High Frequency Trading Volatility, Market Microstructure Noise and Institutional Investors

by

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To my husband Qianshun Cheng,

and my cat Miaomiao.

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LIST OF ABBREVIATIONS

CRSP	The Center for Research in Security Prices
HAR	Heterogeneous Autoregressive
IO	Institutional Ownership
IPO	Initial Public Offering
NBER	The National Bureau of Economic Research
NYSE	The New York Stock Exchange
RV	Realized Volatility
TAQ	Trade and Quote
TSRV	Two-Scales Realized Volatility

SUMMARY

As stocks being traded more intensely daily, many recent studies show that the efficiency and accuracy of some measures developed from low frequency data may not be well guaranteed. It is worth investigating the relationship between institutional investor's behavior and stock return volatility in this new circumstance. We estimate stock return volatility with the two-scales realized volatility (TSRV) estimator which corrects the effect from market microstructure noise on stock prices. Using all transactions of S&P 500 constituent stocks over the most recent 10 years, we find a positive association between the levels of institutional ownership and daily stock return volatility. This association is not constant over time. Institutional investors are more conservative while the market is more volatile, and they become more aggressive when market calms down. We also analyze quarterly changes in stock return volatility and institutional ownership ratio, and we find evidence that past increase in institutional ownership changes will positively impact the changes in volatility for the future, and past increases in volatility changes will decrease the institutional ownership in the future. But there is no causality relationship between institutional ownership and market microstructure noise. Most institutional investors act similarly except banks. We also find evidence for institutional herding and that stocks with higher institutional ownership ratios attract more high turnover traders, which could be the possible channels through which institutional investors affect stock return volatility.

CHAPTER 1

INTRODUCTION

With the development in computer technology, we observe explosive number of transactions taking place in the market over past decades, especially since the financial crisis of 2007-2008. Many stocks had less than 100 daily transactions in the early years of 21st century, and now they could have millions of transactions per day. The huge number of trades brought to market substantial liquidity as well as some problems. Many estimators and measures developed from low frequency data are no longer applicable in the high frequency market. For example, (1) examined a bunch of low frequency liquidity measures and found that many of them are not appropriate to use as high frequency liquidity proxies.

Estimating stock return volatility and variance have the similar problem. It used to be a common practice in finance to estimate variance from the sum of squared log returns. However, this estimation approach overlooks the fact that the observed return series in high frequency market is subject to market microstructure. Therefore the widely used volatility estimator is biased and fails to estimate the true integrated variance that is free of the contamination from microstructure noise ((2)). The impact of market microstructure noise is more dominating if stocks are traded more frequently. Sampling data sparsely at a lower frequency would mitigate this effect, yet cannot ultimately remove the estimation bias. In this thesis, we employ the two-scales realized volatility estimator (also referred as TSRV estimator) proposed by (2). The

TSRV estimator makes use of all data and it is an unbiased and consistent estimator of the integrated volatility.

Institutional investors also experienced fast growth over the past few decades. In 1950, institutional investors held about 7% of total U.S. equity shares, then became 28% in 1970 ((3)). This number increased to 50% in 1990 and 79% in 2010. In our studied period, from January 2008 to December 2017, institutional investors hold an average of 81% of all S&P 500 constituent stock shares. Institutional investors have become the dominant force in financial markets and economic events.

Although many previous researchers examined the relationship between institutional holdings and stock return volatility in a low frequency market, however, studies have not examined whether high frequency trading and the continuing growth in institutional holdings have changed that relationship. In this thesis, we address six important questions: (1) What is the relationship between institutional investors and stock return volatility in the current high frequency market? (2) How does this relationship change over time? (3) Which party plays the leading role in this relationship? (4) Do different types of institutional investors have different relationship with volatility? Does institutional ownership have different relationship with stocks of different ownership levels? (5) Does institutional ownership have any impact on market microstructure noise or vice versa? (6) What are the possible channels through which institutional investors affect stock return volatility?

Our results from daily estimates reveal that institutional ownership of a particular stock seems to positively associate with volatility in stock returns. A 10% increase in institutional ownership ratio is associated with 1.6% increase in volatility after controlling other stock characteristics. This finding is consistent with many previous studies. For example, (4) found a positive contemporaneous association between level of institutional ownership and security return volatility from annual data of 1977-1991. (5) examined all days between 1988 and 1996 with absolute market return larger than 2% and found evidence that a firm's abnormal return is related to the percentage of its institutional ownership ratio. (6) presented a model in which volatility is caused by the trades of large institutions.

However, some previous research found opposite results. For example, (7) examined daily data of the eight-month period between March and November 2000, where the Nasdaq Composite index fell 46.23% in value and concluded that institutional investors tend to hold stocks with less return volatility. This research gives us a clue that the association between institutional investors and stock return volatility may not be constant over time. To verify this hypothesis, we divide our data into subsets and analyze the relationship between institutional ownership ratio and return volatility over time and under different market conditions. Our result shows that the relationship between institutional ownership and volatility is stronger for quarters with better market environment and vice versa. If market is very stable, institutional investors have stronger preference on risky assets; if the whole market is suffering from disorder, they seem to become more careful and try to avoid risk. The strength of relationship between volatility and institutional ownership depends on the overall market condition. This finding sheds new light on the old relationship and interprets the changes of this relationship reported from previous studies.

The positive contemporaneous association between institutional ownership and daily stock return volatility doesn't mean that the changes in one variable cause the changes in the other one. To test whether there is causal relationship between the two variables, we analyze the changes in institutional ownership ratio and changes in volatility, as well as the lags of changes. Since institutional ownership data only updates once a quarter, we have to aggregate daily volatility to get quarterly volatility for each stock. We find that changes in institutional ownership ratio and changes in stock return volatility Granger cause each other, but in different directions. Our result shows that an increase in past institutional ownership changes would increase the changes in volatility, and that an increase in past volatility change would decrease the subsequent changes in institutional ownership. Therefore past institutional investors' buying activity would push up stock volatility, and institutional investors tend to slow down buying stocks or even sell stocks if they observe past increase in volatility. These results are consistent with the findings in (4) where the author used a level - lagged change model and found similar evidence.

Although institutional investors have many characteristics in common, e.g. liquidity preference, ability to absorb and process information, etc., they are far from a homogeneous group. They differ from each other in term of the rules that determine the distribution of risk and return, as well as the definition of their liabilities. For example, hedge funds are private funds that are limited to wealthy investors. They are usually willing to take high short-term risk in exchange for high return potential; Pension funds, on the contrary, their obligation is to provide means for individuals to accumulate saving over their working life so as to finance their consumption needs in retirement. They would try to keep risk at a low level and the returns are heavily dependent on the market; Banks, due to their importance in the financial stability of a country, are usually highly regulated. In this thesis, we further examine whether different types of institutional investors have homogeneous relationship with volatility. Our result supports the homogeneity hypothesis for most types of institutional investors except for banks. Banks are the only type which always coincides with lower stock return volatility.

While institutional ownership ratio and stock return volatility are strongly connected, market microstructure noise has a different story. There is no causal relationship between microstructure noise and institutional ownership. Market microstructure noise is inherent in the trading system and is only affected by its own history.

Finally, we explore the possible channels that link institutional ownership and stock volatility. First, we show evidence that institutional investors prefer to invest in smaller and riskier securities and coincide with higher stock shares turnover which introduce overwhelming liquidity to the market and harm the stability of the market. Second, we observe that stocks with the best preceding quarterly returns will experience the largest increase in institutional holdings and best returns in the current quarter. However, their returns will reverse in the next few quarters which support the notion that institutional investors herd. These two findings indirectly interpret how institutional ownership positively impact stock return volatility.

The thesis is organized as follows. Chapter 2 describes the data and how we construct variables from our data. Chapter 3 documents the contemporaneous and dynamic relationship between volatility and institutional ownership, and analyzes which of them leads the change.

Chapter 4, in addition to Chapter 3, examines different types of institutional investors and stocks with different institutional ownership levels. Chapter 5 analyzes the relationship between institutional ownership and market microstructure noise. Chapter 6 explores two possible channels of the impact. Chapter 7 concludes the thesis.

CHAPTER 2

DATA AND MODEL SETUP

Our studied period is from January 2008 to December 2017. We obtain data from four different sources: Compustat, NYSE Trade and Quote Database (TAQ), Thomson Reuters 13(f), and CRSP. The following sections describe the details of each raw data set and the process of variable construction.

2.1 Stock return volatility and microstructure noise from high-frequency data

Understanding the volatility of an asset is as important as understanding its prices and returns. We obtain millisecond trades from the TAQ database for S&P 500 constituent stocks to estimate daily stock return volatility. In order to have a balanced panel data set, we only keep the stocks with full trading history from January 1^{st}, 2008 to December 31^{st}, 2017, and discard those if IPO occurred after January 1^{st}, 2008 or get delisted / acquired by other companies before December 31^{st}, 2017. Our final data set contains 440 stocks. Since company announcements and many economic indicators are usually released in the pre- or post-market sessions, we exclude all trades that occur before the open and after the close to avoid involving unusual trades. Furthermore, we only keep the trades with no symbol suffix and with zero trade correction indicator, to make sure that all observations are regular trades which are not corrected, changed or signified as cancel or error.

To estimate volatility, let S_t denote the price process of a security, and suppose that $X_t = logS_t$ is the log price which follows an Itô process,

$$dX_t = \mu_t dt + \sigma_t dB_t \tag{2.1}$$

where B_t is a standard Brownian motion, μ_t is the instantaneous drift and σ_t^2 is the instantaneous variance. The parameter of interest is the integration of σ_t^2 over a time period $\int_0^T \sigma_t^2 dt$. In the past, the most common and natural way of estimating this parameter is to use the sum of squared log-returns,

$$[X, X]_T \triangleq \sum_{t_i, t_{i+1} \in [0,T]} (X_{t_{i+1}} - X_{t_i})^2 \tag{2.2}$$

where the X_{t_i}'s are all observations of the return process in $[0, T]$. This estimator is usually called "realized variance" or "realized volatility".

This model is justified theoretically that it would converge to the integrated variance as sampling frequency increases, i.e.

$$plim \sum_{t_i, t_{i+1} \in [0,T]} (X_{t_{i+1}} - X_{t_i})^2 = \int_0^T \sigma_t^2 dt \tag{2.3}$$

However, it fails in reality due to the existence of market microstructure noise. Market microstructure noise comes originally from trading mechanisms such as bid-ask spread, discreteness of price changes, order arrival latency, investor behaviors, etc. The magnitude of market microstructure noise increases with sampling frequency. Therefore, the noise makes a big trouble in estimating the integrated volatility from high frequency data.

(2) came up with a new "Two Time Scales Realized Volatility" estimator (also referred as TSRV) to correct the bias mentioned above. According to their model, we suppose Y_{t_i} is the observed return process and it follows the form

$$Y_{t_i} = X_{t_i} + \epsilon_{t_i} \tag{2.4}$$

where X_{t_i} is the latent true return process that follows (1), and ϵ_{t_i}'s are independent noises around the true return. They have proved that if we ignore the effect of market microstructure noise and use the approach described in (2) to estimate the integrated variance, it in fact turns into

$$\sum_{t_i, t_{i+1} \in [0,T]} (Y_{t_{i+1}} - Y_{t_i})^2 = 2nE\epsilon^2 + O_p(n^{1/2}) \tag{2.5}$$

where n is the number of sampling intervals over $[0, T]$. Thus the "sum of squared log-returns" estimator gives us the variance of noise $E\epsilon^2$ rather than the true integrated volatility $\langle X, X \rangle_T$. The bias is linear in n, therefore the estimator is getting worse if stocks are traded more frequently. We use $[Y, Y]_T^{(all)}$ to denote this realized variance estimator.

Some literatures suggested a way of solving this problem by subsampling from the original data set ((8), (9)). (10) also argued that accurately sampled high frequency data can provide valuable information about integrated variance and still allow us to balance the bias and variance of the estimator. However, it is hardly to be true that throwing away data can be the optimal solution, the best sampling frequency should be "as often as possible" ((11)). The TSRV estimator is built on this idea and uses the full data set.

To construct a TSRV estimator, we first compute the estimator $[Y,Y]_T^{sparse}$ by subsampling every K^{th} observation, starting from the first trade. For example, with $T = 1$ day, or 6.5 regular trading hours, suppose we have one transaction every second, and suppose we sample sparsely every 300^{th} observation, which means we approximately sample every 5 minutes, and the sample size $n_{sparse} = 78$. $[Y,Y]_T^{sparse}$ is the realized variance estimator using all 78 data points in the subsample. We repeat this process for $K-1$ times, i.e. we start subsampling from the second observation to get another $[Y,Y]_T^{sparse}$, then start with the third observation, and the last time we start from the $(K-1)^{th}$ observation. For each subsample we calculate a $[Y,Y]_T^{sparse}$ and the average of them is

$$[Y,Y]_T^{(avg)} = \frac{1}{K}\sum_{i=1}^{K}[Y,Y]_T^{sparse_i} \tag{2.6}$$

$[Y,Y]_T^{(avg)}$ is the second-best approach described in (2). They also showed that

$$[Y,Y]_T^{(avg)} \overset{L}{\approx} \langle X,X\rangle_T + 2\bar{n}E\epsilon^2 + \left[4\frac{\bar{n}}{K}E\epsilon^4 + \frac{4T}{3\bar{n}}\int_0^T \sigma_t^4 dt\right]^{1/2} Z_{total} \tag{2.7}$$

where Z_{total} is a standard normal term, and $\bar{n}$ is the average sample size. Equation (7) shows that $[Y,Y]_T^{(avg)}$ is a better estimator than $[Y,Y]_T^{(all)}$ and $[Y,Y]_T^{(sparse)}$ but still not optimal, because there is still a bias term $2\bar{n}E\epsilon^2$ in $[Y,Y]_T^{(avg)}$. We could correct this bias by combining $[Y,Y]_T^{(avg)}$ and $[Y,Y]_T^{(all)}$,

$$\widehat{\langle X,X\rangle}_T = [Y,Y]_T^{(avg)} - \frac{\bar{n}}{n}[Y,Y]_T^{(all)} \tag{2.8}$$

In equation (8) the noise term $E\epsilon^2$ is removed by the subtraction, therefore the TSRV estimator $\widehat{\langle X,X\rangle}_T$ is unbiased and consistent in estimating the true integrated variance. The square root of $\widehat{\langle X,X\rangle}_T$ is the TSRV volatility estimator that will be used in later analysis. In fact, the second term in equation (8) does not have to be $[Y,Y]_T^{(all)}$. It could be another $[Y,Y]_T^{(avg)}$ by subsampling every Jth observation as long as J is much smaller than K. In general, the formula can be modified as

$$\widehat{\langle X,X\rangle}_T = [Y,Y]_T^{(avg1)} - \frac{\bar{n}_1}{\bar{n}_2}[Y,Y]_T^{(avg2)} \tag{2.9}$$

where $\bar{n}_1$ and $\bar{n}_2$ are the average sample sizes of $[Y,Y]_T^{(avg1)}$ and $[Y,Y]_T^{(avg2)}$ respectively, and $\bar{n}_1$ is much smaller than $\bar{n}_2$.

Equation (5) also provides us an estimate of the variance of microstructure noise. If number of transactions n is large enough, the second term in the RHS of equation (5) can be ignored, therefore we have

$$E\epsilon^2 = \frac{1}{2n}\sum_{t_i,t_{i+1}\in[0,T]}(Y_{t_{i+1}} - Y_{t_i})^2 \tag{2.10}$$

we can get our microstructure noise estimator by taking square root of $E\epsilon^2$.

[Place Figure Figure 1 about here]

In this thesis, T is set to one day (6.5 regular trading hours), J is set to 4 and K is 40. The maximum daily volatility value is 4.24, which occurs to CNP (CenterPoint Energy, Inc.) on May 6^{th}, 2010 the flash crash day. The price of CNP even fell to one cent per share for a short time. The minimum volatility is 6.36×10^{-4} for PBCT (Peoples United Financial Inc.) on November 13^{th}, 2014. The 5^{th} and 95^{th} percentile of daily volatility is 0.006 and 0.038 respectively, with the mean at 0.016 and median at 0.013. Figure 1 shows the histogram of volatility.

[Place Figure Figure 2 about here]

Volatility changes over time. Figure 2 depicts a time series of the median daily volatility across all 440 stocks as well as daily S&P 500 adjusted close price. It can be seen that every spike in the volatility graph reflects a disorder in the market. The first and the largest spike in daily volatility happened during the worst time of the financial crisis, from Sep 2008 to Mar 2009. The second spike in volatility is the result of the flash crash on May 6^{th}, 2010, which was most likely caused by fraud and market manipulation activity. The third volatile period reflects the August 2011 stock markets fall due to the fear of contagion of the European sovereign debt crisis to Spain and Italy, as well as U.S. government credit rating downgrading. The volatility figure also shows the treasury flash crash of October 15^{th}, 2014, the flash crash of August 24^{th}, 2015, the 2015-2016 stock market selloff, which is the result of a combination of factors such as Greek debt default, Chinese stock market turbulence, the end of quantitative easing in U.S., the Brexit, etc.

[Place Figure Figure 3 about here]

The microstructure noise term, in general, is even smaller than volatility, but with a larger range. The maximum noise value is 23.72, which occurs to MON (Monsanto Co) on October 14^{th}, 2008. The minimum value is 2.50×10^{-5}, which is for AAPL (Apple Inc.) on April 21^{st}, 2017. The 5^{th} and 95^{th} percentiles are 6.90×10^{-5} and 4.17×10^{-4} respectively. The mean is 2.15×10^{-4} and the median is 1.44×10^{-4}. Figure 3 shows the histogram of microstructure noise.

[Place Figure Figure 4 about here]

We also plot a time series of the median daily noise and S&P 500 daily close price in Figure 4. The time series plot of median daily noise shows a similar pattern as volatility in general, but we still see some differences in detail.

2.2 Institutional ownership

We collect institutional holdings information from Thomson Reuters Institutional (13f) Holdings database. According to Section 13(f) of the Securities Exchange Act, all institutions with investment discretion over $100 million or more are required to report all "Section 13(f)" security positions over which she exercises sole or shared investment discretion at the end of each calendar quarter. Therefore this database does not cover all institutional holdings but most of them are covered. There are two important date variables in the 13f database: $rdate$ and $fdate$. $rdate$ represents the effective ownership date, and is usually the calendar quarter end as required by 13f regulation. $fdate$ represents the actual file date at which shares are adjusted for stock splits and other distributions. If institutions report their holdings on time, $fdate$ would be the same as $rdate$. However, if a institution reports its holdings late, i.e. $fdate$ later than $rdate$, the institution reports its holdings as of $rdate$ and the share holdings are adjusted for stock splits by the date of filing. Fortunately, less than 0.09% of the records have a late report, and only 0.25% of the late reports are actually affected by stock adjustment. In these cases, we reverse the stock split adjustment using CRSP's shares adjustment factor.

To compute the institutional ownership ratio (IO) of a security, we sum up the holdings of all reporting institutions and divide by the total shares outstanding of the security,

$$IO_{i,t} = \frac{\sum_{j} sharesheld_{i,j,t}}{shrout_{i,t}} \tag{2.11}$$

where $sharesheld_{i,j,t}$ is the number of shares of stock i held by institution j at the end of quarter t, $shrout_{i,t}$ is the total number of shares outstanding of stock i at the same time. Since the institutions' reporting threshold is 100 million dollars, we expect a small downward bias to this IO calculation. (12) pointed out that this bias should be lower for large stocks than for small stocks, so that the bias alone contributes some of the relationship between IO and stock market capitalization. In this thesis we only analyze S&P 500 stocks which are all large in terms of market capitalization, therefore the downward impact from the reporting bias should be trivial.

Since the 13f holdings are reported on a quarterly basis, the $IO_{i,t}$ measure we calculated is a quarterly institutional ownership ratio for each stock. But our other variables, including the TSRV volatility, are on a daily basis. To solve this data frequency inconformity issue, we apply two approaches in the analysis in Chapter 3. The first approach is that we expand the $IO_{i,t}$ to make it a daily variable. We fill the missing daily values with the previous IO ratio, therefore for each stock, the daily IO ratio stays the same for an entire quarter until the next time it is updated. The second approach is that, we sample the quarter end value of all other variables so that we have all variables on a quarterly basis. We use this quarter end subsample in addition to the first approach to do robust check.

As a data check, we flag observations for which institutions hold more than 100% of the shares outstanding reported by CRSP. This is a common problem that has been addressed by many literatures. These observations represent less than 5% of our data, and in about half of those cases, the number of shares held by institutions exceeds shares outstanding by less than 5%. (13) mentioned that this data issue may be related to the fact that 13f data only include long positions. "Shares owned and lent out are included in an institution's holdings, but shares borrowed and sold short are not." Besides, data error and double counting could also be a reason, but (12) expressed that duplications is rare. Our data shows a downward trend in number of such observations since 2008. In this thesis, we winsorize IO ratios to a maximum of 100%.

We also flag observations with extremely small IO. Most of the unusual small values occur due to data errors. For example, we find a few institutional holdings before the IPO of some firms, or after the firms acquired or delisted. In addition, we find a sudden drop in IO for about 60 stocks since the report date of March 31^{st}, 2011. These stocks have a more than 90%

IO ratio before 2011Q2, and suddenly drop to around 1% for no reason. We remove all those unreasonable observations to minimize the effect from error data.

After data cleaning, the *IO* ratio ranges from 21.7% to 100%. The average daily *IO* ratio across all 440 stocks is 80.7%, and the median is 82.4%. Over the past decades, institutions are holding more and more shares in the market. As documented by (3) and (14), institutional investors own 7% of total U.S. equity in 1950 and 28% in 1970. According to our available data, this number increases to 40% by the end of 1981 and 50% by 1991. It reaches the peak in 2008 when institutions hold more than 85% of all U.S. market capitalization. Since 2012, this number fluctuates between 65% and 70%. Figure 5 presents the time series of the percentage of all U.S. market capitalization that are held by institutional investors.

[**Place Figure Figure 5 about here**]

In addition to the overall *IO* calculation, we also compute *IO* ratio for different types of institutions. Thomson Reuters 13f database classifies institutions into five groups or manager types. These groups are: (1)Bank, (2)Insurance Company, (3)Investment Companies and Their Managers, (4)Investment Advisors, and (5)All Others (including Pension Funds, University Endowments, Foundations). "However, this classification is wrong starting from 1998 and beyond (more precisely, Q4 of 1997 and afterwards) due to a mapping error by Thomson that improperly classifies institutions in the first four categories into group 5, with the vast majority of investment advisors being mistakenly allocated to 'all others' group."[1]

Unfortunately, this classification error has not been fixed by Thomson Reuters in later vintages. Since our studied period is from Q1 2008 to Q4 2017, the entire period is affected by this mis-classfication.

[Place Table Table I about here]

Table 1 shows the time series of the number of institutional investors from 1980 to 2018. It can be seen that the classification scheme has errors since 1998. The count of institutions in the first four groups (especially group 4) dropped dramatically while the count of group 5 institutions had a sudden huge increase. We still use this classification to compute the IO of each group as the classification error is consistent across our studied period and thus can still provide some information.

Since many institutions are mistakenly classified into group 5, it is not surprising that group 5 holds the most shares compared to the other 4 groups. The average IO of group 5 is 44.9% of all shares outstanding. Group 4 and group 1 also hold a considerable quantity of shares, their average IO ratios are 22.9% and 10.0% respectively. Group 2 and group 3 each holds about 1% $\sim$ 2% of the total shares outstanding.

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[1] *"Thomson-Reuters 13F Database and Classification of Institutional Investors"*. `https://wrds-www.wharton.upenn.edu/pages/support/applications/institutional-ownership-research/introduction-thomson-reuters-13f-tr-13f-database-and-its-classification-institutional-investors/`

2.3 Other variables

There are also a few other variables that are relevant to our study. First of all, firm size plays an important role in many financial decision making. For example, (4) used data from 1977 to 1991 and revealed that institutional investors prefer firms with larger market capitalization. (12) used quarterly data from 1980 to 1996 and got similar conclusion. (3) proved that although institutional investors have a preference for large capitalization stocks, this preference shifts toward smaller securities over time. In order to control the impact from firm size on the relationship between institutional investors and stock return volatility, we include daily market capitalization in our analysis model.

Second, many literatures have found a significant relationship between liquidity and stock returns ((15), (16)), as well as between liquidity and return volatility ((17), (18), (19)). To avoid issues related to liquidity effect, we include a few liquidity measures in our analysis, such as the (15) illiquidity measure of price impact, daily number of trades, average trade size and daily stock turnover. (15) defined the stock illiquidity measure as the average ratio of daily absolute return to dollar trading volume. We modified this measure to better suit our high frequency data. Our modified daily Amihud ratio is computed as

$$amihud_{i,d} = \frac{1}{N_{i,d}} \sum_{t=2}^{N_{i,d}} \frac{|r_{i,t}|}{dvol_{i,t}} \tag{2.12}$$

where $amihud_{i,d}$ is the modified Amihud illiquidity ratio of stock i on day d, $N_{i,d}$ is the total number of trades of stock i on day d, $|r_{i,t}|$ is the absolute return from trade $t-1$ to trade t, and $dvol_{i,t}$ is the dollar volume of that trade. This ratio gives the daily average of absolute (percentage) price change per dollar in each trade.

Our second liquidity measure, daily number of trades, is simply the $N_{i,d}$ in equation (12). Our third liquidity measure, daily average trade size, is defined as

$$size_{i,d} = \frac{1}{N_{i,d}} \sum_{t=1}^{N_{i,d}} trade\_size_{i,t} \tag{2.13}$$

where $trade\_size_{i,t}$ is the number of shares exchanged for each stock i in each trade t. We sum up the trade size and divide by the count of trades to get daily average trade size.

The last liquidity measure, daily stock turnover, is calculated as the ratio of daily trading volume over shares outstanding. This measure estimates the portion of total shares outstanding that is exchanged on a single day.

$$turnover_{i,d} = \frac{\sum_{t=1}^{N_{i,d}} trade\_size_{i,t}}{shrout_{i,d}} \tag{2.14}$$

Last but not the least important, we need to take extra caution when combining all variables together. Our raw data sets are downloaded from four different sources: Compustat, TAQ, Thomson Reuters 13(f), and CRSP. Each database employs different company identifiers and has different rules for mergers and acquisitions. We first download S&P 500 constituent list from Compustat. However, many CUSIP identifiers provided by Compustat do not match with those from CRSP. In order to keep as much data as possible, we correct some CUSIP according to record details, then download desired daily stock files from CRSP. CRSP also provides historical CUSIP (NCUSIP) and trading symbol (TSYMBOL) for each stock. We use NCUSIP to download institutional holding files from Thomson Reuters 13(f) and use TSYMBOL to download millisecond trades data from TAQ. After merging all variables into one dataset, we lose some observations due to the fact that some companies exist in one database may not exist in other databases. Table 2 reports summary statistics for all the daily variables we created in this chapter.

[**Place Table Table II about here**]

CHAPTER 3

INSTITUTIONAL OWNERSHIP AND STOCK RETURN VOLATILITY

One common viewpoint regarding institutional investors is that they help to maintain market stability. Institutional investors are more informative and less likely to do panic selling. They can trade at lower transaction costs to speed the process of adjusting the asset price to fundamentals. Furthermore, some institutional investors are active traders. Their activities can generate liquidity for securities and that may also dampen volatility.

An alternative view is that institutional investors cause the market to be more volatile. Advocates of this hypothesis argue that institutional investors may herd. (14) summarized five categories of institutional herding—informational cascades, investigative herding, reputational herding, fads, and characteristic herding—he also revealed compelling evidence of institutional herding, along with (20), (21), (22). Another possible channel through which institutional investors increase volatility is high frequency trading. High-frequency traders use mathematical models and algorithms to make decisions. Many trades happen in milliseconds, which could result in rapid market moves. For example the flash crash on May 6^{th}, 2010 seems to be exacerbated by the high frequency trading.

In order to further understand these two hypotheses, we examine the contemporaneous relationship between stock return volatility and institutional ownership ratios. We also examine the dynamic relationship over time to reveal institutional investors' preference under different market conditions.

3.1 Contemporaneous relationship

We begin by dividing our entire data set into 10 subsets. For each quarter, we have 440 stocks and each stock has 60 - 64 daily observations depending on the quarter length. Within each quarter, we sort all observations according to the daily volatility value, and divide them into 10 volatility decile groups. Group 1 represents the least volatile firm-day observations of the quarter, and group 10 represents the most volatile observations. We then aggregate observations in group 1 across all 40 quarters to form the first subset and compute the average value of each variable. Similarly, observations from other volatility decile groups are also aggregated to form a total of 10 subsets.

Table 3 presents the average variable values for observations in each volatility decile group. In general, stocks with higher return volatility have higher institutional ownership ratio (except the 10^{th} decile). This positive relationship suggests that, ignoring everything else, higher ratio of shares owned by institutional investors is associated with more volatile stock returns. The relationship between volatility and Amihud illiquidity ratio is also positive, which is consistent with the fact that stocks with larger price impact from trades are more volatile. We also observe that higher return volatility associates with less market capitalization, more daily number of trades and larger average trade size. These facts reveal a clue that smaller and more frequently traded stocks tend to have higher volatility. It is not surprising that these stocks also have higher daily trading volume and higher daily turnover.

[Place Table Table III about here]

To further evaluate the relationship between volatility and IO ratio, we run cross-sectional regressions of daily volatility on other variables. In this chapter we only consider the overall IO ratio. The analysis of relationship between volatility and different types of institutions is conducted in Chapter 4. We excluded daily volume and daily turnover from the regression since these two variables are highly correlated with other explanatory variables in the model. Since the scales of our variables are very different, from 10^{-8} to 10^{10}, we take a log transformation to all variables so that the magnitude of coefficient estimates are in a normal range and comparable across all explanatory variables.

[Place Table Table IV about here]

Table 4 reports the results of eight different model specifications. The response variable of all eight models are logged daily volatility of stock i on day t ($volatility_{i,t}$), where i is from 1 to 440, and t is from 1 to 2,518. Column (1) specifies the basic model. The explanatory variables in the basic model include logged daily IO ratio $IO_{i,t}$, logged daily Amihud ratio ($amihud_{i,t}$), logged daily market capitalization ($mktcap_{i,t}$), logged daily number of trades ($number\_trades_{i,t}$), logged daily average trade size ($size_{i,t}$), and a time index which takes integer values from 1 to 40 indicating the 40 quarters ($time\_index_t$). This time index captures the overall trend of stock return volatility during the studied period. The basic model result reveals that there is a positive association between stock return volatility and IO ratio after controlling some liquidity measures, firm size and time index. A 10% increase in IO (for example, IO ratio of a stock increases from 50% to 55%) will increase its return volatility by about 1.6%.

The Amihud illiquidity ratio also has a positive relationship with stock return volatility, which provides additional evidence to show that a less liquid stock is usually more volatile. We also find a surprising result that more trades do not help with stabilizing the market, but increasing trade size can do the job. The result shows that a 10% increase in daily number of trade will increase volatility by 4.4%, while a 10% increase in average trade size can reduce volatility by 4.4%. This finding is consistent with the idea that high frequency traders with small trade size introduce more volatility to the market. A larger firm size is also related with less volatility. Finally, since our data starts from 2008, which is one of the most volatile periods in history, we see a decline in volatility over time as the coefficient on time index is -0.028, indicating that stock return volatility decreases by 2.8% each quarter on average.

The second model in column (2) includes month fixed effects, which allows different months of a year to have different intercept estimates. However, we find that this fixed effect does not have a large impact on the slope coefficients as well as the entire model performance. Adding month fixed effects only increases R^2 from 0.68 to 0.69, and all slope coefficient estimates are very similar to column (1).

One concern with the panel data structure is that the daily volatility estimates (as estimated by TSRV for each stock i) are highly time-dependent. The correlation between $log(volatility_{i,t})$ and $log(volatility_{i,t-1})$ is 0.89, and correlation between $log(volatility_{i,t})$ and $log(volatility_{i,t-2})$ is 0.86. It's still very high even after one week as the correlation between $log(volatility_{i,t})$ and $log(volatility_{i,t-5})$ is 0.82. In order to control the autocorrelation effect in volatility, model (3) and (4) add the lagged response variable ($log(volatility_{i,t-1})$) as an explanatory variable, which increases R^2 from 0.68 to 0.84. The lagged response has the largest impact on the response variable among all explanatory variables. The result shows that a 10% increase in yesterday's volatility can increase today's volatility by 6.3%. The magnitude of coefficients on all other explanatory variables become smaller after controlling the lagged response, however the direction of impact and significance level remain the same.

We also apply a set of HAR-RV models developed by (23). The HAR models can better capture the slow volatility autocorrelation decay. Column (5) - (8) are two sets of HAR model specifications. Column (5) and (6) include the lagged volatility $(t-1)$, the average volatility of past week (from $t-1$ to $t-5$) and the average volatility of past month (from $t-1$ to $t-20$). Column (7) and (8) are a little different. These two models also include the lagged volatility $(t-1)$, the average volatility of past week but exclude what's already included (from $t-2$ to $t-5$), and the average volatility of past month excluding the past week (from $t-6$ to $t-20$). The HAR models further increase the R^2 and all results are consistent. Model (7) and (8) clearly show that the impact from past declines over time. The coefficient on volatility of last day is greater than that of the past week, and greater than that of the past month.

Another problem with our data set is that institutional holdings are reported at every quarter end. In the previous regressions, we repeat IO ratio everyday for a quarter so that it can be successfully merged with other daily variables. In other words, for each stock i, its IO takes exactly the same value between two consecutive quarter ends. These repeated values can harm the ability of IO in capturing the variation in daily volatility. In order to do a robust check, we sample observations at each quarter end and run the models again. The new subsample still contains 440 stocks with only 40 observations for each stock.

[Place Table Table V about here]

Table 5 reports the regression results for the quarter end subsample. The results are consistent with the previous table except that the significance level of coefficients on IO decreases after HAR variables included.

Although the regression results are highly consistent across different models and different data samples, we still need to be cautious with the potential autocorrelation in residuals. Ordinary linear regression model assumes independence in response variable, however, our longitudinal data structure is not likely to satisfy this assumption. Although we include lags of the response in model (3) - (8), it does not fix our problem completely because there might still be longer self-dependence overlooked. In addition, adding more lags of response to the model increases the risk of collinearity. A better way to solve this problem is to specify a correlation structure to the response variance matrix while estimating the coefficients, however, this method is out of our computing power since the data set is too large.

Another problem with this analysis is that the relationship revealed from the above tables is static and unconditional. We did not consider the time varying market condition. This is also a missing part from extant literature. In the next section, we will address this issue by conducting a dynamic analysis to examine the changes of institutional investors' preference under different market conditions. Our data covers a recession period since late 2007 as well as a long bull market run since mid 2009, which provides diversified market conditions for the analysis.

In conclusion, institutional ownership and stock return volatility are positively related after controlling market capitalization, liquidity measures, time index and the lagged responses. This impact is small in magnitude, but strongly statistically significant. This positive and significant link between daily volatility and IO ratio provides initial evidence that institutional investors are associated with a more volatile market.

3.2 Dynamic relationship over time

Section 3.1 provides evidence for an unconditional positive relationship between institutional ownership levels and stock return volatility. We caution that the unconditional relationship has not been agreed upon extant literature. Some people found a similar positive connection between the two characteristics. For example, (4) used NYSE stock data from 1977 to 1991 and found a positive association between institutional ownership and return volatility. (24) analyzed all U.S. stocks from 1963 to 1998 and also supported the positive association. (25) found that share ownership by foreign institutions increases firm-level stock return volatility after analyzing 1,458 Chinese firms from 1998 to 2008. However, some people found negative relationship. (26) supported the point of statement that the institutional investors in Chinese capital market decrease the volatility and thus stabilize the market. (7) investigated NASDAQ stocks with at least $50 million of market value from March to November 2000 and found evidence that during that market decline, institutional investors held stocks with less return volatility than individual investors. (27) found mixed results that institutional ownership is negatively (positively) related to volatility among non-dividend (dividend) paying stocks. (3) revealed that institutional investors' preference has shifted over time toward smaller and riskier stocks. (3) regressed institutional ownership on nine stock characteristics including three risk measures, three investment constraint measures, two liquidity measures and one momentum measure. The authors separated their quarterly data into two periods. The first period is from the first quarter of 1983 to the second quarter of 1990. The second period is from the third quarter of 1990 to the fourth quarter of 1997. The risk measures have positive average coefficients in both periods, while the average coefficient of the first period is much smaller than that of the second period. Therefore the authors concluded that institutional investors are shifting their preference from large, safe stocks to smaller and riskier stocks. But if we further look at the overall market condition of those two periods, we find that the U.S. stock market is much better in the second period. During the second period, S&P 500 index price increased by almost twofolds, from 358 to 975, and the standard deviation of monthly S&P 500 return is 0.034. While during the first period, we experienced the infamous Black Monday on Oct 19^{th}, 1987. The standard deviation of monthly S&P 500 return in the first period is 0.047, which is 38% higher than that of the second period. This phenomenon gives us a hint that the preference of institutional investors may change over time and across different market conditions. In this section, we examine whether different market conditions have any impact on the relationship between institutional ownership and stock return volatility.

We begin by dividing our data set into 40 quarters and applying the regression models (1), (3), (5), and (7) specified in the previous section. We run the regression models for each quarter subset separately. In Table 6 we report the estimate of coefficient on IO ratio from each quarter. All four models provide similar results therefore we only report the result from model (1).

[**Place Table Table VI about here**]

From the table we still see that the institutional investors are significantly positively associated with volatility for every quarters and that all estimates is significant at 1% level. However, the magnitude of coefficients varies over time. To further investigate, we compute the average daily volatility for each quarter (the third column in Table 6), and it becomes clear that the magnitude of coefficient on IO are highly negatively correlated to the overall risk level of the market. The minimum coefficient is 0.08 in the second quarter of 2009, while the market just experienced a financial crisis and the average volatility was very high. The maximum coefficient value is 0.31 observed in the first quarter of 2012, at that time we are in the middle of a bull market and the average daily volatility is at a very low level of 0.013. The correlation between contemporaneous coefficients and the average daily stock volatility is -0.54. This relationship is clearly reflected by the following graph.

[**Place Figure Figure 6 about here**]

From Table 6 and Figure 6 we find a negative correlation between overall market condition and the relationship between volatility and IO ratio. When average stock volatility is higher, the coefficient on IO tends to be lower, and vice versa. It seems that in a bull market institutional investors are more aggressive and prefer to hold more risky assets, while in market turmoil, they run from more volatile assets toward safer assets to avoid too much risk.

To further investigate, we need to better determine when the market is in a good condition and when it's bad. The National Bureau of Economic Research (NBER) business cycle dating committee maintains a chronology of peaks and troughs of U.S. business cycles. The committee determined that the last peak occurred in December 2007, and the last trough in June 2009. From a peak to a trough the economy is in recession. When it reaches the trough, the recession ends and an expansion begins. The expansion period that began in June 2009 lasts till after the end of our studied period.

We include the NBER U.S. business cycle in our analysis by creating a dummy variable $recession_t$. $recession_t$ takes value of 1 if t is before the end of June 2009, and 0 otherwise. We also include an interaction term $log(IO_{i,t}) \times recession_t$ to capture the slope difference. The regression results are reported in Table 7. The model specifications are similar to those in Table 4 and 5. All variables except recession indicator and time index are log transformed.

[Place Table Table VII about here]

From the table we observe that, first, all regression results are consistent with Table 4 and 5. Second, we obtain significant positive coefficients on $recession_t$ confirming that the average stock return volatility is higher during recession period. Third, the relationship between IO and volatility is much weaker during recession period since the coefficients on the interaction term are all negative. For example, from column (1), we find that a 10% increase in IO is associated with 1.81% of increase in stock volatility during expansion period. While in recession, a 10% increase in IO is associated with only 0.19% of increase in volatility. This is consistent across all eight models. Therefore we conclude that the association between institutional ownership and stock return volatility is weaker during recession.

The result from recession analysis can help to explain why previous studies get different conclusions. The relationship between institutional ownership and stock return volatility changes over time and under different market conditions, it is very likely to get different results if people use data from different time period. We know that expansion periods are usually much longer than recession periods and the stock market is growing stably most of the time, therefore it is not surprising that most studies found strong positive relationship between institutional holdings and stock return volatility. But during bad times, this relationship is much weaker or it may turn to a negative relationship if one only look at the worst period. For example (7) used some NASDAQ stocks from March 2000 to November 2000 and conclude that institutional investors and stock return volatility are negatively correlated. Their study period overlaps with the internet bubble crash. During these nine months, NASDAQ composite index dropped from 5,048 to 2,645, losing half of its market value.

In conclusion, our analysis shed new light on the relationship between institutional investors and stock return volatility. In general, institutional investors are related with riskier assets. While during recession, their preference for risky stocks would shift in favor of safer stocks. Institutional investors' preference would change based on the overall market condition.

3.3 Granger causality examination

The contemporaneous and dynamic relationship documented in the last two sections have proved that ownership from institutional investors and stock return volatility are positively associated during our studied period. We also explained how this association changes over time and under different market conditions. To further understand their relationship, we would like to know whether there is causality relationship existed between institutional ownership and volatility. The idea is that, if an increase in institutional holdings is associated with a subsequent increase in volatility, the change in volatility of current quarter should be positively related to the change in IO ratio of previous quarters. The other way around, if institutional investors increase their holdings after they observe an volatility increase, the current change of IO ratio should be positively related to the past change in volatility.

In the contemporaneous analysis section, we use daily IO ratios in the regression model even though institutional investors report their holdings only at the end of each quarter. To test whether past institutional investors' activities impact volatility, and whether past volatility changes affect institutional investors' holdings, we need to calculate the changes and lagged changes of variables. Since IO ratio updates quarterly, we calculate the first difference of IO ratio based on quarterly data. For each stock in each quarter, we also compute quarterly TSRV volatility, quarterly noise, average Amihud ratio, average market capitalization, average daily number of trades and average daily trade size. We then calculate the first difference of them to get quarterly changes of these variables.

We begin by testing whether changes in institutional holdings have impact on subsequent volatility changes. Table 8 presents the regression results under four different model specifications. The response variable is $\Delta volatility_{i,t}$, which is the change in quarterly volatility from quarter $t-1$ to t for each stock i, where t is from 2 to 40 and i is from 1 to 440. All variables in the regression are standardized to have a mean of zero and standard deviation of one.

[Place Table Table VIII about here]

The first column of Table 8 reports a linear regression of $\Delta volatility_{i,t}$ on its own lags as well as $\Delta IO_{i,t}$ and lags. We use up to four lags (i.e. up to the same quarter of last year). Our result supports volatility clustering since all lagged response terms have negative coefficients. The coefficient on $\Delta IO_{i,t}$ is also negative, indicating that volatility changes and IO ratio changes exhibit opposite contemporaneous movement. If $IO_{i,t} - IO_{i,t-1}$ is higher, we expect $volatility_{i,t} - volatility_{i,t-1}$ to be lower. Finally, we find that all past ΔIO have positive impact on $\Delta volatility_{i,t}$. $\Delta IO_{i,t-3}$ has the largest coefficient value and the highest significance level, following by the IO ratio change of last quarter ($\Delta IO_{i,t-1}$).

In the second column we include change in market condition as well as the interaction term of ΔIO and market change. Since the first 6 quarters in our studied period are recession period, and the rest are expansion period, we only have 1 market condition change (from recession to expansion) which occured between the 6^{th} quarter and the 7^{th} quarter. Therefore the market change indicator takes value of 1 only for the 7^{th} quarter, for all other quarters this indicator is 0. We want to understand whether market condition change has any impact on the relationship between past ΔIO and $\Delta volatility$. The coefficients on all explanatory variables have the same pattern as in the first column. One new finding from the second column is that the coefficients on all interaction terms are negative. Therefore if a past quarter experiences a market change from recession to expansion, the increase in IO of that quarter tends to have a negative impact on $\Delta volatility_{i,t}$.

Although we have included four lagged response as explanatory variables in model (1) and (2), one may still argue that the autocorrelation in $\Delta volatility$ is more persisting. This is the same problem that we mentioned in Section 3.1. In Section 3.1 we were not able to fix this problem since the daily data set contains more than one million observations and running a generalized least squares (GLS) model with response covariance matrix for such a data set is out of our computing power. Now we have a quarterly data set which is at least 60 times smaller in the number of observations, and creating quarterly lags makes the data set even smaller. It becomes possible to address the autocorrelation issue. Column (3) specifies a GLS model with AR(1) covariance matrix for the response variable and still includes four lag terms of ΔIO. After controlling autocorrelation, we still get similar results. All past ΔIO have positive coefficients except quarter $t-4$. But the coefficients on interactions terms become less significant. In column (4) we control all other variables and still have similar results. Therefore we conclude that the changes in quarterly stock return volatility are negative related to its own past, and positively related to past changes in IO ratio. The changes in IO ratio from the market condition changing quarter are likely to have negative impact on future volatility changes.

Next we do a similar analysis to examine whether past changes in volatility have impact on current IO ratio change. Table 9 reports the regression results. In this analysis we use $\Delta IO_{i,t}$ as the response variable, we still apply similar model specifications as in Table 8 to test the Granger causality from $\Delta volatility$ to ΔIO. Since $IO_{i,t}$ is actually calculated with the value reported at the end of quarter $t-1$ and $volatility_{i,t}$ is the quarterly volatility of quarter t, $\Delta IO_{i,t}$ is actually slightly preceding $\Delta volatility_{i,t}$. We do not include the contemporaneous term $\Delta volatility_{i,t}$ in the model to avoid look ahead bias.

[Place Table Table IX about here]

Column (1) and (2) in Table 9 are linear models with $\Delta volatility$ from four previous quarters. From both models we find that ΔIO is negatively related to its own past. It is also negatively related to $\Delta volatility$ of past three quarters. We include interaction terms of $\Delta volatility$ and market condition change indicator in column (2), (3) and (4) but we don't see a clear pattern from the interaction terms. Column (3) and (4) are generalized least square models with AR(1) covariance matrix for the response. We still observe similar results in these two models.

The regression results combined from Table 8 and Table 9 indicate that $\Delta volatility$ and ΔIO Granger cause each other. The results are consistent with the idea that there is positive impact from past institutional holding changes to subsequent volatility changes and past volatility changes have negative impact on subsequent institutional ownership changes.

CHAPTER 4

ADDITIONAL ANALYSIS ON THE RELATIONSHIP BETWEEN INSTITUTIONAL OWNERSHIP AND VOLATILITY

4.1 Institutional investor types

In the previous chapter, we pooled all institutional investors in one group for analysis. We examined whether all institutional investors as one group have any relationship with stock return volatility. Though institutional investors share some common features, they differ from each other in many different ways such as size, trading horizon, investment objective and constraints. Thomson Reuters database classified institutional investors into five groups: (1)Bank, (2)Insurance Company, (3)Investment Companies and Their Managers, (4)Investment Advisors, and (5)All Others (including Pension Funds, University Endowments, Foundations). Although the classification process is far from perfect as we mentioned in Section 2.2, it still provides some important information for each type of institutions. It is very important to know whether all types of institutional investors perform consentaneously or different types of institutional investors play different roles. In this section we examine the relationship between each institutional investor type and stock return volatility.

In Table 3 we glanced at the univariate relationship between each institutional investor type and volatility. This table exhibits the fact that for all institutional investor groups except group 1 (Bank), higher institutional ownership is associated with higher volatility.

In this section, we would like to further analyze the relationship between each institutional investor type and stock return volatility. We still use the daily data set that was created in Chapter 2 to run a multi-variate regression. The model specifications are very similar to those in Table 4. The only difference is that we now break down IO ratio into five variables: IO ratio group 1 (IO_1) through IO ratio group 5 (IO_5). The five variables capture the percentage of shares of each stock that are held by each type of institutional investors. All variables in the regressions are log transformed except Time Index. Table 10 reports the regression results.

[**Place Table Table X about here**]

The regression results are significant and consistent across different specifications of models for most of the variables. For example, the coefficient values on daily Amihud Ratio, Market Capitalization, daily Number of Trades, daily Average Trade Size and Time Index are all very close to the coefficient values in Table 4 since they are capturing the same relationships. In Section 2.2 we stated that many institutions are mis-classified into group 5, therefore this group is the largest group and represents the majority of institutional investors. More than half of the institutional investors are classified as group 5 institutions and they hold an average of 45% of the shares for S&P 500 stocks. The coefficient on IO_5 is 0.102 in model (1), indicating that a 10% increase in IO_5 is associated with a 1% increase in volatility. The coefficient value stays positive and significant across all models. This is consistent with the relationship between overall IO ratio and *volatility* in Table 4. The second largest group is group 4, which contains

40% of the institutions and they hold 23% of total shares. It is not surprising that IO_4 also has significant positive relationship with stock return volatility.

Group 1 is the third largest group, although it contains only 2% of institutions, they in total hold about 10% of all shares outstanding. We find out that this group is different from all other groups. According to Table 10, group 1 IO ratio has a negative relationship with stock return volatility. A 10% increase in IO_1 is associated with 1.5% decrease in volatility if not controlling lag volatility variables.

Finally, group 2 and 3 are both very small. They each hold 1%-2% of total shares outstanding. Their impact on stock return volatility is also very small as reflected by the magnitude of coefficients on IO_2 and IO_3.

This section provides evidence that different types of institutional investors do have different impact on stock return volatility. Most of them exhibit a positive relationship with volatility, except that banks are totally opposite.

4.2 Different institutional ownership levels

In this section, we would like to investigate whether the overall positive relationship between IO ratio and volatility applies to stocks in any IO ratio levels.

In each quarter, we sort all observations based on their IO values and divide them into 10 same size groups. We then combine the smallest IO ratio group across all quarters to obtain the lowest IO subset. We also combine the largest IO group across all quarters to get the highest IO ratio subset. The average IO ratio of the lowest IO subset is 54%, and the average

IO ratio of the highest IO subset is over 99%. We run the same models from Table 4 on these two subsets individually and report the results in Table 11 and 12.

[Place Table Table XI about here]

[Place Table Table XII about here]

In Table 12 (highest IO subset), all results are consistent with the results in Table 4, therefore the highest IO group shows the same pattern as the entire data sample. However, for the lowest IO group in Table 11, we find that IO ratio is negatively related to stock return volatility. Therefore for stocks with low IO ratio, increasing institutional holdings is associated with lower volatility.

In Table 13 we run regressions with the entire data sample for a robust check. We create two dummy variables for the lowest IO group and the highest IO group. We also include two interaction variables in the model to capture the slope difference for lowest and highest IO ratio groups.

[Place Table Table XIII about here]

According to Table 13, if a stock does not belong to either the lowest IO group or the highest IO group, a 10% increase in its IO ratio level tend to increase its volatility by 3.73%. However, for stocks from the lowest IO group, a 10% increase in IO ratio would decrease volatility by 1.16%. For the highest IO ratio group, stock return volatility would increase by 11.87% for a 10% increase in IO ratio. Therefore Table 13 also provides evidence that the relationship between stock return volatility and IO ratio varies for stocks with different IO ratio levels. Although we find positive relationship for the majority of S&P 500 stocks, it does not apply to stocks in the lowest IO group.

CHAPTER 5

INSTITUTIONAL OWNERSHIP AND MARKET MICROSTRUCTURE NOISE

Microstructure noise is a price deviation from fundamental value induced by market microstructure effects, for example, the frictions inherent in the trading process is one type of the effect which includes bid-ask bounces, discreteness of price changes, trades occurring on different markets or networks. Another type of microstructure effect is informational effects such as differences in informational content of price changes, gradual response of prices to a block trade, strategic component of the order flow. Therefore, microstructure noise is inherent in the market system, it can be easily affected by trading mechanisms such as changes in exchanges' matching system or the smallest tick size. It can also be affected by how people obtain and respond to information, the interaction between investors and exchanges, computer algorithm, and so on.

Literature in the past have addressed the changes in market microstructure in the high frequency world ((28)), the presence of market microstructure noise ((29)), the impact of market microstructure noise on volatility measures and how to deal with this issue ((11), (2), (30), (31), (32), (33), (34)). No one has yet studied the connection between market microstructure noise and institutional investors in the institution-dominating market. In this chapter we analyze the relationship between institutional investors and market microstructure noise. We would like to know whether institutional investors have any impact on noise, or if any market microstructure issues affects institutional investors' holdings.

We start by summarizing the characteristics of groups under different noise levels. For each quarter, we divide all observations into 10 same size groups based on their noise value, then we re-aggregate the same group across all quarters to form 10 decile groups. The summary statistics are reported in Table 14.

[**Place Table Table XIV about here**]

From the table we can see that the least noisy group has an average daily noise level of 7.7×10^{-5}. The most noisy group is about 9 times higher than the least noisy group. The volatility level increases monotonically along with noise level, which represents a positive association between daily noise and daily return volatility. IO ratio also has a positive relationship with stock noise, as well as group 2, 3, 4 and 5 IO ratios. Group 1 has a negative relationship with noise. Therefore in general, stocks with higher IO ratio tend to have higher noise level, but stocks with higher bank ownership have lower noise level. We also find out that a more noisy stock tends to be more illiquid (higher Amihud ratio), and smaller in market capitalization.

In the Chapter 3, we find evidence that higher trading frequency contributes to more volatility, and larger trade size can help reduce volatility. Here we have a different story. Stocks that trade more frequently display less noise than stocks with less frequent tradings. The relationship between noise and trade size is vague. stocks with either too large average trade sizes or too small trade size tend to have higher noise.

[**Place Table Table XV about here**]

[**Place Table Table XVI about here**]

Table 15 reports the results of multiple linear regression models. The model specifications are similar to the volatility analysis in Table 4. The first two models are basic models. Model 3 and 4 include a lagged response. Model 5 and 6 are HAR models which include lagged noise, average noise of past week, average noise of past month. The last two models are exclusive HAR models. We don't include the volatility variable in the models since it is shown in Chapter 3 that volatility is very well explained by the combination of other variables. All variable except Time Index are log transformed.

From the results we can see that after controlling other variables, IO ratio and daily noise are still positively related. The coefficients on time index reveal that daily stock noise level goes down over time. Daily average trade size seems to have a mixed pattern in the univariate analysis, and it is negatively related to noise after controlling other variables. Daily stock noise is also correlated with it's own history, but it is not the case that a nearer history has larger impact. Daily stock noise relies more on the average of past, rather than a single day since the average noise of past week has the largest coefficient value and highest significance level. Our robustness check with only quarter end subsample shows a consistent result in Table 16.

The next analysis aims to examine whether there is any causal effect between IO ratio and daily noise level. We created quarterly variables for changes and lagged changes in noise and IO ratio. Again we apply four different model specifications. The first model includes up to four lags (i.e. up to one year ago) of ΔIO and $\Delta noise$. The second model, in addition to the first model, includes the interaction terms of ΔIO and market condition change indicator. The third model specifies an AR(1) structure for the response covariance matrix with 4 lags of ΔIO

and 4 interaction terms. The last model is similar to the third, and adds the changes of other control variables.

[**Place Table Table XVII about here**]

[**Place Table Table XVIII about here**]

From Table 17 we have three main findings. First, changes in daily stock noise is negatively related to its own past, which is similar to the pattern we found in volatility changes. Second, coefficients on current and past ΔIO (including interaction terms) are all insignificant, indicating that none of the past and current changes in IO ratio, no matter whether the quarter has a market condition change or not, has any impact on the changes in microstructure noise. Lastly, the control variables are not related to $\Delta noise$ either. These findings seem to suggest that noise is an intrinsic term in the trading system which is not affected by any exogenous factors but only correlates with its own past.

From Table 18 we can see that past $\Delta noise$ do not impact ΔIO either. ΔIO only relates to it's own past, the changes in market capitalization and changes in average trade size in this model.

Therefore, we conclude that the positive relationship between noise and IO ratio in the contemporary analysis is spurious relationship. The past changes in IO ratio do not have any Granger causal impact on noise changes, and vice versa.

CHAPTER 6

EXPLORING THE CHANNEL AND ASSET PRICING IMPLICATIONS

In Chapter 3 we revealed the fact that institutional investors are associated with higher stock return volatility and that the changes in institutional holdings are positively related with the changes in volatility. In this chapter, we explore two possible channels through which institutional investors affect volatility. The first possible channel is that institutional investors involve with higher turnover traders who introduce overwhelming liquidity to the market and increase the volatility of stock returns. (19) revealed that ETFs attract high-turnover investors to the underlying securities and impound a new layer of liquidity shocks. They also found that the non-fundamental demand shocks in the ETF market are the main driver of stock volatility rather than fundamental demand. (35) also showed that institutional investors with short trading horizons sell their stock holdings to a larger extent than those with longer trading horizons and therefore amplify the effect of market turmoil. The second possible channel is that institutional investors herd as a result of inferring information from each other's trades. These herding activities push stock prices away from their fundamental value and revert to the normal level with future adjustment, which would also generate extra volatility in the market.

6.1 Extra liquidity layer

We first sort our daily observations by IO values and separate them into ten decile groups. For each group, we calculate the average value of some other variables and the summary is reported in Table 19.

[Place Table Table XIX about here]

The variable $turnover_{i,t}$ is defined as the fraction of shares outstanding of stock i that are traded on day t (i.e. daily trading volume divided by shares outstanding). In this table, the average daily turnover of the lowest IO ratio group is 0.01, which indicates that in average 1% of all shares outstanding are traded daily for these stocks. Stocks in the highest IO ratio group have 1.6% of their total outstanding shares traded per day. The average turnover ratio of the highest IO group is 60% higher than that of the lowest IO group. The table presents an increasing trend in turnover along with IO ratio.

However, the positive association between turnover ratio and IO ratio does not necessarily mean that institutional investors involve with more frequent tradings and larger trade size. In contrast, the table shows that stocks that are more held by institutions have less daily number of trades, smaller size per trade, and smaller daily trading volume. In the meantime, we find that the average market capitalization and average shares outstanding decrease monotonically from decile 1 to decile 10. Therefore the summary table reveals that smaller and riskier stocks are more likely to be held by institutional investors rather than by individuals, even though they have less trades and less trading volumes, they still have high turnover rate.

It is still possible that institutional investors hold more of small, risky stocks and increase their trading frequency and turnover. To test this hypothesis, we need to build a model and control stock market capitalization. We create a new categorical variable based on the value of market capitalization. Usually firms with market capitalization value of more than $10 billion are classified as large cap; firms with market capitalization value of less than $2 billion are small cap; middle cap is in between. Since we only study S&P 500 stocks which represent the 500 largest companies in the U.S. stock market, we raised the dividing line to better form the three groups. In this thesis, market capitalization value of less than $5 billion is classified as small cap, which accounts for roughly the bottom 20% of our data. Market capitalization value of more than $30 billion is classified as large cap, which represents the top 20% of the data. The middle 60% records are then grouped as mid cap. We include interaction terms of market cap category with number of trades, average trade size, and turnover. The default group is large cap and the original market capitalization variable is removed from the model if the new categorical variable is included. Table 20 reports the regression result.

[Place Table Table XX about here]

The table reveals some interesting findings. First of all, IO ratio is negatively related with market capitalization as we discovered from Table 19. Second, IO ratio and number of trades has negative relationship in general, but this relationship varies for different cap groups. For large cap stocks, 10% increase in daily number of trades is associated with 1.025% of decrease in IO. For mid cap and small cap stocks, 10% increase in number of trades is associated with about 0.6% of decrease in IO. Third, IO ratio is also negatively related with average trade size for all three market cap groups. The coefficient on trade size for small cap is more than double of that for large cap and mid cap groups.

In conclusion, our results support the idea that smaller, riskier stocks tend to have higher fraction of shares held by institutions. These stocks have higher turnover ratio and suffer from an extra layer of liquidity shock even though institutional investors trade them less frequent and with smaller trade size.

6.2 Institutional herding and return reversal

Another possible channel through which institutional investors affect stock return volatility is institutional herding. Herding activities from institutional investors result in them overreacting to market shocks then a reversal in stock returns. Therefore institutional investors generate some extra volatility by pushing the price away and back.

To analyze the connection between institutional holdings and potential future return reversal, we begin by sorting observations based on the change of IO ratio. Since IO ratio only changes once a quarter, we have to also aggregate daily returns into quarterly returns.

[Place Table Table XXI about here]

From Table 21 we can see that ΔIO ranges from -5.8% to 5.9% for the 10 decile groups while the initial IO ratios do not have much difference. Groups with larger IO change, no matter positive change or negative change, tend to have smaller market capitalization and higher volatility, which is consistent with our result in the previous section that institutional investors are more active with smaller and riskier stocks.

The bottom penal of Table 21 summarizes the average quarterly return of each group for the last quarter $t-1$, the current quarter t, and four future quarters $t+1$ through $t+4$. The numbers reveal three facts. First, from the last quarter performance, we observe that the group with poorest return from last quarter has the largest decrease in IO ratio, and the group with the best return from last quarter is experiencing the largest IO ratio increase. It is consistent with the idea that institutional investors choose to hold more stocks with good performance and sell those with terrible performance. Second, institutional investors' activities have immediate price impact on stocks. During the quarter that IO ratio is changing (quarter t), the group with largest ΔIO has the best return. The contemporaneous returns move in the same direction as ΔIO. Last, we observe return reversal in the next two quarters. Stocks that get sold the most in the current quarter (the smallest ΔIO group) are usually oversold and their prices bounce back in the next quarter. In quarter $t+1$ we observe an obvious return reversal, return of the smallest ΔIO group is about 4 times higher than the return of the largest ΔIO group, which is totally opposite to the pattern in quarter t. This return reversal phenomenon would definitely generate more volatility for stock returns.

CHAPTER 7

CONCLUSION

In the past decade, the development in technology has changed not only our life, but also the way of trading securities. Due to the highly developed computerized trading system, the number of trades is growing explosively. We are now able to complete hundreds of transactions in one second. In the meantime, institutional investors are increasing their holdings fast. By the end of 2017, institutional investors are holding about 66% of all U.S. market capitalization and about 80% of all shares outstanding of S&P 500 stocks. There is no doubt that institutional investors are playing a more and more important role in the market.

In this thesis, we examine all transactions of S&P 500 stocks from the beginning of 2008 to the end of 2017. We start by showing that stocks with greater institutional ownership display higher volatility than otherwise similar securities. This connection between institutional ownership and stock return volatility is not constant over time. It becomes stronger when market is growing stably, and weaker when market is very volatile. Although institutional investors prefer to hold riskier securities, they are more conservative during market turmoil periods.

We next show that institutional investors ownership ratio and stock return volatility Granger cause each other. Past changes in institutional ownership positively impact the changes in volatility in the future, and past changes in volatility have negative impact on changes of institutional ownership in subsequent quarters.

We then study whether the positive relationship between institutional ownership and volatility is true for all stocks. We find that for stocks with very low institutional ownership level, increase it's ownership can help reduce the volatility, which is opposite to what we find for the majority group. We also try to distinguish the impact from different types of institutional investors. All types of institutional investors exhibit similar positive relationship with volatility except that banks have a negative relationship with volatility.

Similar to volatility, market microstructure noise also has positive contemporaneous relationship with institutional ownership. But institutional ownership and noise do not Granger cause each other. The changes in market microstructure noise only depends on its own past as it is a more intrinsic term from the trading system.

Finally, this thesis analyzes the possible channels through which institutional investors affect stock return volatility. We find out that stocks with higher institutional ownership ratios tend to have higher turnover ratios which could possibly increase their return volatility. In addition, we find strong evidence of institutional herding and return reversal that could be another source of extra volatility. Institutional investors prefer to buy stocks with better past performance and sell those with worse performance. Due to the existence of institutional herding, they often end up with over-selling or over-buying stocks which result in return reversal afterwards.

Future research should delve into more details about the channels through which institutional investors increase stock return volatility, and that whether institutional investors activities could be used to predict future financial turmoil.

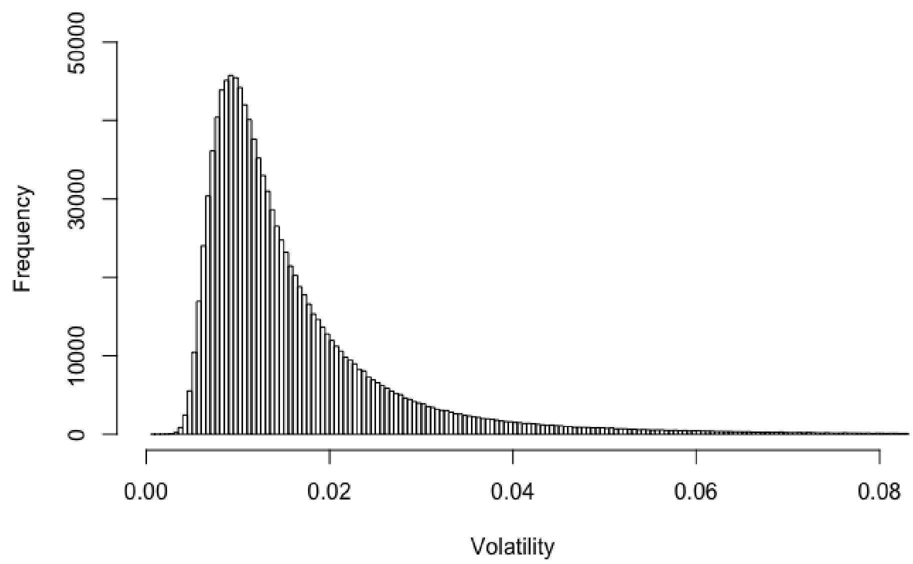

Figure 1. Histogram of Daily Volatility.
This histogram shows the distribution of daily volatility of 440 equities from Jan 2, 2008 to Dec 29, 2017, for a total of 1,107,920 observations. The daily volatility is calculated using tick-by-tick transaction data with TSRV estimator (briefly described in Section 2.1). Arguments of the TSRV estimator are set uniformly across all equities and through the entire study period. T is 6.5 regular trading hours. J is 4. K is 40. The estimated daily volatility ranges from 6.36×10^{-4} to 4.24, while 90% of them fall into the range of 0.006 and 0.038. The average is 0.016 and median is 0.013.

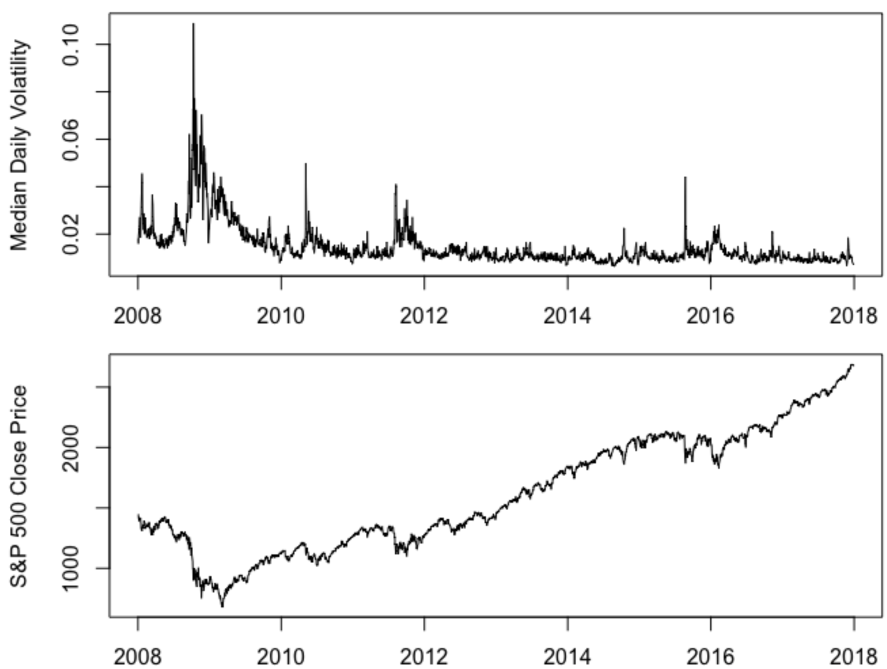

Figure 2. Median Daily Volatility and S&P 500 Close Price.
The top figure shows the time series trend of median daily volatility from Jan 2, 2008 to Dec 29, 2017. The bottom figure shows the daily close price of S&P 500 index of the same period. It is obvious that every time the market goes down, the median daily volatility goes up dramatically.

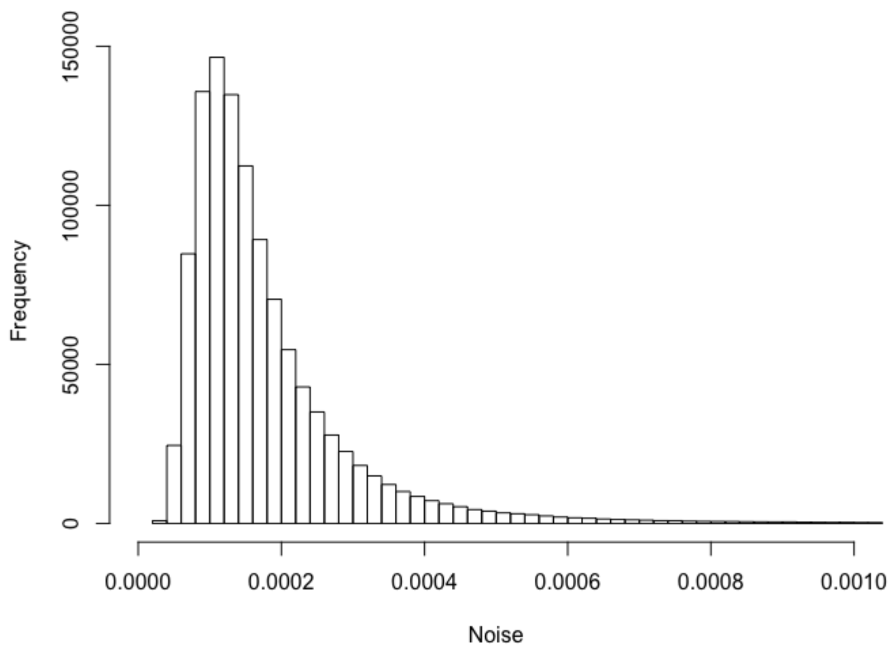

Figure 3. Histogram of Daily Noise.
This histogram shows the distribution of daily noise of 440 equities from Jan 2, 2008 to Dec 29, 2017, for a total of 1,107,920 observations. The daily noise is calculated using tick-by-tick transaction data (briefly described in Section 2.1). The estimated daily noise ranges from 2.5×10^{-5} to 23.7, while 90% of them fall into the range of 6.9×10^{-5} and 4.2×10^{-4}. The average is 2.2×10^{-4} and median is 1.4×10^{-4}.

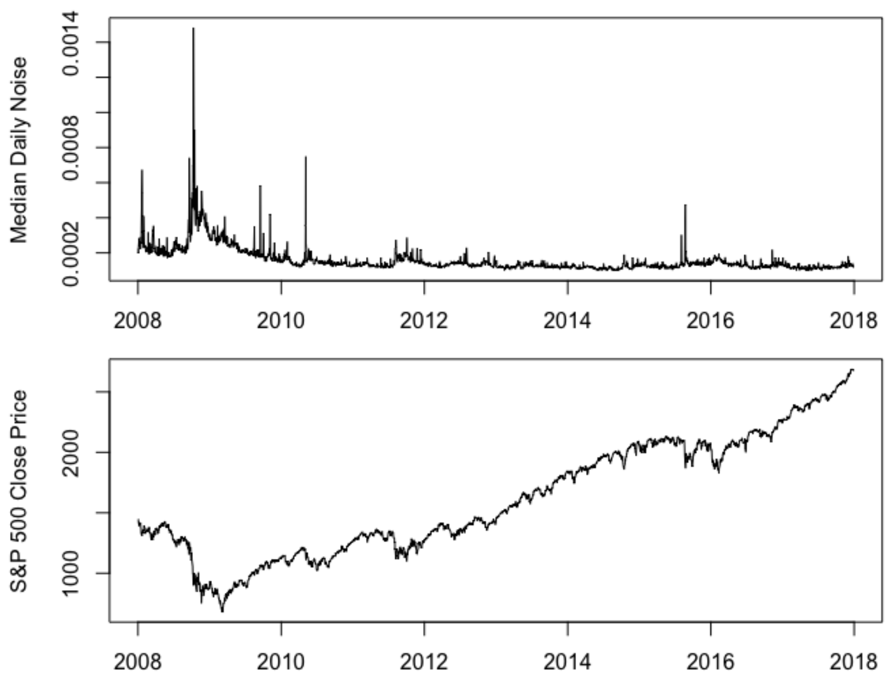

Figure 4. Median Daily Noise and S&P 500 Close Price.
The top figure shows the time series trend of median daily noise from Jan 2, 2008 to Dec 29, 2017. The bottom figure shows the daily close price of S&P 500 index of the same period.

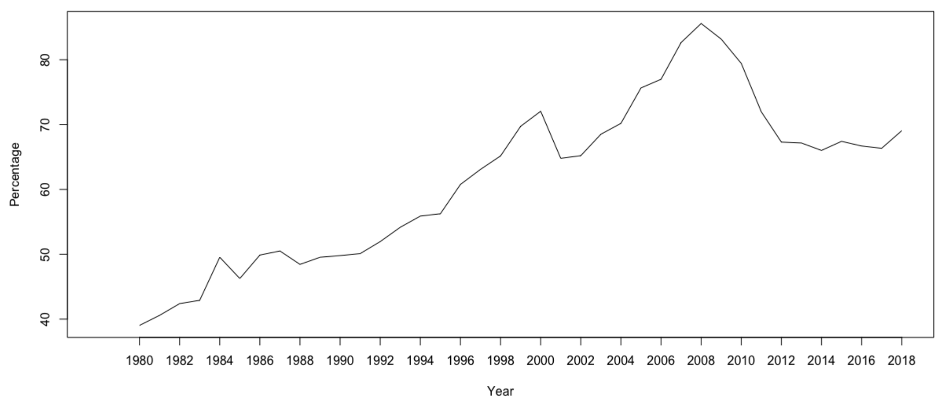

Figure 5. Time Series Percentage of U.S. Market Capitalization Held by Institutional Investors.
The total U.S. market capitalization data is downloaded from the World Bank website (`https://data.worldbank.org/indicator/CM.MKT.LCAP.CD?locations=US`). The total institutional holdings are calculated with Thomson Reuters 13(f) data. For each year end, we sum up the holding values of all stocks and all institutional investors.

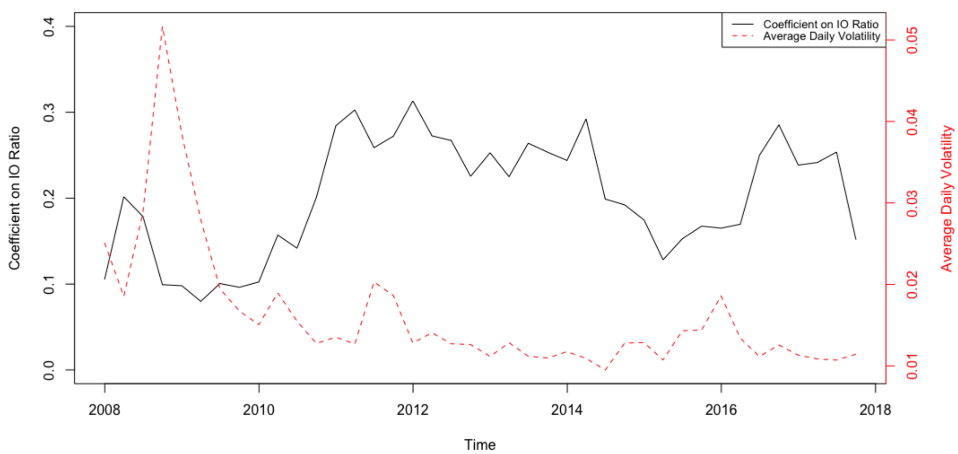

Figure 6. Average Daily Volatility and Coefficient on IO Ratio. We separate the entire data set into 40 quarters. For each quarter, we run the same model as in Table 4 column (1) and record the coefficient estimate on *IO* Ratio. The left panel (black line) shows coefficient estimate from each quarter. The right panel (red dashed line) shows the average daily volatility of each quarter.

TABLE I Time Series of the Number of Institutions by Manager Type

Year	Bank	Insurance Companies	Investment Companies	Investment Advisors	Others	Total
1980	234	72	55	139	83	583
1981	239	67	56	161	99	622
1982	241	71	60	188	88	648
1983	257	68	59	232	86	702
1984	244	72	63	292	98	769
1985	254	74	65	361	103	857
1986	241	70	74	421	114	920
1987	241	76	78	471	116	982
1988	234	74	66	509	102	985
1989	234	74	59	540	103	1,010
1990	235	75	60	576	107	1,053
1991	240	76	61	651	96	1,124
1992	242	74	69	717	93	1,195
1993	239	79	76	768	87	1,249
1994	222	81	68	823	84	1,278
1995	217	84	99	945	92	1,437
1996	203	77	97	995	86	1,458
1997	199	82	98	1144	102	1,625
1998	206	86	96	1245	447	2,080
1999	183	25	26	325	1,432	1,991
2000	176	29	19	343	1,739	2,306
2001	164	26	16	219	1,646	2,071
2002	149	22	13	168	1,790	2,142
2003	146	24	12	148	1,889	2,219
2004	139	21	12	195	2,060	2,427
2005	127	22	11	228	2,215	2,603
2006	116	20	11	397	2,428	2,972
2007	108	19	10	612	2,482	3,231
2008	102	20	11	723	2,436	3,292
2009	106	19	8	811	2,278	3,222
2010	107	17	9	911	2,224	3,268
2011	106	19	9	1,083	2,248	3,465
2012	103	20	10	1,198	2,306	3,637
2013	100	21	10	1,404	2,408	3,943
2014	97	21	10	1,555	2,588	4,271
2015	101	23	9	1,621	2,730	4,484
2016	100	23	8	1,697	2,739	4,567
2017	98	22	8	1,901	2,757	4,786
2018	93	22	8	1,797	2,648	4,568

TABLE II Summary Statistics

	#observation	mean	sd	min	median	max
Volatility	1,107,920	0.016	0.013	0.001	0.013	4.24
Noise (10^{-3})	1,107,920	0.215	23.995	0.025	0.144	23,716.14
IO Ratio Total	1,198,568	80.7%	13.5%	21.7%	82.4%	100.0%
IO Ratio Group 1	1,198,568	10.0%	2.9%	0.6%	9.8%	32.6%
IO Ratio Group 2	1,198,568	1.8%	1.9%	0.0%	1.2%	20.5%
IO Ratio Group 3	1,198,568	1.1%	0.9%	0.0%	0.9%	12.8%
IO Ratio Group 4	1,198,568	22.9%	7.3%	3.6%	22.2%	55.7%
IO Ratio Group 5	1,198,568	44.9%	10.2%	6.0%	44.8%	92.6%
Amihud Ratio (10^{-6})	1,107,920	0.081	0.456	0.000	0.035	114.10
Market Capitalization (Billion$)	1,107,920	27.4	50.9	0.11	11.6	904.9
Number of Trades (Thousand)	1,107,920	23.8	31.3	0.4	15.1	1,578.0
Average Trade Size (Shares)	1,107,920	161.6	89.5	28.3	147.1	4,398.7
Volume (Million Shares)	1,107,920	5.1	18.0	0.1	2.2	2,744.0
Turnover	1,107,920	0.01	0.01	0.00	0.01	0.88

TABLE III Characteristics of Volatility Decile Groups

Average Value	Volatility Decile									
of Daily Variables	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Volatility	0.008	0.010	0.011	0.012	0.014	0.015	0.017	0.019	0.023	0.034
IO Ratio Total	73.7%	77.0%	79.1%	80.4%	81.4%	82.2%	83.0%	83.6%	84.1%	83.0%
IO Ratio Group 1	10.6%	10.5%	10.3%	10.2%	10.1%	10.0%	10.0%	9.8%	9.6%	9.0%
IO Ratio Group 2	1.7%	1.7%	1.8%	1.8%	1.8%	1.8%	1.8%	1.9%	1.9%	1.8%
IO Ratio Group 3	1.0%	1.0%	1.0%	1.1%	1.1%	1.1%	1.1%	1.2%	1.2%	1.2%
IO Ratio Group 4	20.6%	21.8%	22.5%	23.0%	23.3%	23.5%	23.6%	23.7%	23.8%	23.6%
IO Ratio Group 5	39.9%	42.0%	43.4%	44.4%	45.1%	45.8%	46.4%	47.0%	47.6%	47.3%
Amihud Ratio (10^{-6})	0.038	0.041	0.044	0.048	0.052	0.057	0.064	0.075	0.101	0.289
Market Capitalization (Billion$)	48.3	40.0	34.2	30.4	27.3	24.3	22.1	19.5	16.4	11.8
Number of Trades (Thousand)	16.8	18.7	19.6	20.5	21.5	22.4	23.7	25.6	28.9	40.4
Average Trade Size (Shares)	151.7	151.2	151.0	152.0	153.4	155.0	157.4	161.2	169.4	213.7
Volume (Million Shares)	3.1	3.5	3.7	3.9	4.2	4.4	4.7	5.1	6.2	12.4
Turnover	0.005	0.006	0.007	0.007	0.008	0.009	0.011	0.013	0.016	0.029

TABLE IV Contemporaneous Regression Analysis

	Response Variable: Volatility (i,t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Volatility (i,t-1)			0.6333***	0.6270***	0.3457***	0.3385***	0.4019***	0.3941***
			(1031.97)	(1015.27)	(329.91)	(323.42)	(466.23)	(457.00)
Avg Volatility (i,t-1,t-5)					0.2260***	0.2184***		
					(142.15)	(137.65)		
Avg Volatility (i,t-1,t-20)					0.1880***	0.2034***		
					(142.59)	(152.90)		
Avg Volatility (i,t-2,t-5)							0.2253***	0.2222***
							(206.91)	(204.53)
Avg Volatility (i,t-6,t-20)							0.1353***	0.1469***
							(138.08)	(148.49)
IO Ratio Total (i,t)	0.1603***	0.1639***	0.0519***	0.0543***	0.0237***	0.0249***	0.0230***	0.0241***
	(93.02)	(96.12)	(42.06)	(44.13)	(20.18)	(21.23)	(19.57)	(20.62)
Amihud Ratio (i,t)	0.1595***	0.1606***	0.0579***	0.0594***	0.0324***	0.0331***	0.0320***	0.0328***
	(396.86)	(403.14)	(190.85)	(195.60)	(109.20)	(111.84)	(108.09)	(110.80)
Market Capitalization (i,t)	-0.2144***	-0.2118***	-0.0942***	-0.0944***	-0.0829***	-0.0817***	-0.0826***	-0.0814***
	(-469.31)	(-467.97)	(-272.13)	(-273.19)	(-250.68)	(-247.50)	(-249.97)	(-246.82)
Number of Trades (i,t)	0.4408***	0.4384***	0.1992***	0.2006***	0.1753***	0.1743***	0.1745***	0.1735***
	(886.60)	(888.89)	(468.60)	(471.93)	(428.81)	(425.91)	(427.35)	(424.56)
Average Trade Size (i,t)	-0.4413***	-0.4410***	-0.2066***	-0.2088***	-0.1868***	-0.1868***	-0.1862***	-0.1863***
	(-387.32)	(-391.06)	(-244.62)	(-247.68)	(-232.92)	(-233.50)	(-232.63)	(-233.29)
Time Index (t)	-0.0280***	-0.0283***	-0.0104***	-0.0107***	-0.0067***	-0.0068***	-0.0066***	-0.0068***
	(-762.91)	(-776.71)	(-334.51)	(-341.63)	(-213.39)	(-215.06)	(-211.24)	(-213.07)
Month Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Effective Observations	1,105,271	1,105,271	1,104,832	1,104,832	1,096,491	1,096,491	1,096,491	1,096,491
R^2	0.6812	0.6882	0.8377	0.8387	0.8540	0.8553	0.8545	0.8558

TABLE V Contemporaneous Regression Analysis with Quarter End Subsample

	Response Variable: Volatility (i,t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Volatility (i,t-1)			0.6461***	0.6384***	0.2709***	0.2150***	0.3614***	0.3153***
			(147.55)	(142.83)	(35.01)	(27.68)	(57.89)	(48.78)
Avg Volatility (i,t-1,t-5)					0.3990***	0.4408***		
					(34.82)	(34.51)		
Avg Volatility (i,t-1,t-20)					0.1311***	0.1374***		
					(15.22)	(12.67)		
Avg Volatility (i,t-2,t-5)							0.3463***	0.3824***
							(42.30)	(43.57)
Avg Volatility (i,t-6,t-20)							0.0967***	0.0992***
							(14.43)	(11.84)
IO Ratio Total (i,t)	0.1538***	0.1648***	0.0439***	0.0430***	0.0138.	0.0167*	0.0135.	0.0162*
	(11.52)	(12.69)	(4.90)	(4.85)	(1.68)	(2.09)	(1.65)	(2.04)
Amihud Ratio (i,t)	0.1281***	0.1360***	0.0344***	0.0319***	0.0143***	0.0154***	0.0146***	0.0156***
	(40.23)	(43.06)	(15.47)	(14.09)	(6.65)	(7.37)	(6.83)	(7.50)
Market Capitalization (i,t)	-0.2190***	-0.2040***	-0.0816***	-0.0874***	-0.0574***	-0.0582***	-0.0561***	-0.0571***
	(-61.91)	(-57.07)	(-32.12)	(-34.11)	(-23.92)	(-24.71)	(-23.41)	(-24.26)
Number of Trades (i,t)	0.4274***	0.4031***	0.1437***	0.1529***	0.1071***	0.1103***	0.1055***	0.1090***
	(106.92)	(96.85)	(43.65)	(45.92)	(34.60)	(35.91)	(34.12)	(35.54)
Average Trade Size (i,t)	-0.4020***	-0.3749***	-0.1256***	-0.1326***	-0.1069***	-0.1089***	-0.1063***	-0.1086***
	(-44.37)	(-42.05)	(-19.82)	(-21.06)	(-18.42)	(-19.16)	(-18.34)	(-19.15)
Time Index (t)	-0.0256***	-0.0261***	-0.0074***	-0.0076***	-0.0039***	-0.0044***	-0.0039***	-0.0044***
	(-83.90)	(-87.77)	(-30.98)	(-31.89)	(-16.73)	(-19.35)	(-16.75)	(-19.40)
Month Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Effective Observations	17,568	17,568	17,568	17,568	17,568	17,568	17,568	17,568
R^2	0.6437	0.6641	0.8409	0.8446	0.8670	0.8742	0.8675	0.8748

TABLE VI Coefficients on IO Ratio and Average Volatility by Quarter

Quarter	Estimate	Volatility	Quarter	Estimate	Volatility	Quarter	Estimate	Volatility
2008 Q1	0.105	0.025	2011 Q3	0.259	0.020	2015 Q1	0.175	0.013
2008 Q2	0.202	0.019	2011 Q4	0.272	0.019	2015 Q2	0.128	0.011
2008 Q3	0.179	0.029	2012 Q1	0.313	0.013	2015 Q3	0.153	0.014
2008 Q4	0.099	0.052	2012 Q2	0.273	0.014	2015 Q4	0.167	0.014
2009 Q1	0.098	0.038	2012 Q3	0.267	0.013	2016 Q1	0.165	0.019
2009 Q2	0.080	0.028	2012 Q4	0.225	0.013	2016 Q2	0.170	0.013
2009 Q3	0.101	0.019	2013 Q1	0.253	0.011	2016 Q3	0.250	0.011
2009 Q4	0.096	0.017	2013 Q2	0.225	0.013	2016 Q4	0.285	0.013
2010 Q1	0.102	0.015	2013 Q3	0.264	0.011	2017 Q1	0.238	0.011
2010 Q2	0.157	0.019	2013 Q4	0.253	0.011	2017 Q2	0.241	0.011
2010 Q3	0.142	0.015	2014 Q1	0.244	0.012	2017 Q3	0.254	0.011
2010 Q4	0.201	0.013	2014 Q2	0.292	0.011	2017 Q4	0.152	0.011
2011 Q1	0.284	0.014	2014 Q3	0.199	0.010			
2011 Q2	0.303	0.013	2014 Q4	0.192	0.013			

TABLE VII Contemporaneous Regression Analysis with Recession Indicator

	Response Variable: Volatility (i,t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Volatility (i,t-1)			0.6258***	0.6182***	0.3455***	0.3382***	0.4017***	0.3937***
			(1004.31)	(984.10)	(329.70)	(323.17)	(465.80)	(456.44)
Avg Volatility (i,t-1,t-5)					0.2262***	0.2186***		
					(142.26)	(137.77)		
Avg Volatility (i,t-1,t-20)					0.1860***	0.2006***		
					(139.96)	(149.49)		
Avg Volatility (i,t-2,t-5)							0.2250***	0.2217***
							(206.64)	(204.06)
Avg Volatility (i,t-6,t-20)							0.1339***	0.1449***
							(135.58)	(145.22)
Recession (t)	0.1738***	0.1865***	0.0415***	0.0475***	0.0036***	0.0070***	0.0030**	0.0065***
	(110.92)	(120.11)	(36.34)	(41.54)	(3.30)	(6.32)	(2.77)	(5.87)
IO Ratio Total (i,t)	0.1812***	0.1853***	0.0610***	0.0641***	0.0277***	0.0290***	0.0269***	0.0283***
	(97.01)	(100.50)	(44.99)	(47.39)	(21.47)	(22.63)	(20.92)	(22.10)
IO Ratio Total (i,t)×Recession (t)	-0.1615***	-0.1662***	-0.0537***	-0.0569***	-0.0209***	-0.0221***	-0.0208***	-0.0221***
	(-41.52)	(-43.27)	(-19.06)	(-20.25)	(-7.65)	(-8.12)	(-7.65)	(-8.15)
Amihud Ratio (i,t)	0.1247***	0.1235***	0.0502***	0.0508***	0.0313***	0.0317***	0.0310***	0.0314***
	(282.19)	(282.34)	(152.96)	(154.85)	(99.26)	(100.53)	(98.45)	(99.73)
Market Capitalization (i,t)	-0.2303***	-0.2288***	-0.0997***	-0.1006***	-0.0838***	-0.0830***	-0.0834***	-0.0826***
	(-501.41)	(-503.61)	(-279.44)	(-282.36)	(-245.05)	(-242.69)	(-244.17)	(-241.87)
Number of Trades (i,t)	0.4278***	0.4249***	0.1987***	0.2003***	0.1753***	0.1744***	0.1745***	0.1736***
	(864.73)	(867.75)	(468.16)	(472.17)	(428.85)	(426.12)	(427.39)	(424.76)
Average Trade Size (i,t)	-0.3807***	-0.3770***	-0.1935***	-0.1945***	-0.1846***	-0.1838***	-0.1842***	-0.1835***
	(-325.37)	(-326.18)	(-223.39)	(-225.12)	(-224.08)	(-223.98)	(-223.96)	(-223.89)
Time Index (t)	-0.0215***	-0.0215***	-0.0090***	-0.0091***	-0.0065***	-0.0065***	-0.0065***	-0.0065***
	(-421.50)	(-424.72)	(-230.71)	(-234.27)	(-173.23)	(-173.97)	(-171.86)	(-172.63)
Month Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Effective Observations	1,105,271	1,105,271	1,104,832	1,104,832	1,096,491	1,096,491	1,096,491	1,096,491
R^2	0.6907	0.6987	0.8383	0.8394	0.8541	0.8553	0.8545	0.8558

TABLE VIII Regression of ΔVolatility on Past ΔIO

	Response Variable: ΔVolatility (i,t)			
	(1)	(2)	(3)	(4)
ΔVolatility (i,t-1)	-0.3870***	-0.5453***		
	(-49.81)	(-68.89)		
ΔVolatility (i,t-2)	-0.2575***	-0.4536***		
	(-36.42)	(-59.90)		
ΔVolatility (i,t-3)	-0.2384***	-0.3209***		
	(-36.66)	(-41.86)		
ΔVolatility (i,t-4)	-0.1754***	-0.1868***		
	(-27.56)	(-25.02)		
ΔIO Ratio Total (i,t)	-0.0246***	-0.0183**	0.0109	0.0053
	(-3.90)	(-2.98)	(1.41)	(0.72)
ΔIO Ratio Total (i,t-1)	0.0719***	0.0395***	0.0606***	0.0457***
	(11.53)	(6.54)	(7.62)	(5.97)
ΔIO Ratio Total (i,t-2)	0.0504***	0.0453***	0.0303***	0.0274***
	(8.01)	(7.76)	(3.91)	(3.68)
ΔIO Ratio Total (i,t-3)	0.0788***	0.0619***	0.0421***	0.0336***
	(12.55)	(10.61)	(5.54)	(4.59)
ΔIO Ratio Total (i,t-4)	0.0166**	0.0247***	-0.0540***	-0.0477***
	(2.69)	(4.28)	(-7.32)	(-6.73)
ΔIO Ratio Total (i,t) ×Recession (t)		-0.0760**	-0.1789***	-0.1165***
		(-2.65)	(-4.94)	(-3.35)
ΔIO Ratio Total (i,t-1) ×Recession (t-1)		-0.1336***	-0.0642	-0.0161
		(-4.65)	(-1.59)	(-0.41)
ΔIO Ratio Total (i,t-2) ×Recession (t-2)		-0.0996***	-0.0075	-0.0147
		(-3.46)	(-0.18)	(-0.37)
ΔIO Ratio Total (i,t-3) ×Recession (t-3)		-0.0710*	-0.0058	-0.0093
		(-2.46)	(-0.14)	(-0.24)
ΔIO Ratio Total (i,t-4) ×Recession (t-4)		-0.0865**	-0.0104	0.0138
		(-3.00)	(-0.28)	(0.38)
ΔAmihud Ratio (i,t)				0.1201***
				(19.20)
ΔMarket Capitalization (i,t)				-0.0249***
				(-4.31)
ΔNumber of Trades (i,t)				0.2097***
				(29.76)
ΔAverage Trade Size (i,t)				-0.0326***
				(-5.15)
Effective Observations	15,321	15,321	15,321	15,321
R^2	0.1926	0.3303	0.4441	0.4915
AIC			39,574	38,359

TABLE IX Regression of ΔIO on Past ΔVolatility

	Response Variable: ΔIO ratio total (i,t)			
	(1)	(2)	(3)	(4)
ΔVolatility (i,t-1)	-0.0265**	-0.0729***	-0.0840***	-0.0812***
	(-2.65)	(-6.71)	(-8.49)	(-8.19)
ΔVolatility (i,t-2)	-0.0228*	-0.0957***	-0.0817***	-0.0770***
	(-2.51)	(-9.16)	(-7.89)	(-7.33)
ΔVolatility (i,t-3)	-0.0177*	-0.1149***	-0.0987***	-0.0963***
	(-2.12)	(-11.49)	(-9.79)	(-9.37)
ΔVolatility (i,t-4)	0.0641***	-0.0106	0.0050	0.0075
	(7.86)	(-1.08)	(0.48)	(0.70)
ΔVolatility (i,t-1) ×Recession (t-1)		-0.0060	-0.0258	-0.0279
		(-0.09)	(-0.42)	(-0.46)
ΔVolatility (i,t-2) ×Recession (t-2)		0.0309	0.0477	0.0453
		(0.46)	(0.68)	(0.64)
ΔVolatility (i,t-3) ×Recession (t-3)		0.2132**	0.2479***	0.2564***
		(3.09)	(3.37)	(3.49)
ΔVolatility (i,t-4) ×Recession (t-4)		0.0907	0.0379	0.0283
		(1.31)	(0.52)	(0.39)
ΔIO ratio total (i,t-1)	-0.1748***	-0.1972***		
	(-22.16)	(-25.15)		
ΔIO ratio total (i,t-2)	-0.1096***	-0.1123***		
	(-13.65)	(-14.57)		
ΔIO ratio total (i,t-3)	-0.0794***	-0.0673***		
	(-9.87)	(-8.72)		
ΔIO ratio total (i,t-4)	-0.0415***	-0.0435***		
	(-5.22)	(-5.71)		
ΔAmihud Ratio (i,t)				0.0025
				(0.33)
ΔMarket Capitalization (i,t)				0.0190**
				(2.59)
ΔNumber of Trades (i,t)				-0.0026
				(-0.32)
ΔAverage Trade Size (i,t)				-0.0304***
				(-3.98)
Effective Observations	15,321	15,321	15,321	15,321
R^2	0.0479	0.1287	0.3518	0.3529
AIC			42,009	42,023

TABLE X Contemporaneous Regression Analysis for Institution Types

	Response Variable: Volatility (t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Volatility (t-1)			0.6254***	0.6187***	0.3440***	0.3368***	0.3999***	0.3921***
			(1,011.90)	(994.56)	(328.71)	(323.31)	(464.32)	(455.19)
Avg Volatility (i,t-1,t-5)					0.2256***	0.2181***		
					(142.18)	(137.69)		
Avg Volatility (i,t-1,t-20)					0.1828***	0.1979***		
					(138.57)	(148.57)		
Avg Volatility (i,t-2,t-5)							0.2239***	0.2208***
							(206.01)	(203.56)
Avg Volatility (i,t-6,t-20)							0.1315***	0.1428***
							(134.06)	(144.16)
IO ratio - type I (i,t)	-0.1539***	-0.1556***	-0.0576***	-0.0591***	-0.0379***	-0.0376***	-0.0375***	-0.0371***
	(-145.60)	(-148.79)	(-75.01)	(-77.17)	(-51.66)	(-51.38)	(-51.15)	(-50.87)
IO ratio - type II (i,t)	-0.0095***	-0.0086***	-0.0040***	-0.0037***	-0.0029***	-0.0028***	-0.0029***	-0.0028***
	(-26.07)	(-23.80)	(-15.04)	(-14.19)	(-11.47)	(-11.34)	(-11.46)	(-11.34)
IO ratio - type III (i,t)	0.0081***	0.0081***	0.0008*	0.0009*	-0.0022***	-0.0023***	-0.0022***	-0.0023***
	(15.73)	(15.83)	(2.17)	(2.32)	(-6.25)	(-6.59)	(-6.25)	(-6.59)
IO ratio - type IV (i,t)	0.0910***	0.0932***	0.0344***	0.0357***	0.0221***	0.0219***	0.0217***	0.0216***
	(96.35)	(99.69)	(50.41)	(52.30)	(33.88)	(33.76)	(33.42)	(33.30)
IO ratio - type V (i,t)	0.1019***	0.1027***	0.0336***	0.0348***	0.0158***	0.0169***	0.0153***	0.0164***
	(77.85)	(79.28)	(35.51)	(36.91)	(17.51)	(18.79)	(16.95)	(18.24)
Amihud Ratio (i,t)	0.1539***	0.1549***	0.0570***	0.0585***	0.0322***	0.0330***	0.0318***	0.0326***
	(384.89)	(390.66)	(187.84)	(192.51)	(108.23)	(111.10)	(107.14)	(109.99)
Market Capitalization (i,t)	-0.2064***	-0.2040***	-0.0927***	-0.0930***	-0.0822***	-0.0810***	-0.0819***	-0.0807***
	(-454.15)	(-453.07)	(-267.83)	(-269.00)	(-248.06)	(-245.02)	(-247.40)	(-244.38)
Number of Trades (i,t)	0.4439***	0.4415***	0.2035***	0.2051***	0.1786***	0.1777***	0.1778***	0.1769***
	(902.46)	(905.31)	(476.99)	(480.68)	(433.95)	(431.04)	(432.41)	(429.61)
Average Trade Size (i,t)	-0.4519***	-0.4516***	-0.2133***	-0.2157***	-0.1912***	-0.1912***	-0.1906***	-0.1907***
	(-400.96)	(-404.99)	(-252.18)	(-255.52)	(-237.50)	(-238.16)	(-237.15)	(-237.89)
Time Index (t)	-0.0276***	-0.0279***	-0.0106***	-0.0109***	-0.0069***	-0.0070***	-0.0068***	-0.0069***
	(-738.22)	(-751.92)	(-332.11)	(-339.48)	(-214.87)	(-216.82)	(-212.73)	(-214.83)
Month Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Effective Observations	1,105,205	1,105,205	1,104,766	1,104,766	1,096,425	1,096,425	1,096,425	1,096,425
R^2	0.6895	0.6965	0.8388	0.8399	0.8546	0.8558	0.8550	0.8563

TABLE XI Contemporaneous Regression Analysis with Low IO Ratio Subsample

	Response Variable: Volatility (i,t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Volatility (i,t-1)			0.6433***	0.6378***	0.3495***	0.3429***	0.4050***	0.3981***
			(347.22)	(342.21)	(106.59)	(104.68)	(150.49)	(147.88)
Avg Volatility (i,t-1,t-5)					0.2302***	0.2248***		
					(47.15)	(46.11)		
Avg Volatility (i,t-1,t-20)					0.1689***	0.1807***		
					(43.01)	(45.68)		
Avg Volatility (i,t-2,t-5)							0.2259***	0.2238***
							(67.43)	(66.90)
Avg Volatility (i,t-6,t-20)							0.1207***	0.1295***
							(41.41)	(44.13)
IO Ratio Total (i,t)	-0.1025***	-0.1007***	-0.0470***	-0.0468***	-0.0428***	-0.0423***	-0.0429***	-0.0424***
	(-20.88)	(-20.71)	(-13.82)	(-13.80)	(-13.27)	(-13.17)	(-13.34)	(-13.24)
Amihud Ratio (i,t)	0.1956***	0.1971***	0.0690***	0.0706***	0.0436***	0.0446***	0.0432***	0.0443***
	(159.53)	(162.09)	(74.71)	(76.43)	(48.38)	(49.48)	(48.08)	(49.19)
Market Capitalization (i,t)	-0.2441***	-0.2420***	-0.1038***	-0.1041***	-0.0927***	-0.0917***	-0.0921***	-0.0911***
	(-197.16)	(-197.03)	(-109.53)	(-110.01)	(-102.21)	(-101.13)	(-101.72)	(-100.64)
Number of Trades (i,t)	0.5077***	0.5048***	0.2196***	0.2209***	0.1945***	0.1936***	0.1936***	0.1927***
	(330.24)	(330.75)	(162.73)	(163.70)	(149.51)	(148.55)	(149.03)	(148.10)
Average Trade Size (i,t)	-0.4143***	-0.4139***	-0.1859***	-0.1877***	-0.1660***	-0.1664***	-0.1657***	-0.1661***
	(-154.37)	(-155.60)	(-94.42)	(-95.37)	(-88.81)	(-89.15)	(-88.81)	(-89.17)
Time Index (t)	-0.0288***	-0.0291***	-0.0104***	-0.0106***	-0.0070***	-0.0071***	-0.0069***	-0.0071***
	(-244.62)	(-248.63)	(-106.61)	(-108.65)	(-72.30)	(-73.14)	(-71.81)	(-72.69)
Month Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Effective Observations	110,537	110,537	110,493	110,493	109,663	109,663	109,663	109,663
R^2	0.7417	0.7470	0.8765	0.8772	0.8893	0.8902	0.8897	0.8906

TABLE XII Contemporaneous Regression Analysis with High IO Ratio Subsample

	Response Variable: Volatility (i,t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Volatility (i,t-1)			0.6313***	0.6261***	0.3313***	0.3255***	0.3900***	0.3835***
			(317.46)	(313.35)	(98.86)	(97.28)	(141.19)	(138.85)
Avg Volatility (i,t-1,t-5)					0.2279***	0.2204***		
					(43.75)	(42.35)		
Avg Volatility (i,t-1,t-20)					0.2143***	0.2283***		
					(48.52)	(51.33)		
Avg Volatility (i,t-2,t-5)							0.2309***	0.2277***
							(64.96)	(64.13)
Avg Volatility (i,t-6,t-20)							0.1548***	0.1651***
							(47.05)	(49.85)
IO Ratio Total (i,t)	1.2788***	1.2986***	0.4582***	0.4756***	0.2642***	0.2755***	0.2569***	0.2688***
	(21.08)	(21.47)	(10.43)	(10.78)	(6.38)	(6.64)	(6.21)	(6.49)
Amihud Ratio (i,t)	0.1568***	0.1568***	0.0579***	0.0588***	0.0312***	0.0316***	0.0308***	0.0313***
	(117.89)	(118.74)	(57.27)	(58.13)	(31.72)	(32.22)	(31.42)	(31.94)
Market Capitalization (i,t)	-0.1951***	-0.1940***	-0.0784***	-0.0789***	-0.0599***	-0.0592***	-0.0597***	-0.0590***
	(-108.25)	(-108.46)	(-57.84)	(-58.33)	(-46.30)	(-45.83)	(-46.22)	(-45.75)
Number of Trades (i,t)	0.3920***	0.3915***	0.1776***	0.1791***	0.1521***	0.1516***	0.1514***	0.1510***
	(261.95)	(263.50)	(139.20)	(140.30)	(124.31)	(123.76)	(123.82)	(123.30)
Average Trade Size (i,t)	-0.3793***	-0.3821***	-0.1748***	-0.1776***	-0.1549***	-0.1552***	-0.1542***	-0.1546***
	(-88.58)	(-89.95)	(-55.26)	(-56.20)	(-51.74)	(-51.97)	(-51.59)	(-51.83)
Time Index (t)	-0.0287***	-0.0289***	-0.0110***	-0.0113***	-0.0071***	-0.0072***	-0.0070***	-0.0071***
	(-234.75)	(-237.74)	(-105.83)	(-107.48)	(-67.97)	(-68.31)	(-67.27)	(-67.75)
Month Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Effective Observations	110,513	110,513	110,470	110,470	109,653	109,653	109,653	109,653
R^2	0.6644	0.6702	0.8245	0.8254	0.8434	0.8445	0.8437	0.8449

TABLE XIII Contemporaneous Regression Analysis with Low and High IO Ratio Indicators

	Response Variable: Volatility (i,t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Volatility (i,t-1)			0.6301***	0.6236***	0.3448***	0.3376***	0.4008***	0.3930***
			(1,024.45)	(1,007.41)	(329.32)	(322.86)	(465.25)	(456.04)
Avg Volatility (i,t-1,t-5)					0.2255***	0.2178***		
					(141.95)	(137.41)		
Avg Volatility (i,t-1,t-20)					0.1863***	0.2016***		
					(141.42)	(151.63)		
Avg Volatility (i,t-2,t-5)							0.2245***	0.2213***
							(206.39)	(203.93)
Avg Volatility (i,t-6,t-20)							0.1341***	0.1456***
							(136.91)	(147.21)
IO Ratio Total (i,t)	0.3725***	0.3800***	0.1399***	0.1452***	0.0920***	0.0942***	0.0908***	0.0930***
	(121.92)	(125.73)	(63.60)	(66.14)	(43.96)	(45.15)	(43.45)	(44.65)
IO Ratio Total (i,t) × Low IO (i,t)	-0.4888***	-0.4951***	-0.1937***	-0.1992***	-0.1382***	-0.1401***	-0.1372***	-0.1392***
	(-88.31)	(-90.47)	(-48.74)	(-50.26)	(-36.55)	(-37.21)	(-36.35)	(-37.03)
IO Ratio Total (i,t) × High IO (i,t)	0.8140***	0.8398***	0.2460***	0.2676***	0.0968*	0.1155**	0.0904*	0.1098**
	(13.99)	(14.59)	(5.90)	(6.44)	(2.45)	(2.94)	(2.30)	(2.80)
Amihud Ratio (i,t)	0.1598***	0.1609***	0.0585***	0.0600***	0.0329***	0.0337***	0.0325***	0.0334***
	(399.37)	(405.88)	(192.93)	(197.86)	(111.00)	(113.77)	(109.88)	(112.72)
Market Capitalization (i,t)	-0.2079***	-0.2053***	-0.0923***	-0.0925***	-0.0817***	-0.0805***	-0.0813***	-0.0802***
	(-452.22)	(-450.70)	(-265.11)	(-266.07)	(-245.53)	(-242.43)	(-244.86)	(-241.79)
Number of Trades (i,t)	0.4424***	0.4400***	0.2011***	0.2026***	0.1768***	0.1759***	0.1760***	0.1752***
	(893.53)	(896.20)	(472.37)	(475.92)	(431.53)	(428.74)	(430.04)	(427.36)
Average Trade Size (i,t)	-0.4398***	-0.4395***	-0.2072***	-0.2095***	-0.1874***	-0.1875***	-0.1869***	-0.1870***
	(-386.69)	(-390.56)	(-244.98)	(-248.15)	(-233.22)	(-233.89)	(-232.93)	(-233.67)
Time Index (t)	-0.0282***	-0.0286***	-0.0106***	-0.0109***	-0.0069***	-0.0070***	-0.0068***	-0.0069***
	(-770.51)	(-784.80)	(-339.02)	(-346.41)	(-217.43)	(-219.26)	(-215.26)	(-217.24)
Month Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Effective Observations	1,105,271	1,105,271	1,104,832	1,104,832	1,096,491	1,096,491	1,096,491	1,096,491
R^2	0.6845	0.6915	0.8382	0.8392	0.8543	0.8556	0.8548	0.8561

TABLE XIV Characteristics of Microstructure Noise Decile Groups

Average Value	Noise Decile									
of Daily Variables	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Noise (10^{-3})	0.077	0.100	0.115	0.131	0.147	0.164	0.186	0.214	0.261	0.756
Volatility	0.010	0.012	0.013	0.014	0.015	0.016	0.017	0.018	0.020	0.027
IO Ratio Total	70.9%	76.3%	78.3%	79.9%	81.5%	82.6%	83.6%	84.4%	85.5%	84.4%
IO Ratio Group 1	10.8%	10.7%	10.5%	10.3%	10.1%	10.0%	9.8%	9.6%	9.4%	8.9%
IO Ratio Group 2	1.7%	1.7%	1.7%	1.7%	1.8%	1.8%	1.9%	1.9%	1.9%	2.0%
IO Ratio Group 3	1.0%	1.0%	1.0%	1.0%	1.1%	1.1%	1.1%	1.2%	1.2%	1.2%
IO Ratio Group 4	19.5%	21.1%	21.7%	22.4%	23.1%	23.6%	24.1%	24.4%	24.7%	24.6%
IO Ratio Group 5	37.9%	41.8%	43.3%	44.4%	45.4%	46.1%	46.7%	47.4%	48.3%	47.7%
Amihud Ratio (10^{-6})	0.017	0.025	0.032	0.039	0.046	0.054	0.064	0.077	0.099	0.357
Market Capitalization (Billion$)	99.3	42.5	29.8	22.9	18.1	15.3	13.1	11.9	11.0	10.4
Number of Trades (Thousand)	43.7	30.9	26.4	23.3	20.9	19.5	18.4	18.0	17.4	19.5
Average Trade Size (Shares)	171.1	162.6	158.3	155.0	152.4	152.1	152.6	154.5	157.8	199.7
Volume (Million Shares)	8.5	6.0	5.1	4.5	4.0	3.8	3.7	3.8	4.0	7.7
Turnover	0.006	0.008	0.009	0.009	0.010	0.011	0.012	0.013	0.015	0.018

TABLE XV Contemporaneous Regression Analysis for Microstructure Noise

	Response Variable: Noise (i,t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Noise (i,t-1)			0.5434***	0.5365***	0.1847***	0.1826***	0.2402***	0.2372***
			(742.92)	(730.44)	(167.90)	(166.30)	(262.52)	(259.47)
Avg Noise (i,t-1,t-5)					0.2251***	0.2203***		
					(127.04)	(124.30)		
Avg Noise (i,t-1,t-20)					0.3522***	0.3545***		
					(218.22)	(219.19)		
Avg Noise (i,t-2,t-5)							0.2750***	0.2715***
							(231.18)	(228.16)
Avg Noise (i,t-6,t-20)							0.2726***	0.2748***
							(220.89)	(222.20)
IO Ratio Total (i,t)	0.2068***	0.2107***	0.1116***	0.1148***	0.0766***	0.0793***	0.0716***	0.0742***
	(111.52)	(114.55)	(73.38)	(75.70)	(54.68)	(56.68)	(51.65)	(53.61)
Amihud Ratio (i,t)	0.3306***	0.3318***	0.1741***	0.1769***	0.1135***	0.1157***	0.1068***	0.1090***
	(764.48)	(771.92)	(423.45)	(429.45)	(283.66)	(288.20)	(268.52)	(272.91)
Market Capitalization (i,t)	-0.0468***	-0.0444***	-0.0040***	-0.0033***	0.0096***	0.0104***	0.0121***	0.0130***
	(-95.11)	(-90.97)	(-9.97)	(-8.17)	(25.61)	(27.85)	(32.69)	(34.95)
Number of Trades (i,t)	-0.0530***	-0.0548***	-0.0315***	-0.0327***	-0.0195***	-0.0205***	-0.0171***	-0.0181***
	(-99.02)	(-102.95)	(-71.86)	(-74.73)	(-48.33)	(-50.77)	(-42.76)	(-45.17)
Average Trade Size (i,t)	-0.0810***	-0.0813***	-0.0324***	-0.0331***	-0.0125***	-0.0129***	-0.0137***	-0.0140***
	(-66.07)	(-66.78)	(-32.23)	(-32.99)	(-13.59)	(-14.02)	(-15.04)	(-15.40)
Time Index (t)	-0.0284***	-0.0288***	-0.0141***	-0.0145***	-0.0082***	-0.0085***	-0.0077***	-0.0079***
	(-721.13)	(-732.83)	(-376.25)	(-383.63)	(-223.00)	(-228.46)	(-208.44)	(-213.68)
Month Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Effective Observations	1,105,271	1,105,271	1,104,832	1,104,832	1,096,491	1,096,491	1,096,491	1,096,491
R^2	0.6405	0.6466	0.7602	0.7617	0.7974	0.7982	0.8018	0.8026

TABLE XVI Contemporaneous Regression Analysis for Microstructure Noise with Quarter End Subsample

	Response Variable: Noise (i,t)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Noise (i,t-1)			0.5661***	0.5552***	0.1437***	0.1117***	0.2264***	0.1967***
			(108.24)	(105.06)	(17.50)	(13.51)	(33.96)	(29.36)
Avg Noise (i,t-1,t-5)					0.2971***	0.2879***		
					(21.11)	(20.47)		
Avg Noise (i,t-1,t-20)					0.3507***	0.3838***		
					(26.19)	(28.75)		
Avg Noise (i,t-2,t-5)							0.3513***	0.3489***
							(37.88)	(37.66)
Avg Noise (i,t-6,t-20)							0.2475***	0.2709***
							(24.73)	(27.14)
IO Ratio Total (i,t)	0.1808***	0.1953***	0.0928***	0.1016***	0.0495***	0.0610***	0.0440***	0.0553***
	(12.86)	(14.13)	(8.50)	(9.35)	(5.04)	(6.30)	(4.56)	(5.83)
Amihud Ratio (i,t)	0.3183***	0.3306***	0.1395***	0.1489***	0.0818***	0.0938***	0.0734***	0.0854***
	(94.91)	(98.36)	(45.31)	(47.26)	(28.11)	(32.09)	(25.58)	(29.63)
Market Capitalization (i,t)	-0.0471***	-0.0263***	-0.0084**	0.0007	0.0069**	0.0210***	0.0104***	0.0243***
	(-12.64)	(-6.91)	(-2.89)	(0.22)	(2.62)	(7.84)	(4.06)	(9.26)
Number of Trades (i,t)	-0.0610***	-0.0933***	-0.0392***	-0.0546***	-0.0267***	-0.0496***	-0.0237***	-0.0463***
	(-14.48)	(-21.06)	(-12.00)	(-15.62)	(-9.07)	(-15.96)	(-8.22)	(-15.20)
Average Trade Size (i,t)	-0.0756***	-0.0424***	0.0076	0.0210**	0.0268***	0.0481***	0.0260***	0.0468***
	(-7.92)	(-4.47)	(1.03)	(2.82)	(4.01)	(7.24)	(3.97)	(7.18)
Time Index (t)	-0.0285***	-0.0290***	-0.0114***	-0.0120***	-0.0065***	-0.0072***	-0.0059***	-0.0065***
	(-88.63)	(-91.64)	(-38.63)	(-40.41)	(-23.52)	(-26.04)	(-21.50)	(-24.04)
Month Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Effective Observations	17,568	17,568	17,568	17,568	17,568	17,568	17,568	17,568
R^2	0.6433	0.6563	0.7860	0.7890	0.8275	0.8331	0.8343	0.8396

TABLE XVII Regression of ΔNoise on Past ΔIO

	Response Variable: ΔNoise (i,t)			
	(1)	(2)	(3)	(4)
ΔNoise (i,t-1)	-0.3243***	-0.3250***		
	(-83.65)	(-83.75)		
ΔNoise (i,t-2)	-0.2464***	-0.2472***		
	(-68.52)	(-68.64)		
ΔNoise (i,t-3)	-0.1665***	-0.1670***		
	(-53.21)	(-53.29)		
ΔNoise (i,t-4)	-0.0845***	-0.0846***		
	(-35.96)	(-36.00)		
ΔIO ratio total (i,t)	0.0029	0.0035.	0.0112	0.0112
	(1.56)	(1.80)	(1.28)	(1.28)
ΔIO ratio total (i,t-1)	0.0021	0.0016	0.0043	0.0036
	(1.17)	(0.81)	(0.49)	(0.40)
ΔIO ratio total (i,t-2)	0.0005	-0.0001	-0.0025	-0.0028
	(0.30)	(-0.03)	(-0.29)	(-0.32)
ΔIO ratio total (i,t-3)	-0.0002	-0.0013	-0.0107	-0.0111
	(-0.10)	(-0.71)	(-1.26)	(-1.30)
ΔIO ratio total (i,t-4)	0.0002	0.0000	-0.0002	-0.0004
	(0.10)	(-0.02)	(-0.03)	(-0.05)
ΔIO ratio total (i,t) ×Recession (t)		0.0067	0.0319	0.0345
		(0.72)	(0.77)	(0.84)
ΔIO ratio total (i,t-1) ×Recession (t-1)		0.0088	-0.0173	-0.0160
		(0.95)	(-0.39)	(-0.36)
ΔIO ratio total (i,t-2) ×Recession (t-2)		0.0104	0.0055	0.0056
		(1.11)	(0.12)	(0.13)
ΔIO ratio total (i,t-3) ×Recession (t-3)		0.0067	0.0178	0.0180
		(0.72)	(0.40)	(0.40)
ΔIO ratio total (i,t-4) ×Recession (t-4)		-0.0016	-0.0094	-0.0092
		(-0.17)	(-0.22)	(-0.22)
ΔAmihud Ratio (i,t)				0.0087
				(1.13)
ΔMarket Capitalization (i,t)				-0.0047
				(-0.63)
ΔNumber of Trades (i,t)				0.0057
				(0.67)
ΔAverage Trade Size (i,t)				0.0011
				(0.14)
Effective Observations	15,321	15,321	15,321	15,321
R^2	0.3138	0.3146	0.0345	0.0346
AIC			43,506	43,543

TABLE XVIII Regression of ΔIO on Past ΔNoise

	Response Variable: ΔIO Ratio Total (i,t)			
	(1)	(2)	(3)	(4)
ΔNoise (i,t-1)	0.0042	0.0047	0.0037	0.0033
	(0.25)	(0.29)	(0.29)	(0.26)
ΔNoise (i,t-2)	-0.0009	-0.0014	-0.0014	-0.0016
	(-0.06)	(-0.09)	(-0.09)	(-0.11)
ΔNoise (i,t-3)	0.0002	-0.0010	0.0005	0.0004
	(0.02)	(-0.07)	(0.03)	(0.03)
ΔNoise (i,t-4)	0.0108	0.0083	0.0107	0.0106
	(1.05)	(0.85)	(1.02)	(1.01)
ΔNoise (i,t-1) ×Recession (t-1)		1.0434	-0.6086	-0.6317
		(0.19)	(-0.13)	(-0.14)
ΔNoise (i,t-2) ×Recession (t-2)		-3.3203	-4.1080	-4.2281
		(-0.59)	(-0.66)	(-0.68)
ΔNoise (i,t-3) ×Recession (t-3)		-6.6980	-5.6819	-5.3657
		(-1.18)	(-0.94)	(-0.89)
ΔNoise (i,t-4) ×Recession (t-4)		2.7301	4.1458	4.0253
		(0.47)	(0.69)	(0.67)
ΔIO ratio total (i,t-1)	-0.1750***	-0.1917***		
	(-22.19)	(-24.54)		
ΔIO ratio total (i,t-2)	-0.1137***	-0.1083***		
	(-14.29)	(-14.14)		
ΔIO ratio total (i,t-3)	-0.0878***	-0.0734***		
	(-11.03)	(-9.58)		
ΔIO ratio total (i,t-4)	-0.0502***	-0.0551***		
	(-6.40)	(-7.25)		
ΔAmihud Ratio (i,t)				0.0121
				(1.61)
ΔMarket Capitalization (i,t)				0.0202**
				(2.74)
ΔNumber of Trades (i,t)				0.0013
				(0.16)
ΔAverage Trade Size (i,t)				-0.0363***
				(-4.77)
Effective Observations	15,321	15,321	15,321	15,321
R^2	0.0416	0.1190	0.3449	0.3464
AIC			42,125	42,130

TABLE XIX Characteristics of IO Ratio Decile Groups

Average Value	IO Decile									
of Daily Variables	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
IO Ratio Total	54.0%	67.0%	72.5%	76.9%	80.7%	84.1%	87.3%	90.9%	94.7%	99.3%
Volatility	0.015	0.014	0.015	0.016	0.016	0.016	0.017	0.017	0.017	0.019
Amihud Ratio (10^{-6})	0.125	0.074	0.067	0.078	0.060	0.069	0.076	0.078	0.077	0.106
Market Capitalization (Billion$)	73.6	48.7	38.6	27.7	23.6	18.5	14.4	11.6	10.7	7.2
Shares Outstanding (Billion Shares)	1.7	1.0	0.8	0.6	0.5	0.4	0.3	0.2	0.2	0.2
Number of Trades (Thousand)	40.4	32.7	31.0	25.7	24.4	20.2	17.6	16.5	15.1	14.4
Average Trade Size (Shares)	210.3	171.6	171.3	160.6	158.8	153.1	149.5	146.7	142.3	149.7
Volume (Million Shares)	13.6	7.5	6.5	4,7	4.4	3.5	3.0	2.7	2.5	2.4
Turnover	0.010	0.009	0.009	0.010	0.010	0.011	0.011	0.012	0.013	0.016

TABLE XX Regressions of IO Ratio on Stock Features

	Response Variable: IO Ratio Total (i,t)			
	(1)	(2)	(3)	(4)
Amihud Ratio (i,t)	-0.0175***	-0.0178***	-0.0010***	-0.0012***
	(-73.57)	(-74.71)	(-4.97)	(-5.82)
Market Capitalization (i,t)	-0.0311***	-0.0315***		
	(-75.93)	(-76.76)		
Number of Trades (i,t)	-0.0361***	-0.0358***	-0.1025***	-0.1025***
	(-77.32)	(-76.60)	(-159.50)	(-159.41)
Number of Trades (i,t) × Mid Cap (i,t)			0.0400***	0.0400***
			(52.52)	(52.52)
Number of Trades (i,t) × Small Cap (i,t)			0.0428***	0.0428***
			(44.14)	(44.16)
Average Trade Size (i,t)	-0.1072***	-0.1072***	-0.0760***	-0.0759***
	(-172.59)	(-172.52)	(-69.49)	(-69.46)
Average Trade Size (i,t)× Mid Cap (i,t)			0.0107***	0.0108
			(8.26)	(8.32)
Average Trade Size (i,t)× Small Cap (i,t)			-0.0822***	-0.0821***
			(-48.45)	(-48.44)
Turnover (i,t)	0.0840***	0.0838***	0.1338***	0.1338***
	(177.83)	(177.15)	(197.40)	(197.44)
Turnover (i,t)× Mid Cap (i,t)			-0.0214***	-0.0214***
			(-26.36)	(-26.36)
Turnover (i,t)× Small Cap (i,t)			-0.0283***	-0.0283***
			(-27.34)	(-27.38)
Time Index (t)	0.0033***	0.0033***	0.0028***	0.0028***
	(165.19)	(166.29)	(146.59)	(147.40)
Month Fixed Effects	No	Yes	No	Yes
Effective Observations	1,105,271	1,105,271	1,105,271	1,105,271
R^2	0.2194	0.2198	0.2222	0.2225

TABLE XXI Stock Features, Lag and Lead Returns of ΔIO Ratio Decile Groups

	ΔIO Decile									
	Decile 1	Decile 2	Decile 3	Decile 4	Decile 5	Decile 6	Decile 7	Decile 8	Decile 9	Decile 10
Initial IO	78.1%	80.1%	79.4%	78.9%	83.8%	83.8%	78.6%	80.2%	81.9%	83.0%
ΔIO (Percentage Point)	-5.8	-2.3	-1.3	-0.6	-0.1	0.1	0.6	1.3	2.4	5.9
Volatility	0.185	0.144	0.124	0.117	0.130	0.125	0.116	0.120	0.130	0.147
Market Capitalization (Billion$)	15.5	24.7	32.6	36.2	33.5	34.5	36.0	26.1	20.3	16.2
Avg Quarterly Return (t-1)	-0.012	0.018	0.025	0.022	0.031	0.041	0.040	0.046	0.060	0.075
Avg Quarterly Return (t)	0.026	0.032	0.044	0.036	0.029	0.036	0.041	0.036	0.042	0.062
Avg Quarterly Return (t+1)	0.095	0.053	0.047	0.041	0.033	0.036	0.027	0.024	0.018	0.023
Avg Quarterly Return (t+2)	0.091	0.060	0.046	0.035	0.038	0.038	0.022	0.032	0.037	0.034
Avg Quarterly Return (t+3)	0.076	0.063	0.052	0.039	0.055	0.048	0.050	0.048	0.058	0.021
Avg Quarterly Return (t+4)	0.038	0.042	0.047	0.044	0.060	0.057	0.055	0.056	0.064	0.087

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