823	1.141	0.872	0.885	0.799	1.007
2	0.987	1.090	0.922	0.994	1.032	1.089
3	0.960	1.176	0.983	0.957	0.940	1.173
4	0.977	1.419	1.163	1.114	1.004	1.376
High-5	1.112	1.484	1.420	1.904	1.111	1.455
High−Low	0.343**	0.424**	0.522**	0.900***	0.338**	0.571***
	(2.52)	(2.25)	(2.18)	(3.66)	(2.24)	(2.82)
FF	0.411***	0.906***	0.474**	0.733***	0.372***	1.091***
	(4.29)	(4.45)	(2.53)	(4.14)	(3.40)	(5.64)

Panel C: Bivariate sorts on VOIB_SHR

	ILLIQ		TURN		SPRD	
Quintile	Low	High	Low	High	Low	High
Low-1	0.856	1.072	0.853	0.884	0.867	0.954
2	0.897	1.211	0.953	0.891	0.934	1.125
3	0.999	1.152	0.982	0.972	0.932	1.156
4	0.974	1.416	1.186	1.221	1.018	1.406
High-5	1.132	1.460	1.387	1.885	1.134	1.460
High−Low	0.298*	0.492***	0.468**	0.913***	0.257*	0.643***
	(1.94)	(2.62)	(2.10)	(4.20)	(1.67)	(3.12)
FF	0.451***	0.983***	0.431**	0.803***	0.341***	1.173***
	(4.20)	(4.99)	(2.38)	(5.14)	(3.37)	(5.89)

Table 3: Fama-MacBeth regression estimates for $VOIB$

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates between January 1993 to December 2012. The dependent variable is the risk-adjusted return calculated using the Fama-French (1993) factors with loadings conditional on size and book-to-market ratio. All independent variables (except $R1$ and $R212$) are lagged one month. OIB is the monthly order imbalance defined as $(B-S)/(B+S)$, where B (S) is the trades initiated by buyers (sellers). $VOIB$ is the six-month moving average of the standard deviation of daily OIB in a month. $POIB$ is the logistic transform of the ratio of number of days with positive OIB and total number of days in the month. The order imbalance is calculated using the number of trades in Columns 1 to 4 and using number of shares traded in Columns 5 to 8. $SIZE$ represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio. $R1$ is the lagged one month return. $R212$ is the cumulative returns over the second through twelfth months prior to the current month. $ILLIQ$ represents Amihud measure of illiquidity. Turnover ($TURN$) is the logarithm of the monthly share trading volume divided by shares outstanding. $StdTURN$ is the standard deviation of $TURN$ in the past 36 months. All variables are winsorized at the 0.5% and 99.5% levels. Newey-West t-statistics are reported in parentheses. *,**, and *** denote statistical significant at the 10%, 5%, and 1% level, respectively.

	$VOIB\_NUM$				$VOIB\_SHR$			
Model	1	2	3	4	5	6	7	8
Intercept	-0.137	-0.102	-0.010	0.597	-0.232	-0.326	-0.312	0.057
	(-1.13)	(-0.17)	(-0.02)	(1.06)	(-1.61)	(-0.48)	(-0.46)	(0.09)
$VOIB$	1.093***	1.050**	0.868**	0.892**	1.152***	1.220**	1.104**	1.399**
	(3.34)	(2.35)	(2.11)	(1.97)	(3.53)	(2.51)	(2.24)	(2.46)
$SIZE$		-0.012	-0.013	-0.125		-0.005	-0.002	-0.059
		(-0.32)	(-0.35)	(-0.27)		(-0.14)	(-0.05)	(-1.58)
BM		0.037	0.039	-0.105***		0.034	0.035	0.008
		(0.75)	(0.78)	(-2.63)		(0.68)	(0.69)	(0.17)
$R212$		-0.085	-0.053	-0.082**		-0.079	-0.052	-0.215
		(-0.24)	(-0.15)	(-2.29)		(-0.23)	(-0.15)	(-0.63)
$R1$		-0.029***	-0.028***	0.015		-0.028***	-0.028***	-0.029***
		(-5.28)	(-5.06)	(0.32)		(-5.26)	(-5.07)	(-4.95)
OIB			-0.377	-0.208			-0.286	-0.018
			(-0.88)	(-0.61)			(-1.35)	(-0.07)
$POIB$			-0.060	-0.029***			-0.044	-0.087**
			(-1.53)	(-4.88)			(-1.24)	(-2.38)
$ILLIQ$				1.509***				1.457***
				(3.13)				(3.05)
$TURN$				0.489***				0.513***
				(6.47)				(6.93)
$StdTURN$				-0.504***				-0.491***
				(-7.11)				(-6.89)
Adj. R-sq.	0.003	0.023	0.025	0.033	0.003	0.024	0.025	0.033
N	1614	1602	1602	1436	1614	1602	1602	1436

Table 4: Portfolio sorts for liquidity shocks

For each month from January 1993 to December 2012, we sort all stocks in the sample into quintile portfolios based on $SVOIB\_NUM$, $SVOIB\_SHR$, $SILLIQ$, $STURN$, and $SSPRD$ at month t. $VOIB\_NUM$ is the six-month moving average of the standard deviation of daily OIB_NUM in a month, where OIB_NUM is defined as $(B-S)/(B+S)$ with B (S) being the number of trades initiated by buyers (sellers). $SVOIB\_NUM$ is the difference between the standard deviation of daily OIB_NUM in a month and $VOIB\_NUM$ in the last month. The shock to order flow volatility calculated using the number of shares traded is termed $SVOIB\_SHR$. $ILLIQ$ represents Amihud measure of illiquidity. Turnover ($TURN$) is the logarithm of the monthly share trading volume divided by shares outstanding. Spread ($SPRD$) is the proportional quoted spread, calculated as the monthly averages of all observations for each stock. $SILLIQ$, $STURN$, and $SSPRD$ are the shocks to $ILLIQ$, $TURN$, and $SPRD$ calculated similarly to $SVOIB$. The equally-weighted portfolio returns are reported for the contemporaneous month in Panel A and for the next month in Panel B. The return difference between the high and low deciles and the alpha with respect to the Fama-French (1993) factors are also reported with Newey-West t-statistics in parentheses. All returns are reported in percent. *,**, and *** denote statistical significant at the 10%, 5%, and 1% level, respectively.

Panel A: Contemporaneous returns

Quintile	$SVOIB\_NUM$	$SVOIB\_SHR$	$SILLIQ$	$STURN$	$SSPRD$
Low-1	2.955	3.008	4.258	-0.415	4.326
2	1.194	1.246	2.076	0.684	2.092
3	0.903	0.927	0.961	1.028	0.947
4	0.784	0.726	0.077	1.462	0.169
High-5	0.282	0.297	-1.057	3.633	-1.12
High−Low	-2.673***	-2.711***	-5.315***	4.048***	-5.446***
	(-12.10)	(-12.56)	(-21.92)	(10.63)	(-20.01)
FF	-2.515***	-2.555***	-5.481***	3.647***	-5.472***
	(-12.97)	(-14.28)	(-23.75)	(12.91)	(-19.61)

Panel B: Next month's returns

Quintile	$SVOIB\_NUM$	$SVOIB\_SHR$	$SILLIQ$	$STURN$	$SSPRD$
Low-1	1.512	1.406	1.833	0.716	1.486
2	1.114	1.058	1.202	0.956	1.060
3	0.933	1.096	0.899	0.990	0.846
4	0.998	1.001	0.995	1.273	0.986
High-5	0.989	1.072	0.676	1.697	1.163
High−Low	-0.524***	-0.334**	-1.157***	0.981***	-0.323*
	(-2.99)	(-2.14)	(-5.55)	(6.06)	(-1.85)
FF	-0.586***	-0.356**	-1.356***	1.042***	-0.420***
	(-3.39)	(-2.55)	(-7.53)	(6.69)	(-2.61)

Table 5: Bivariate portfolio sorts based on $SVOIB$ and other liquidity shocks

For each month from January 1993 to December 2012, we first sort stocks into high and low groups based on $SILLIQ$, $STURN$, and $SSPRD$ separately and then sort on $SVOIB$ into quintile portfolios in each group at month t. $VOIB$ is the six-month moving average of the standard deviation of daily OIB in a month, where OIB is the monthly order imbalance defined as $(B-S)/(B+S)$ with B (S) being the trades initiated by buyers (sellers). $SVOIB$ is the difference between the standard deviation of daily OIB in a month and $VOIB$ in the last month. The order imbalance is calculated using the number of trades in Panel A and using number of shares traded in Panel B. $ILLIQ$ represents Amihud measure of illiquidity. Turnover ($TURN$) is the logarithm of the monthly share trading volume divided by shares outstanding. Spread ($SPRD$) is the proportional quoted spread, calculated as the monthly averages of all observations for each stock. $SILLIQ$, $STURN$, and $SSPRD$ are the shocks to $ILLIQ$, $TURN$, and $SPRD$ calculated similarly to $SVOIB$. The equally-weighted portfolio returns in both month t and month $t+1$ are reported. The return difference between the high and low deciles and the alpha with respect to the Fama-French (1993) factors are also reported with Newey-West t-statistics in parentheses. All returns are reported in percent. *,**, and *** denote statistical significant at the 10%, 5%, and 1% level, respectively.

Panel A: Bivariate sorts on SVOIB_NUM

	SILLIQ		STURN		SSPRD	
Quintile	Low	High	Low	High	Low	High
Low-1	1.887	0.893	1.040	1.880	1.619	1.374
2	1.389	0.965	0.934	1.314	1.142	1.037
3	1.240	0.716	0.853	1.139	1.104	0.812
4	1.197	0.937	0.885	1.187	1.021	1.006
High-5	1.238	0.720	0.752	1.257	1.018	0.910
High−Low	-0.531***	-0.252**	-0.425***	-0.554***	-0.577***	-0.558***
	(-3.95)	(-2.07)	(-3.70)	(-4.14)	(-4.94)	(-4.03)
FF	-0.541***	-0.240**	-0.404***	-0.575***	-0.562***	-0.584***
	(-4.24)	(-1.98)	(-3.52)	(-4.30)	(-4.82)	(-4.28)

Panel B: Bivariate sorts on SVOIB_SHR

	SILLIQ		STURN		SSPRD	
Quintile	Low	High	Low	High	Low	High
Low-1	1.687	0.937	1.024	1.718	1.504	1.238
2	1.264	0.893	0.875	1.305	1.084	1.028
3	1.374	0.795	0.878	1.146	1.118	0.957
4	1.264	0.856	0.866	1.216	1.085	0.972
High-5	1.361	0.749	0.821	1.391	1.112	0.944
High−Low	-0.273**	-0.247*	-0.296**	-0.268**	-0.342***	-0.384***
	(-2.19)	(-1.79)	(-2.38)	(-2.08)	(-3.09)	(-3.38)
FF	-0.241**	-0.235*	-0.295***	-0.237**	-0.330***	-0.373***
	(-2.04)	(-1.87)	(-2.60)	(-1.98)	(-2.99)	(-3.42)

Table 6: Fama-MacBeth regression estimates for $SVOIB$

This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates between January 1993 to December 2012. The dependent variable is the risk-adjusted return calculated using the Fama-French (1993) factors with loadings conditional on size and book-to-market ratio. All independent variables (except $R1$ and $R212$) are lagged one month. OIB is the monthly order imbalance defined as $(B-S)/(B+S)$, where B (S) is the trades initiated by buyers (sellers). $VOIB$ is the six-month moving average of the standard deviation of daily OIB in a month. $POIB$ is the logistic transform of the ratio of number of days with positive OIB and total number of days in the month. $SVOIB$ is the difference between the standard deviation of daily OIB in a month and $VOIB$ in the last month. The order imbalance is calculated using the number of trades in Columns 1 to 3 and using number of shares traded in Columns 4 to 6. $SIZE$ represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio. $R1$ is the lagged one month return. $R212$ is the cumulative returns over the second through twelfth months prior to the current month. $TURN$ is the logarithm of the monthly share trading volume divided by shares outstanding. $StdTURN$ is the standard deviation of $TURN$ in the past 36 months. Illiquidity represents Amihud measure of illiquidity. ACC represents accruals, measured as in Sloan (1996). AG is the asset growth computed in Cooper, Gulen and Shill (2008). $ISSUE$ represents new issues as in Pontiff and Woodgate (2008). $IVOL$ is the idiosyncratic volatility computed as in Ang, Hodrick, Xing, and Zhang (2006). $PROFIT$ is the profitability variable as in Fama and French (2006). SUE is the standardized unexpected earnings, computed as the most recently announced quarterly earnings less the earnings four quarters ago, standardized by its standard deviation estimated over the prior eight quarters. MAX is the maximum daily return in the last month. $DISP$ is the analyst dispersion in earnings forecasts and $DISPD$ is a dummy that equals to one if the stock is covered by less than two analysts and zero otherwise. $SSTT$ is the small size trade imbalance as in Hvidkjaer (2008). $SOIB$, $SPOIB$, $STURN$, $SStdTURN$, $SILLIQ$, and $SDISP$ are defined similarly as $SVOIB$. All variables are winsorized at the 0.5% and 99.5% levels. N is the average number of stocks per month in the regressions. Newey-West t-statistics are reported in parentheses. *,**, and *** denote statistical significant at the 10%, 5%, and 1% level, respectively.

	$VOIB\_NUM$			$VOIB\_SHR$		
Model	1	2	3	4	5	6
Intercept	-0.554	1.550**	0.777	-1.168*	0.956	-0.192
	(-0.95)	(2.39)	(1.06)	(-1.81)	(1.38)	(-0.25)
$VOIB$	1.147**	0.313	0.541	1.796***	0.998	1.705**
	(2.17)	(0.44)	(0.65)	(3.25)	(1.46)	(2.44)
$SVOIB$	-3.168***	-3.026***	-3.282***	-1.169**	-1.385**	-1.362**
	(-5.29)	(-4.43)	(-4.64)	(-2.10)	(-2.21)	(-2.24)
OIB	-0.291	-0.079	-0.537	-0.266	-0.086	0.183
	(-0.69)	(-0.12)	(-0.31)	(-1.23)	(-0.24)	(0.24)
$SOIB$			0.505			-0.232
			(0.42)			(-0.36)
$POIB$	-0.099***	-0.020	0.006	-0.077**	0.014	0.022
	(-2.63)	(-0.40)	(0.06)	(-2.18)	(0.36)	(0.27)
$SPOIB$			-0.008			0.016
			(-0.09)			(0.20)

Table 6 (continued):

	VOIB_NUM			*VOIB_SHR*		
Model	1	2	3	4	5	6
SIZE	-0.027	-0.125***	-0.099**	0.049	-0.098**	-0.054
	(-0.73)	(-3.28)	(-2.45)	(1.30)	(-2.57)	(-1.33)
BM	0.041	0.006	0.009	0.035	-0.009	-0.003
	(0.82)	(0.11)	(0.17)	(0.70)	(-0.16)	(-0.05)
*R*212	-0.088	-0.317	-0.304	-0.066	-0.303	-0.279
	(-0.26)	(-0.98)	(-1.00)	(-0.20)	(-0.93)	(-0.91)
*R*1	-0.030***	-0.035***	-0.035***	-0.029***	-0.034***	-0.034***
	(-5.34)	(-4.88)	(-5.34)	(-5.26)	(-4.83)	(-5.28)
ILLIQ	1.615***	4.578	5.275	1.460***	2.556**	0.021
	(3.72)	(1.54)	(1.27)	(3.33)	(2.10)	(0.02)
SILLIQ			-18.131**			-18.888**
			(-2.12)			(-2.26)
TURN	0.133*	0.481***	0.519***	0.189***	0.542***	0.589***
	(1.86)	(6.09)	(6.01)	(2.66)	(6.80)	(6.65)
STURN			0.023			-0.004
			(0.30)			(-0.05)
StdTURN		-0.415***	-0.480***		-0.430***	-0.491***
		(-6.05)	(-6.90)		(-6.02)	(-6.72)
SStdTURN			-0.031			-0.044
			(-0.16)			(-0.24)
IVOL		-2.097	-7.630		-1.946	8.756
		(-0.27)	(-0.76)		(-0.25)	(0.87)
ACC		-0.612	-0.450		-0.582	-0.368
		(-1.08)	(-0.78)		(-1.03)	(-0.67)
AG		0.004	0.020		0.009	0.013
		(0.03)	(0.16)		(0.08)	(0.11)
ISSUE		-0.631*	-0.726**		-0.606*	-0.695**
		(-1.88)	(-2.18)		(-1.83)	(-2.16)
PROFIT		0.036**	0.036**		0.034**	0.034**
		(2.20)	(2.15)		(2.09)	(1.98)
SUE		0.002	0.037		0.004	0.027
		(0.03)	(0.45)		(0.05)	(0.30)
MAX		0.552	1.346		0.545	1.207
		(0.29)	(0.70)		(0.28)	(0.64)
DISP		-0.429***	-0.526**		-0.433***	-0.494**
		(-3.22)	(-2.50)		(-3.29)	(-2.24)
SDISP			-0.004			-0.026
			(-0.02)			(-0.10)
DISPD		0.040	0.044		0.030	-0.063
		(0.31)	(0.33)		(0.23)	(-0.40)
SSTT		-28.477***	-30.794***		-26.868***	-27.728***
		(-5.32)	(-4.49)		(-5.00)	(-4.35)
Adj. R-sq.	0.03	0.052	0.06	0.03	0.052	0.059
N	1595	1145	1129	1595	1145	1129

Table 7: Fama-MacBeth regression estimates for robustness checks using $VOIB\_NUM$
This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates between January 1993 to December 2012. Model 1 (Model 2) uses raw return (mid quote return from open to close) as the dependent variable. In Model 3, the order imbalance calculation is based on dollar volume. In Model 4, $VOIB$ is calculated as the three-month moving average of the standard deviation of daily OIB and all shock variables are calculated using three-month moving averages accordingly. Model 5 excludes the great financial crisis period of 2008 and 2009 and Model 6 uses data after January 2001 only. All independent variables (except $R1$ and $R212$) are lagged one month. OIB is the monthly order imbalance defined as $(B-S)/(B+S)$, where B (S) is the trades initiated by buyers (sellers). $VOIB$ is the six-month moving average of the standard deviation of daily OIB in a month. $POIB$ is the logistic transform of the ratio of number of days with positive OIB and total number of days in the month. $SVOIB$ is the difference between the standard deviation of daily OIB in a month and $VOIB$ in the last month. $SIZE$ represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio. $R1$ is the lagged one month return. $R212$ is the cumulative returns over the second through twelfth months prior to the current month. $TURN$ is the logarithm of the monthly share trading volume divided by shares outstanding. $StdTURN$ is the standard deviation of $TURN$ in the past 36 months. Illiquidity represents the Amihud measure of illiquidity. ACC represents accruals, measured as in Sloan (1996). AG is asset growth computed in Cooper, Gulen and Shill (2008). $ISSUE$ represents new issues as in Pontiff and Woodgate (2008). $IVOL$ is the idiosyncratic volatility computed as in Ang, Hodrick, Xing, and Zhang (2006). $PROFIT$ is the profitability variable as in Fama and French (2006). SUE is the standardized unexpected earnings, computed as the most recently announced quarterly earnings less the earnings four quarters ago, standardized by its standard deviation estimated over the prior eight quarters. MAX is the maximum daily return in the last month. $DISP$ is the analyst dispersion in earnings forecasts and $DISPD$ is a dummy that equals to one if the stock is covered by less than two analysts and zero otherwise. $SSTT$ is the small size trade imbalance as in Hvidkjaer (2008). $SOIB$, $SPOIB$, $STURN$, $SStdTURN$, $SILLIQ$, and $SDISP$ are defined similarly as $SVOIB$. All variables are winsorized at the 0.5% and 99.5% levels. N is the average number of stocks per month in the regressions. Newey-West t-statistics are reported in parentheses. *,**, and *** denote statistical significant at the 10%, 5%, and 1% level, respectively.

	Model 1 (raw ret)	Model 2 (open-close ret)	Model 3 ($OIB\$$)	Model 4 (MA=3)	Model 5 (excluding crisis)	Model 6 (post-2001)	Model 7 (pre-2001)
Intercept	2.410**	2.613**	-0.190	0.924	0.917	1.927**	-1.051
	(2.20)	(2.50)	(-0.26)	(1.31)	(1.15)	(2.19)	(-0.90)
$VOIB$	0.031	0.640	1.492**	0.442	0.141	0.150	1.162
	(0.03)	(0.59)	(2.17)	(0.61)	(0.17)	(0.13)	(1.12)
$SVOIB$	-3.237***	-3.306***	-1.387**	-3.047***	-3.368***	-3.449***	-3.017***
	(-4.10)	(-2.66)	(-2.23)	(-5.07)	(-5.03)	(-3.36)	(-3.58)
OIB	-0.255	-0.550	0.122	0.115	-1.438	-2.132	1.997**
	(-0.14)	(-0.23)	(0.29)	(0.09)	(-0.78)	(-0.78)	(2.15)
$SOIB$	0.287	0.909	0.014	-0.102	0.976	1.219	-0.628
	(0.21)	(0.46)	(0.03)	(-0.13)	(0.76)	(0.65)	(-0.70)

Table 7 (continued):

	Model 1 (raw ret)	Model 2 (open-close ret)	Model 3 ($OIB\$$)	Model 4 (MA=3)	Model 5 (excluding crisis)	Model 6 (post-2001)	Model 7 (pre-2001)
$POIB$	0.018	0.100	0.005	-0.010	0.065	0.075	-0.105
	(0.18)	(0.93)	(0.09)	(-0.12)	(0.71)	(0.52)	(-1.15)
$SPOIB$	-0.008	-0.019	0.004	0.043	-0.029	-0.133	0.190*
	(-0.09)	(-0.17)	(0.08)	(0.56)	(-0.34)	(-1.06)	(1.82)
$SIZE$	-0.151**	-0.142**	-0.052	-0.106***	-0.095**	-0.159***	-0.005
	(-2.45)	(-2.39)	(-1.35)	(-2.77)	(-2.16)	(-3.32)	(-0.07)
BM	0.133	0.135	-0.013	0.009	0.015	-0.007	0.036
	(1.61)	(1.39)	(-0.24)	(0.18)	(0.26)	(-0.11)	(0.36)
$R212$	-0.084	-0.034	-0.266	-0.230	0.016	-0.642	0.232
	(-0.24)	(-0.09)	(-0.87)	(-0.76)	(0.10)	(-1.40)	(0.95)
$R1$	-0.026***	-0.016*	-0.035***	-0.035***	-0.034***	-0.028***	-0.045***
	(-3.70)	(-1.72)	(-5.18)	(-5.37)	(-4.96)	(-3.19)	(-5.25)
$ILLIQ$	5.502	2.977	3.168	6.385	5.807	8.294	0.478
	(1.18)	(1.53)	(1.50)	(1.25)	(1.25)	(1.23)	(0.93)
$SILLIQ$	-28.576**	-12.052	-20.114**	-14.161*	-17.314*	-3.489	-41.395***
	(-2.53)	(-0.91)	(-2.43)	(-1.87)	(-1.93)	(-0.32)	(-3.34)
$TURN$	0.573***	0.700***	0.578***	0.458***	0.490***	0.421***	0.673***
	(6.06)	(5.66)	(6.42)	(5.40)	(5.46)	(3.99)	(4.82)
$STURN$	0.020	-0.073	0.001	0.121	0.042	-0.029	0.106
	(0.24)	(-0.46)	(0.01)	(1.46)	(0.49)	(-0.40)	(0.65)
$StdTURN$	-0.504***	-0.457***	-0.492***	-0.465***	-0.479***	-0.415***	-0.583***
	(-5.41)	(-3.72)	(-6.72)	(-6.67)	(-6.61)	(-4.71)	(-5.54)
$SStdTURN$	-0.150	0.116	-0.059	0.109	0.002	-0.096	0.073
	(-0.69)	(0.41)	(-0.32)	(0.43)	(0.01)	(-0.38)	(0.27)
$IVOL$	-12.298	-20.104*	10.251	-3.169	-7.626	0.300	19.275
	(-0.99)	(-1.65)	(1.03)	(-0.34)	(-0.77)	(0.02)	(1.43)
ACC	-0.315	-0.660	-0.428	-0.461	-0.586	-0.251	-0.766
	(-0.52)	(-0.95)	(-0.75)	(-0.81)	(-1.10)	(-0.29)	(-1.41)
AG	-0.007	-0.161	0.033	-0.034	0.015	0.111	-0.124
	(-0.06)	(-1.05)	(0.25)	(-0.38)	(0.11)	(0.57)	(-1.48)
$ISSUE$	-0.542*	-0.617	-0.700**	-0.395	-0.749**	-0.751*	-0.686
	(-1.69)	(-1.40)	(-2.13)	(-0.90)	(-2.15)	(-1.73)	(-1.35)
$PROFIT$	0.038**	0.030	0.035**	0.040**	0.045***	0.046**	0.019
	(2.15)	(1.38)	(2.09)	(2.52)	(2.68)	(2.14)	(0.77)
SUE	0.094	0.188	0.032	0.057	-0.010	0.031	0.046
	(1.06)	(1.37)	(0.36)	(0.69)	(-0.13)	(0.28)	(0.39)
MAX	2.234	4.480	1.064	1.851	1.267	1.295	1.428
	(1.04)	(1.57)	(0.55)	(0.89)	(0.61)	(0.49)	(0.52)
$DISP$	-0.453**	-0.795*	-0.557***	-0.462**	-0.583**	-0.322	-0.850**
	(-1.96)	(-1.67)	(-2.68)	(-2.43)	(-2.56)	(-1.34)	(-2.19)
$SDISP$	-0.137	-0.141	0.011	0.075	0.042	-0.170	0.259
	(-0.49)	(-0.40)	(0.04)	(0.36)	(0.16)	(-0.51)	(0.75)
$DISPD$	-0.022	-0.047	-0.073	0.022	0.073	0.022	0.080
	(-0.14)	(-0.18)	(-0.47)	(0.17)	(0.56)	(0.12)	(0.44)
$SSTT$	-35.852***	-26.902**	-24.234***	-46.740***	-32.938***	-14.715***	-56.342***
	(-4.63)	(-2.19)	(-4.66)	(-4.36)	(-4.36)	(-3.31)	(-3.88)
Adj. R-sq.	0.087	0.088	0.059	0.058	0.057	0.061	0.058
N	1130	805	1129	1145	1144	1067	1228

Table 8: Fama-MacBeth regression estimates for robustness checks using $VOIB\_SHR$ This table presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates between January 1993 to December 2012. Model 1 (Model 2) uses raw return (mid quote return from open to close) as the dependent variable. In Model 3, the order imbalance calculation is based on dollar volume. In Model 4, $VOIB$ is calculated as the three-month moving average of the standard deviation of daily OIB and all shock variables are calculated using three-month moving averages accordingly. Model 5 excludes the great financial crisis period of 2008 and 2009 and Model 6 uses data after January 2001 only. All independent variables (except $R1$ and $R212$) are lagged one month. OIB is the monthly order imbalance defined as $(B-S)/(B+S)$, where B (S) is the trades initiated by buyers (sellers). $VOIB$ is the six-month moving average of the standard deviation of daily OIB in a month. $POIB$ is the logistic transform of the ratio of number of days with positive OIB and total number of days in the month. $SVOIB$ is the difference between the standard deviation of daily OIB in a month and $VOIB$ in the last month. $SIZE$ represents the logarithm of market capitalization in billions of dollars. BM is the logarithm of the book-to-market ratio. $R1$ is the lagged one month return. $R212$ is the cumulative returns over the second through twelfth months prior to the current month. $TURN$ is the logarithm of the monthly share trading volume divided by shares outstanding. $StdTURN$ is the standard deviation of $TURN$ in the past 36 months. Illiquidity represents the Amihud measure of illiquidity. ACC represents accruals, measured as in Sloan (1996). AG is asset growth computed in Cooper, Gulen and Shill (2008). $ISSUE$ represents new issues as in Pontiff and Woodgate (2008). $IVOL$ is the idiosyncratic volatility computed as in Ang, Hodrick, Xing, and Zhang (2006). $PROFIT$ is the profitability variable as in Fama and French (2006). SUE is the standardized unexpected earnings, computed as the most recently announced quarterly earnings less the earnings four quarters ago, standardized by its standard deviation estimated over the prior eight quarters. MAX is the maximum daily return in the last month. $DISP$ is the analyst dispersion in earnings forecasts and $DISPD$ is a dummy that equals to one if the stock is covered by less than two analysts and zero otherwise. $SSTT$ is the small size trade imbalance as in Hvidkjaer (2008). $SOIB$, $SPOIB$, $STURN$, $SStdTURN$, $SILLIQ$, and $SDISP$ are defined similarly as $SVOIB$. All variables are winsorized at the 0.5% and 99.5% levels. N is the average number of stocks per month in the regressions. Newey-West t-statistics are reported in parentheses. *,**, and *** denote statistical significant at the 10%, 5%, and 1% level, respectively.

	Model 1 (raw ret)	Model 2 (open-close ret)	Model 3 (MA=3)	Model 4 (excluding crisis)	Model 5 (post-2001)	Model 6 (pre-2001)
Intercept	1.572	1.523	0.003	-0.173	0.715	-1.634
	(1.52)	(1.46)	(0.00)	(-0.21)	(0.87)	(-1.17)
$VOIB$	1.155*	1.569*	1.453**	1.467**	1.781**	1.584
	(1.68)	(1.65)	(2.14)	(2.14)	(1.98)	(1.40)
$SVOIB$	-1.629**	-1.321*	-1.286***	-1.392**	-0.842	-2.188***
	(-2.44)	(-1.90)	(-2.63)	(-2.34)	(-0.94)	(-3.32)
OIB	0.175	0.702	0.361	-0.256	0.720	-0.670
	(0.23)	(0.75)	(0.61)	(-0.35)	(0.62)	(-1.41)
$SOIB$	-0.164	-0.576	-0.249	0.028	-0.949	0.908**
	(-0.22)	(-0.54)	(-0.49)	(0.05)	(-0.95)	(2.21)

Table 8 (continued):

	Model 1 (raw ret)	Model 2 (open-close ret)	Model 3 (MA=3)	Model 4 (excluding crisis)	Model 5 (post-2001)	Model 6 (pre-2001)
POIB	0.047	0.080	0.039	0.048	-0.037	0.115
	(0.54)	(0.78)	(0.57)	(0.61)	(-0.31)	(1.28)
SPOIB	0.008	0.078	0.032	0.012	-0.044	0.111
	(0.10)	(0.73)	(0.54)	(0.16)	(-0.39)	(1.17)
SIZE	-0.111*	-0.088	-0.061	-0.044	-0.093**	0.010
	(-1.92)	(-1.54)	(-1.62)	(-1.02)	(-2.01)	(0.14)
BM	0.122	0.143	0.003	0.001	-0.012	0.012
	(1.47)	(1.44)	(0.05)	(0.01)	(-0.17)	(0.12)
*R*212	-0.060	-0.003	-0.221	0.045	-0.636	0.289
	(-0.17)	(-0.01)	(-0.73)	(0.28)	(-1.38)	(1.22)
*R*1	-0.025***	-0.016*	-0.035***	-0.033***	-0.027***	-0.045***
	(-3.57)	(-1.78)	(-5.30)	(-4.89)	(-3.14)	(-5.17)
ILLIQ	-1.060	-2.102	1.471***	-0.022	-0.152	0.297
	(-0.55)	(-0.55)	(3.10)	(-0.02)	(-0.08)	(0.59)
SILLIQ	-29.593***	-14.019	-13.151*	-18.253**	-4.923	-41.077***
	(-2.67)	(-1.02)	(-1.72)	(-2.09)	(-0.46)	(-3.32)
TURN	0.641***	0.792***	0.529***	0.568***	0.490***	0.747***
	(6.67)	(5.42)	(6.02)	(6.13)	(4.44)	(5.32)
STURN	-0.008	-0.081	0.091	0.012	-0.045	0.062
	(-0.09)	(-0.56)	(1.13)	(0.14)	(-0.64)	(0.38)
StdTURN	-0.519***	-0.511***	-0.477***	-0.491***	-0.407***	-0.625***
	(-5.40)	(-3.27)	(-6.57)	(-6.49)	(-4.33)	(-5.84)
SStdTURN	-0.146	0.048	0.073	-0.010	-0.122	0.081
	(-0.68)	(0.16)	(0.28)	(-0.06)	(-0.48)	(0.30)
IVOL	13.607	-18.256	3.441	8.844	1.770	19.856
	(1.09)	(-1.44)	(0.37)	(0.90)	(0.12)	(1.49)
ACC	-0.222	-0.378	-0.413	-0.515	-0.112	-0.774
	(-0.38)	(-0.55)	(-0.74)	(-1.04)	(-0.13)	(-1.43)
AG	-0.014	-0.201	-0.019	0.009	0.105	-0.133
	(-0.13)	(-1.13)	(-0.21)	(0.07)	(0.56)	(-1.61)
ISSUE	-0.501	-0.600	-0.351	-0.725**	-0.738*	-0.626
	(-1.58)	(-1.41)	(-0.83)	(-2.16)	(-1.78)	(-1.25)
PROFIT	0.036**	0.026	0.037**	0.044**	0.043*	0.020
	(1.98)	(1.16)	(2.31)	(2.52)	(1.90)	(0.77)
SUE	0.080	0.216	0.059	-0.026	0.010	0.055
	(0.88)	(1.61)	(0.68)	(-0.29)	(0.08)	(0.46)
MAX	2.002	4.157	1.759	1.153	1.120	1.346
	(0.93)	(1.50)	(0.86)	(0.57)	(0.44)	(0.48)
DISP	-0.416*	-0.690	-0.457**	-0.549**	-0.295	-0.811**
	(-1.75)	(-1.44)	(-2.41)	(-2.29)	(-1.12)	(-2.09)
SDISP	-0.160	-0.199	0.094	0.020	-0.202	0.253
	(-0.54)	(-0.52)	(0.47)	(0.07)	(-0.53)	(0.72)
DISPD	-0.134	-0.058	-0.042	-0.049	-0.199	0.154
	(-0.64)	(-0.17)	(-0.27)	(-0.31)	(-0.89)	(0.85)
SSTT	-32.901***	-23.396**	-41.491***	-29.573***	-15.425***	-47.276***
	(-4.59)	(-2.07)	(-3.96)	(-4.21)	(-3.70)	(-3.37)
Adj. R-sq.	0.087	0.088	0.058	0.057	0.057	0.057
N	1130	805	1145	1144	1228	1228

Table 9: Bivariate portfolio sorts controlling for proxies for stock visibility

Each month between January 1993 to December 2012, stocks are first sorted into tercile portfolios based on one of the lagged control variables, and then into lagged $SVOIB$ quintile within each control variable quintile. Then the return differences between high and low quintile $SVOIB$ portfolios and the Fama-French (1993) alphas are reported. The Newey-West t-statistics are reported in parentheses. $VOIB$ is the six-month moving average of the standard deviation of daily OIB in a month, where OIB is defined as $(B-S)/(B+S)$ with B (S) being the trades initiated by buyers (sellers). $SVOIB$ is the difference between the standard deviation of daily OIB in a month and $VOIB$ in the last month. The order imbalance is calculated using the number of trades in Columns 1 to 3 and using number of shares traded in Columns 4 to 6. $SIZE$ represents the logarithm of market capitalization in billions of dollars. $ANALYST$ is the logarithm of number of analysts following the stock and is set to zero if the stock is not covered by any analyst. $INST$ is the percentage of shares held by institutional investors. $IVOL$ is the idiosyncratic stock return volatility. *,**, and *** denote statistical significant at the 10%, 5%, and 1% level, respectively.

	$VOIB\_NUM$		$VOIB\_SHR$	
Panel A: Controlling for $SIZE$				
$SVOIB/SIZE$	Small	Large	Small	Large
Low	1.830	0.931	1.645	0.941
2	1.348	1.006	1.269	0.941
3	1.117	0.972	1.315	0.970
4	1.225	0.959	1.153	0.959
High	0.983	0.894	1.123	0.952
High−Low	-0.865***	-0.054	-0.532***	-0.015
	(-4.99)	(-0.64)	(-3.35)	(-0.19)
FF	-0.830***	-0.089	-0.474***	-0.059
	(-4.77)	(-1.06)	(-3.06)	(-0.74)
Panel B: Controlling for $ANALYST$				
$SVOIB/ANALYST$	Low	High	Low	High
Low	1.802	1.103	1.605	1.089
2	1.171	1.091	1.155	1.013
3	1.077	1.019	1.097	1.086
4	0.981	1.044	1.036	1.037
High	0.900	1.070	1.038	1.104
High−Low	-0.908***	-0.108	-0.562***	-0.072
	(-5.57)	(-1.16)	(-3.39)	(-0.87)
FF	-0.867***	-0.155	-0.523***	-0.118
	(-5.37)	(-1.56)	(-3.28)	(-1.46)

Table 9 (continued):

	VOIB_NUM		*VOIB_SHR*	
Panel C: Controlling for INST				
SVOIB/INST	Low	High	Low	High
Low	1.765	1.095	1.644	1.057
2	1.402	1.121	1.227	0.996
3	0.988	1.050	1.180	1.143
4	0.951	1.074	1.051	1.024
High	1.011	1.077	1.013	1.198
High−Low	-0.808***	-0.098	-0.610***	0.100
	(-4.82)	(-0.90)	(-3.43)	(1.14)
FF	-0.791***	-0.136	-0.579***	0.078
	(-4.80)	(-1.24)	(-3.38)	(0.88)
Panel D: Controlling for IVOL				
SVOIB/IVOL	Low	High	Low	High
Low	1.196	1.826	1.146	1.600
2	1.053	1.181	0.987	1.157
3	0.984	1.106	1.032	1.235
4	0.940	1.089	0.949	1.101
High	0.902	0.990	0.961	1.096
High−Low	-0.292***	-0.856***	-0.197***	-0.473***
	(-3.99)	(-4.96)	(-2.66)	(-3.08)
FF	-0.315***	-0.863***	-0.201***	-0.478***
	(-4.54)	(-4.78)	(-2.87)	(-3.18)

Table 10: Effects of liquidity shocks and visibility

In Panel A, for each month from January 1993 to December 2012, we sort all stocks in the sample into quintile portfolios based on $SVOIB\_NUM$ at month t. We calculate OIB_NUM as the monthly order imbalance defined as $(B-S)/(B+S)$, where B (S) is the number of trades initiated by buyers (sellers). $VOIB\_NUM$ is the six-month moving average of the standard deviation of daily OIB_NUM in a month. $SVOIB\_NUM$ is the difference between the standard deviation of daily OIB_NUM in a month and $VOIB\_NUM$ in the last month. Future returns after the shocks in the next three years are broken into five periods and equally-weighted portfolio returns are reported. In Panel B, we repeat the same analysis using order imbalance calculated from the number of shares traded. Panel C presents the time-series averages of individual stock cross-sectional OLS regression coefficient estimates. The control variables are same as those in Column 3 of Table 6. For brevity, Panel C only reports $SVOIB$ coefficients. All variables are winsorized at the 0.5% and 99.5% levels. Newey-West t-statistics are reported in parentheses. *,**, and *** denote statistical significant at the 10%, 5%, and 1% level, respectively.

Panel A: Price impact in the long run

	FF alpha			FM coefficient		
	SVOIB_NUM	*SVOIB_SHR*	*SILLIQ*	*SVOIB_NUM*	*SVOIB_SHR*	*SILLIQ*
Month2-3	-0.092	-0.097	-0.176*	-1.005	-1.021*	-8.888
	(-0.69)	(-0.89)	(-1.80)	(-1.53)	(-1.75)	(-1.22)
Month4-6	0.080	0.094	0.005	-0.447	0.072	-11.219*
	(0.47)	(0.61)	(0.03)	(-0.89)	(0.15)	(-1.76)
Month7-12	0.149**	0.163**	0.046	1.113***	1.338***	-2.293
	(1.99)	(2.35)	(0.40)	(2.88)	(3.61)	(-0.61)

Panel B: Fama-MacBeth regression coefficient estimates conditioning on SIZE

	Small			Large		
	SVOIB_NUM	*SVOIB_SHR*	*SILLIQ*	*SVOIB_NUM*	*SVOIB_SHR*	*SILLIQ*
Month2-3	-1.596**		-17.345**	1.582		-7.791
	(-2.57)		(-2.06)	(0.91)		(-0.75)
		-2.091***	-18.984**		-0.727	-6.321
		(-3.51)	(-2.26)		(-0.58)	(-0.61)
Month4-6	-1.369**		-20.571***	0.033		-1.119
	(-2.44)		(-2.83)	(0.03)		(-0.14)
		-1.162**	-21.476***		0.744	-0.588
		(-2.23)	(-2.98)		(0.73)	(-0.07)
Month7-12	0.733*		-2.588	-0.564		-12.997**
	(1.83)		(-0.66)	(-0.60)		(-2.03)
		0.889**	-2.615		0.242	-13.141**
		(2.18)	(-0.66)		(0.34)	(-2.07)

Table 10 (continued):

Panel C: Fama-MacBeth regression coefficient estimates conditioning on $ANALYST$

	Low			High		
	$SVOIB\_NUM$	$SVOIB\_SHR$	$SILLIQ$	$SVOIB\_NUM$	$SVOIB\_SHR$	$SILLIQ$
Month2-3	-1.132*		-13.453*	0.759		-6.041
	(-1.84)		(-1.66)	(0.42)		(-0.60)
		-1.392**	-14.229*		-0.266	-6.839
		(-2.32)	(-1.77)		(-0.21)	(-0.67)
Month4-6	-0.743		-19.962***	0.509		-0.358
	(-1.40)		(-2.68)	(0.34)		(-0.04)
		-0.386	-20.408***		1.147	0.294
		(-0.74)	(-2.77)		(1.09)	(0.04)
Month7-12	0.943**		0.547	1.818		-12.381*
	(2.51)		(0.14)	(1.44)		(-1.92)
		0.949**	0.590		1.778**	-11.171*
		(2.52)	(0.15)		(2.01)	(-1.74)

Panel D: Fama-MacBeth regression coefficient estimates conditioning on $INST$

	Low			High		
	$SVOIB\_NUM$	$SVOIB\_SHR$	$SILLIQ$	$SVOIB\_NUM$	$SVOIB\_SHR$	$SILLIQ$
Month2-3	-1.140		-21.858**	2.389		-6.648
	(-1.51)		(-2.37)	(1.47)		(-0.69)
		-0.988	-21.981**		0.570	-7.457
		(-1.34)	(-2.36)		(0.52)	(-0.78)
Month4-6	-0.556		-8.436	2.952**		-6.761
	(-0.89)		(-1.00)	(2.02)		(-0.85)
		-0.432	-7.984		2.688**	-7.004
		(-0.72)	(-0.92)		(2.35)	(-0.89)
Month7-12	1.528***		5.344	-1.197		-22.583***
	(3.69)		(1.20)	(-1.05)		(-3.23)
		1.896***	5.679		0.141	-23.945***
		(4.15)	(1.27)		(0.16)	(-3.50)

Panel E: Fama-MacBeth regression coefficient estimates conditioning on $IVOL$

	Low			High		
	$SVOIB\_NUM$	$SVOIB\_SHR$	$SILLIQ$	$SVOIB\_NUM$	$SVOIB\_SHR$	$SILLIQ$
Month2-3	-0.766		0.055	-1.469*		-11.902
	(-1.16)		(0.01)	(-1.78)		(-1.46)
		-0.847	-0.231		-1.549**	-13.304
		(-1.36)	(-0.03)		(-2.09)	(-1.64)
Month4-6	0.051		0.485	-0.792		-16.641**
	(0.09)		(0.07)	(-1.16)		(-2.23)
		0.336	1.446		-0.528	-16.952**
		(0.61)	(0.20)		(-0.83)	(-2.27)
Month7-12	0.368		-7.811	1.070**		1.648
	(0.79)		(-1.42)	(2.15)		(0.39)
		0.435	-7.398		1.452***	1.373
		(1.10)	(-1.36)		(2.98)	(0.33)