Market Crashes and Institutional Trading

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Abstract

We study institutional trading in U.S. equities focusing on the financial crisis of 2007-09 to examine theoretical predictions about illiquidity and trader behavior. Our main findings are as follows: (i) Institutions experience a dramatic increase in trading costs in 2008 surrounding key events during the crisis. Trading costs partially recover by the end of 2009 but are significantly larger than those estimated before the crisis. (ii) Liquidity deteriorates more sharply and recovery patterns are slower for smaller, more volatile, and higher (ex-ante) liquidity beta stocks. (iii) Execution risk, measured as the standard deviation of trading costs, is significantly elevated during the crisis for all stocks. (iv) There exists a substitution effect wherein buy-side institutions defensively tilt their trading activity towards more liquid stocks and away from illiquid stocks in response to widespread liquidity impairments. Thus, ex-ante low liquidity-sensitive stocks serve the role of *liquidity hedge* during episodic events. (v) Trading cost differences across institutional desks decline over time but exhibit a sharp increase in mid-2007. We attribute the increase to some institutions demanding liquidity when liquidity is priced at a premium by market participants.

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Abstract

We study institutional trading in U.S. equities focusing on the financial crisis of 2007-09 to examine theoretical predictions about illiquidity and trader behavior. Our main findings are as follows: (i) Institutions experience a dramatic increase in trading costs in 2008 surrounding key events during the crisis. Trading costs partially recover by the end of 2009 but are significantly larger than those estimated before the crisis. (ii) Liquidity deteriorates more sharply and recovery patterns are slower for smaller, more volatile, and higher (ex-ante) liquidity beta stocks. (iii) Execution risk, measured as the standard deviation of trading costs, is significantly elevated during the crisis for all stocks. (iv) There exists a substitution effect wherein buy-side institutions defensively tilt their trading activity towards more liquid stocks and away from illiquid stocks in response to widespread liquidity impairments. Thus, ex-ante low liquidity-sensitive stocks serve the role of liquidity hedge during episodic events. (v) Trading cost differences across institutional desks decline over time but exhibit a sharp increase in mid-2007. We attribute the increase to some institutions demanding liquidity when liquidity is priced at a premium by market participants.

1. Introduction

Time variations in the liquidity of individual stocks and the market as a whole present a significant challenge for institutional managers. Market downturns are often characterized by a simultaneous decline in both asset prices and liquidity. For this reason, institutional managers need to be concerned about not only asset price declines but also their ability to liquidate portfolios at low cost during a downturn.

There are several reasons why institutions face a severe liquidity problem during downturns. From the perspective of liquidity supply, some theoretical papers (e.g., Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), He and Krishnamurthy (2010)) postulate that shocks to the financing of intermediaries, who act as liquidity providers, lower their ability to commit capital for market making activities. Other papers predict that the increase in uncertainty in times of market stress can increase investor risk aversion (Huang and Wang (2009)), or tighten risk management by institutions (Garleanu and Pedersen (2007)) and thereby, lower liquidity provision. On the demand side, Shleifer and Vishny (1997) argue that less-sophisticated investors, who judge the competence of money managers based on short-terms returns, withdraw funds after poor performance during a downturn. To meet investor redemptions, institutions are forced to liquidate positions across the board which results in correlated liquidity demand across fundamentally unrelated securities (Kyle and Xiong (2001)).

We examine institutional trading in U.S. equities focusing on the financial crisis of 2007-09. Brunnermeier (2009) classifies the crisis as the most severe since the Great Depression, characterized by significant market declines, liquidity dry-ups, bank failures, defaults, and coordinated international bailouts. From its peak in October 2007 to its low in March 2009, global equity markets fell by $37 trillion, or about 59 percent. Anecdotal evidence suggests that money managers experienced large declines in portfolio values, triggering margin calls, investor withdrawals and fire sales of assets. For these reasons, the market turmoil in 2007-09 presents an excellent laboratory to study theoretical predictions on liquidity and institutional trading behavior during a market crash.

We focus on the behavior of institutions because they trade in large quantities and illiquidity varies more for large trade sizes. Moreover, mutual fund flows or risk management strategies in response to large price drops can cause exogenous trading demands that result in forced liquidation (Coval and Stafford (2007)). Institutions facing exogenous shocks must choose which securities from their portfolios to trade. A better understanding of institutional preference for asset characteristics during normal conditions and how preferences are altered within periods of market stress provides guidance on the mechanism by which risk is priced in financial markets. This is because institutional investors account for a majority of U.S. equity ownership and an even greater percentage of equity trading volume.[1]

We examine a proprietary database of institutional investor U.S. equity transactions compiled by ANcerno Ltd. (formerly the Abel/Noser Corporation). The sample contains approximately 43 million daily trade orders that are initiated by 955 institutional investors over an 11-year period, 1999-2009, representing over $23 trillion in trading volume. The explosive growth in electronic trading has led institutions to split orders, leading to a large increase in the number of trades, accompanied by a substantial decline in average trade sizes, as reflected in the publicly available databases such as the Trade and Quote (TAQ) database. However, the TAQ database does not contain information on the orders that give rise to trades. The ANcerno database is distinctive in that it contains a complete history of trading activity by each institution. Further, the dataset contains information on the order initiated by an institution, each typically resulting in multiple executions, and stock identifiers that help obtain relevant data from other sources. We measure institutional trading cost based on the execution shortfall, which accounts for order splitting strategies by the trading desk.[2] The order data is particularly well suited for examining how institutions trade during normal markets and how trading is altered during crisis episodes.

We examine the time-series of institutional trading costs from 1999-2009. We observe a secular decline in trading costs as well as execution risk (measured as the standard deviation of trading costs)

[1] Boehmer and Kelley (2009) establish that institutions are important traders in the markets and contribute to the informational efficiency of prices.
[2] Other studies using the execution shortfall measure include Keim and Madhavan (1997), Jones and Lipson (2001), Conrad, Johnson and Wahal (2001), and Anand, Irvine, Puckett, and Venkataraman (2010).

from 1999 until 2007.[3] However, we observe a sudden and dramatic increase in trading cost in 2008, particularly in the Fall of 2008. Specifically, one-way trading costs increase from 0.13 percent in 2007 to 0.30 percent in October 2008 (an increase of 130 percent) and execution risk increases from 1.53 percent in 2007 to 3.83 percent in October 2008 (an increase of 150 percent). Trading costs continue to remain at crisis-peak levels in early 2009 but recover to 0.18 percent by the end of 2009. The sharp increase in trading costs and the slow recovery patterns are consistent with He and Krishnamurthy (2010), who link recovery patterns to the slow movement of intermediary capital into affected markets.

Theory predicts that liquidity decline around episodic events should be particularly severe for risky securities. This is because financially constrained liquidity providers are less willing to commit capital in riskier, illiquid securities. We find that smaller, more volatile and higher ex-ante liquidity beta stocks experience a more severe liquidity decline during the crisis.[4] We also find that recovery patterns for liquidity costs after the crash are slower for smaller, more volatile and higher liquidity beta stocks. We conclude that liquidity-beta captures two related attributes that are important to traders: (a) sensitivity to episodic events, and (b) resiliency after episodic events.

Consistent with Brunnermeier (2009), we document a substitution effect wherein institutions respond to widespread liquidity impairments by tilting their trading activity away from liquidity-sensitive securities. In other words, institutions choose to trade those securities in a downturn whose liquidity is less sensitive to the crash. Interestingly, we observe a reversal in institutions' trading behavior toward the end of 2009, as institutions' trading patterns more closely resemble their pre-crisis behavior. Collectively, the patterns present some intriguing evidence on the channel through which an asset's liquidity risk characteristic may be important to investors. The results suggest that low liquidity-sensitive securities serve the role of a *liquidity hedge* during an episodic event. The evidence should inform our understanding on how the preferences of institutional traders affect the pricing of liquidity risk.

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[3] The trend in liquidity is consistent with the results in recent studies using bid-ask spread-based measures of trading costs (see, for example, Jones (2006), Hasbrouck (2009) and Chordia, Roll and Subrahmanyam (2008)).

[4] Acharya and Pedersen (2005) identify three forms of liquidity risk: (i) commonality in liquidity with market liquidity, $cov(c^i,c^M)$; (ii) return sensitivity to market liquidity, $cov(r^i, c^M)$; and (iii) liquidity sensitivity to market returns, $cov(c^i, r^M)$. We focus on $cov(c^i, c^M)$ in our analysis.

We examine the extent to which institutions are equally affected by the liquidity decline during the financial crisis. We posit that some buy-side institutions might be net liquidity suppliers, who benefit from the higher price of liquidity during the crisis. We calculate a Style Index rank for all institutions in our sample based on the percentage of their monthly trading volume that is in the same (or opposite) direction as the contemporaneous daily returns of the stocks that they trade. Institutions with high Style Index trade more often with the market, while institutions with low Style Index trade more often against the market. We find that the cross-sectional difference in trading cost in the month following the Style Index ranking is considerably larger when liquidity is more expensive. Interestingly, the trading cost increase in 2008-2009 is borne almost entirely by high Style Index institutions; the low Style Index institutions actually lower their trading costs during the crisis. These results exist despite an increase in the standard deviation of execution costs for both types of institutions. A closer examination reveals only marginal differences in the types of stocks that the two types of institutions trade. Our evidence suggests that some buy-side institutions were able to insulate themselves from an increase in trading costs, or even earn a premium for liquidity provision during the financial crisis.

This paper is organized as follows. Section 2 describes the key events during the financial crisis and presents the testable predictions regarding trading costs. The trading cost measures and sample selection are described in Section 3. In Section 4, we present the determinants of institutional trading costs and the differential impact of the financial crisis on stock liquidity. In Section 5, we demonstrate that some institutions benefit from the market conditions during the crisis. Section 6 concludes.

2. Testable predictions and related literature

2.1 Hypothesis development: Financial crisis and secondary market liquidity

The financial crisis that began in August 2007 has been described by several recent papers (see Brunnermeier (2009), Acharya and Richardson (2009), Krishnamurthy (2010)). The root of the financial crisis can be traced to a decline in lending standards in the debt markets, particularly for mortgage loans. Financial institutions such as commercial banks, investment banks, and hedge funds, who either held the loans or structured credit instruments tied to the loans, suffered heavy losses during the crisis. Since these financial institutions carry high leverage, the heavy losses led to an enormous decline in aggregate risk (equity) capital across institutions, estimated to be in the range of $985 billion.[5] Further, the financial crisis was characterized by the failure of several large institutions, including Bear Sterns in March 2008 and Lehman Brothers in September 2008 that raised concerns about counterparty risk. These concerns led intermediaries to increase margin requirements and credit standards on their bilateral trades. The loss in risk capital and the tightening of credit caused a severe decline in funding liquidity.

When risk capital is reduced, intermediaries need to either replace the lost risk capital by issuing new equity or by selling assets and reducing leverage. Krishnamurthy (2010) estimates that institutions raised around $732 billion in new capital, including injections from TARP funds, from the second quarter of 2007 to the second quarter of 2009, suggesting that intermediary risk capital reduced by around $239 billion during the crisis. The process of deleveraging in response to a financing shock can cause a number of traders to sell similar securities at the same time (Adrian and Shin (2009)). Bernardo and Welch (2003) present a model of financial crash where traders rush to liquidate following negative shocks because early liquidators receive better prices than late liquidators. Theoretical papers recognize that funding shocks lead to feedback mechanisms that can further destabilize markets (see Garleanu and Pedersen (2007), Brunnermeier and Pedersen (2009)).

Events observed in financial markets during the crisis are consistent with the framework presented in the theoretical papers. For example, in August 2007, many quantitative hedge funds sold equities in order to raise cash to meet margin calls from brokers on structured instruments (see Khandani and Lo (2007)). The high correlation in equity trading strategies among quant-funds caused the stock market to decline by almost 8% within a week (quant-event).[6] During the crisis, investors in hedge funds and mutual funds, who have the right to withdraw capital, redeemed hundreds of billions of dollars.

[5] See Table 3 in Krishnamurthy (2010).

[6] Kyle and Xiong (2001) show theoretically that large shocks to one security (e.g., asset backed security) in a trader's portfolio can be contagious to other securities (e.g., equities) that are held by the same investor. Consistent with this prediction, Khandani and Lo (2007) observe that the crisis in credit markets spilled over to equity markets when hedge funds sold stocks in order to meet margin calls from brokers on their structured finance holdings.

Margins requirements on loans rose significantly, accompanied by a sharp increase in borrowing costs, leading to a decline in lending activity among intermediaries. Specifically, the TED spread, which is the difference between LIBOR (London Interbank Offered Rate) and U.S. Treasury bill rate, increased from about 0.5% in July 2007 to a record 4.5% during the peak of the financial crisis.[7] Krishnamurthy (2010) observes that monthly dealer repo activity dropped from about \$4 trillion in July 2007 to \$2.5 trillion in January 2009.

Along with a decline in market liquidity, theory predicts that liquidity during crisis episodes will decline more for firms with risky characteristics. Vayanos (2004) and Brunnermeier and Pedersen (2009) predict that financially constrained liquidity providers are less willing to make markets in volatile, illiquid securities.[8] An important assumption for the liquidity-adjusted CAPM (Acharya and Pederson (2005)) is that liquidity declines more for stocks with high ex-ante liquidity-beta during a downturn.

Market-wide funding shocks and their differing impact on riskier firms can alter the trading preferences of institutions. Institutions faced with an exogenous increase in trading costs must choose which securities from their portfolio to trade. Brunnermeier (2009) proposes that investors are particularly sensitive to liquidation costs during an episodic event and predicts a *substitution* effect wherein institutions become reluctant to trade illiquid assets and instead choose to trade liquid assets. On the other hand, it is possible that buy-side institutions do not alter their trading activity based on liquidation costs if institutions consider liquidation costs to be of second-order importance relative to the risk-return attributes of the portfolio.[9]

These discussions support the following testable hypotheses.

Hypothesis I.A: The financial crisis period is characterized by a decline in market liquidity.

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[7] Brunnermeier (2009) notes that, because the LIBOR reflects the interest on interbank (risky) unsecured short term loans, the TED spread is a useful measure to gauge the severity of the funding crisis.

[8] See Table 4 in Krishnamurthy (2010) for evidence during the financial crisis. For asset-backed securities, the repo haircuts increase from 10% in Spring 2007 to 40% in Fall 2008. During the same period, the repo rates remain stable at 2% for short-term U.S. Treasuries.

[9] Evidence in Griffin, Harris, Shu and Topaloglu (2010), who examine institutional and individual trading during the Nasdaq bubble, present the possibility that institutions are positive-feedback traders. They show that institutions profited by riding the Nasdaq bubble until its peak and that their coordinated selling caused the bubble to burst. They document that the behavior is particularly strong for their sample of hedge funds. We have been informed by ANcerno that our sample includes relatively few hedge funds.

Hypothesis II: In times of market stress, liquidity declines more for smaller, more volatile, and higher ex-ante liquidity beta securities.

Hypothesis III.A: Institutions choose to trade less risky and more liquid assets during the financial crisis (i.e., substitution effect).

2.2. Related empirical literature on market liquidity and institutional trading

The financial crisis of 2007-09 highlights the crucial role played by intermediaries in liquidity provision. Related to this idea, a set of papers have studied the impact of the funding constraints faced by New York Stock Exchange (NYSE) specialists on stock liquidity. Using proprietary data on the inventory positions of NYSE-specialist firms, Comerton-Forde, Hendershott, Jones, Moulton and Seasholes (2010) find that specialists are less willing to provide liquidity when they lose money on inventories. Hameed, Kang and Viswanathan (2010) show that the bid-ask spreads for NYSE stocks are higher when market returns are lower, i.e., during periods when liquidity providers lose money.

We build on this body of evidence by examining how the economic environment faced by *both* liquidity suppliers and demanders impacts liquidity. While the papers discussed above examine a long sample period that ends in 2004, our study examines a sample period that includes the 2007-09 financial crises. Examining institutional trading surrounding 'rare' or episodic events provides new perspectives on the trading behavior of investors under normal market conditions and whether the behavior is altered during crisis episodes. Estimating stock liquidity based on institutional trades (as compared to bid-ask spread) also provides additional perspective on the liquidity risk faced by large market participants.

Our study complements a growing body of research that examines the impact of the financial crisis on institutional traders. Aragon and Strahan (2009) observe that the accounts of many hedge fund clients of Lehman Brothers were frozen following Lehman's bankruptcy. They document that stocks held by these hedge fund experience a greater decline in liquidity than other stocks, suggesting hedge funds were *de-facto* liquidity providers for these stocks. Cella, Ellu and Giannetti (2010) also examine the Lehman collapse and find that the stocks held by investors with short trading horizons experience more price drops and larger price reversals than those held by long-term investors. They conclude that investors' short horizons amplify the effects of market-wide negative shocks.

Evidence consistent with large-scale equity selloffs by hedge funds is provided by Ben-David, Franzoni and Moussawi (2010). He, Khang and Krishnamurthy (2010) examine flow-of-funds and SEC filings data and document large scale selloffs of securitized assets by hedge funds and broker/dealers. They show that these assets were purchased by commercial banks and are largely funded by the government-backed debt issued by the banks. In contrast, Boyson, Helwege and Jindra (2010), who also examine activities of commercial banks, investment banks and hedge funds, conclude that these institutions avoid fire sales during the crisis by relying on other sources of funding. The focus of our paper is different in that we present a detailed analysis of the trading behavior of a category of *buy-side* institutions, namely mutual and pension funds, and how their trading behavior is altered in response to liquidity shocks in the equity market.

3. Execution shortfall measure and sample descriptive statistics

3.1. Execution shortfall

We measure trading costs based on the execution shortfall, which compares the execution price of an order with the opening stock price of the day. The choice of a pre-trade benchmark price follows prior literature.[10] We define execution shortfall for an order as follows:

$$Execution\ Shortfall(b,t) = [(P_1(b,t) - P_0(b,t)) / P_0(b,t)] * D(b,t) \quad (1)$$

where $P_1(b,t)$ measures the value-weighted execution price of order 't', $P_0(b,t)$ is the price at the open of the day, and $D(b,t)$ is a variable that equals 1 for a buy order and equals -1 for a sell order.[11] We define a

[10] Some studies (see Berkowitz, Logue and Noser (1988) and Hu (2009)) argue that the execution price should be compared with volume-weighted average price (VWAP), a popular benchmark among practitioners. Madhavan (2002) and Sofianos (2005) discuss the VWAP strategies and many limitations of the VWAP benchmark.

[11] An alternative pre-trade benchmark is the stock price when the institution sends a portion of the order to each broker associated with the order. Execution shortfall based on this benchmark does not account for price movements between decision time (open) and order placement time with brokers. Execution costs using this benchmark are smaller but the main results are unchanged. We acknowledge that neither benchmark can perfectly capture all dimensions of the trading decision. They represent two approaches for accommodating the drift in price.

daily trade order as the aggregation of all executions by the same institution in the same stock on the same side (buy/sell) on the same day. The measure 'stitches' or aggregates the institution's trading in a stock across many brokers during the trading day and to some extent accounts for cancellation of a partly-executed order with one broker and resubmission of the cancelled portion of the order to another broker during the day.

3.2. Execution shortfall versus other liquidity measures

The asset pricing literature has mainly relied on liquidity measures based on volume (for example, Amihud's (2002) ILLIQ measure in Acharya and Pedersen (2005)) or return reversals (Pastor and Stambaugh (2003)). These measures are useful for asset pricing tests because the data necessary to estimate measures are available over long sample periods. But these measures do not directly capture the trading costs for investors. Some studies have used the bid-ask spread from TAQ or CRSP databases as a liquidity measure (e.g., Chordia, Roll and Subrahmanyam (2000), Hameed, Kang, and Viswanathan (2010)). The bid-ask spread is an excellent measure of the round-trip liquidity cost for investors who trade using small market orders. However, institutional trading desks execute large orders and are particularly concerned about the price impact of an earlier trade on prices received for subsequent trades. For this reason, institutions break-up the order and trade small quantities over time. Further, the typical institution attempts to lower trading costs using complex strategies that both demand (using market orders) and supply (using limit orders) liquidity.

Unlike the ANcerno database, most publicly available databases such as the TAQ database do not have information on orders that give rise to trades. It is therefore difficult to identify the trades associated with an institution and directly measure institutional trading costs. We rely on the execution shortfall measure because it captures several dimensions of institutional trading costs including the bid-ask spread, the price impact of trade, order splitting and the cost of delayed trading. Unlike the bid-ask spread which is always positive, the execution shortfall for an institution can be positive or negative depending on market conditions and how the institution trades (for example, using mainly limit orders, or market orders, or a combination of the two). Notably, the execution shortfall captures the *one-way* liquidity cost for institutions and should be multiplied by two for comparison with the bid-ask spread.

3.3. Sample descriptive statistics

We obtain data on institutional trades for the period from January 1, 1999 to December 30, 2009 from ANcerno Ltd. (formerly the Abel/Noser Corporation). ANcerno is a well known consulting firm that works with institutions to monitor their trading costs. ANcerno clients include pension plan sponsors such as CALPERS, the Commonwealth of Virginia, and the YMCA retirement fund, and money managers such as Massachusetts Financial Services (MFS), Putman Investments, Lazard Asset Management and Fidelity. Academic studies using ANcerno data include Goldstein, Irvine, Kandel and Wiener (2009), Chemmanur, He and Hu (2009), Goldstein, Irvine, and Puckett (2010), and Puckett and Yan (2010).

For each execution, the database reports identity codes for the institution and the broker involved in each trade, the CUSIP and ticker for the stock, the stock price at placement time with broker, the date of execution, the execution price, the number of shares executed, whether the execution is a buy or sell, and the commissions paid on the execution. The institution's identity is restricted to protect the privacy of ANcerno clients; but the unique client code facilitates identification of an institution both in the cross section and through time. Conversations with ANcerno confirm that the database captures the complete history of all transactions of the institutions. ANcerno institutional clients traded approximately 700 billion shares, representing more than $23 trillion worth of stock trades during our sample period. Thus, while our data represent the trading activities of a subset of pension funds and money managers, they represent a significant fraction of total *buy-side* institutional volume.[12]

To minimize observations with errors and to obtain the necessary data for our empirical analysis, we impose the following screens: (1) Delete daily trade orders with execution shortfall greater than an absolute value of 10 percent, (2) Delete daily trade orders with order volume greater than the stock's CRSP volume on the execution date, or with an order size greater than the 99th percentile of order sizes in

[12] For the sample period preceding the explosion in trading activity from algorithmic trading desks (1999-2005), we estimate that ANcerno institutional clients are responsible for approximately 8% of total CRSP daily dollar volume.

the month, (3) Delete daily trade orders associated with internal allocations or corporate events such as private placements of stock, (4) Include only common stocks listed on NYSE or NASDAQ with data available on CRSP and TAQ databases, and (5) Delete institutions with less than 100 daily trade orders in a month. We obtain market capitalization, return, trading volume, and exchange listing from CRSP and order imbalance from TAQ.

We present the summary statistics for the ANcerno data in Table 1. The sample contains a total of 955 buy-side institutions, responsible for approximately 43 million daily trade orders in 8,514 U.S. stocks over the 11-year sample period. The typical order size is 16,165 shares, which represents 2.9% of the stock's daily volume over the previous 30 trading days. Table I, Panel B shows the trends over time. The number of institutions in the database remains relatively constant from year to year. The number of U.S. stocks traded declines from 5,726 in 1999 to 3,938 in 2009. Order size initially increases from 14,371 shares in 1999 to 19,984 shares in 2002 and then declines in the later part of the sample. However, as a percent of daily volume, order size trends downwards, from 4.8% in 1999 to 1.8% in 2009. The buy dollar volume as a percentage of total trading volume is close to 50% in all years. This statistic is not surprising since the database captures the entire buying and selling activity for institutions who are consulting clients of ANcerno.

In Table 1, Panel C, we sort each stock based on market capitalization in the month prior to the trade. Quintile ranks are assigned based on NYSE market capitalization quintile cutoffs. As expected, institutions are particularly active in large cap stocks. The average institutional order size for large cap stocks is 19,398 shares, but the order represents only 0.7% of average daily trading volume. For firms in the smallest quintile, the average institutional order size of 11,418 shares represents over 11% of the daily trading volume. Clearly, institutional orders are more difficult to execute for small stocks.

We report execution shortfall for the full sample of institutional trades and also separately for quintiles based on firm characteristics (i.e., market cap, volatility and ex-ante liquidity beta). For each analysis (full sample or characteristic quintile), we calculate execution shortfall as the volume weighted average cost across orders in the related sample. Execution risk is based on the standard deviation of trading costs across orders for the related sample.

We calculate each trading cost statistic on a monthly and daily basis. If reported annually as in Table 2, Panel A, the statistics are equally weighted averages across monthly observations in a year. T-statistic for differences across years is based on the standard errors of monthly estimates for the year. For monthly statistics (for example, in Table 2, Panel B), the test statistics are based on the average of daily estimates and the standard errors of these estimates.

4. Results on institutional trading costs

4.1. Trends in institutional trading costs

Table 2, Panel A, reports average annual institutional trading costs in U.S. equities from 1999 to 2009. We find that institutional trading costs decline during the period before the financial crisis. Trading costs (one-way) during the beginning of the sample period (1999) are around 0.22 percent. Consistent with Bessembinder's (2003) findings using TAQ data, we observe a decline in trading costs to 0.16 percent after the move to decimal trading in 2002. Trading costs continue to decline and are estimated to be 0.13 percent in 2007. Patterns based on the median trading costs are similar.

Roll and Subrahmanyam (2009) observe that the certainty in execution costs is important for market participants who trade into and out of positions in a short period of time. We examine execution risk, measured as the standard deviation of trading costs. Execution risk in 1999 is estimated to be 2.30 percent. Execution risk mirrors the trends observed for trading costs and declines to 1.53 percent in 2007.

The results in Table 2, Panel A are consistent with those documented by several recent studies including Jones (2006), Hasbrouck (2009), and Chordia, Roll and Subrahmanyam (2010), who examine trading activity and bid-ask spreads over a longer sample period. Chordia, Roll and Subrahmanyam (2010) report that the turnover for NYSE-listed stocks increases from about 5% to about 26% and the average number of transactions increase about ninety-fold from the beginning of 1993 to the end of 2008. Further, the bid-ask spreads for large and small trades exhibit a significant negative trend and are accompanied by more efficient securities prices. Declining trends in trading costs during this time period are also observed in equity markets outside the United States. Griffin, Kelly and Nardari (2010) examine data from 28 emerging markets and 28 developed markets and estimate decreases in trading costs of around 60 percent between 1994 and 2005.

The decline in trading costs over the last decade can be attributed to several factors. U.S. equity markets have witnessed landmark structural changes in market design (e.g., decimalization), regulation (e.g., Regulation NMS), and technology (e.g., ECNs, online brokerage accounts), which have made trading easier and cheaper for institutional and retail investors. Chordia, Roll and Subrahmanyam (2010) specifically point to the role played by quantitative trading strategies employed by hedge funds in causing stock prices to be more efficient. Hendershott, Jones and Menkveld (2009) observe that many aspects of the institutional trading process have been increasingly automated. Algorithmic trading, defined as the use of computer algorithms to manage the trading process, accounted for a third of the trading volume in U.S. equities in 2007. Traditional markets such as NYSE face intense competition for order flow from alternative trading systems (ATS). Notably, the NYSE's market share of trading volume has declined from over 80 percent in the late-1990s to about 33 percent by the end of 2008.[13] The structural changes have lowered trading friction, improved price efficiency and increased competition for liquidity provision.

In light of these long terms trends observed worldwide, a striking result in Table 2, Panel A, is that the long-term trend in trading costs is reversed with the advent of the financial crisis. Institutions experience a sudden and dramatic increase in trading costs, from 0.13 percent in 2007 to 0.21 percent in 2008, an increase of 66 percent which is statistically significant (t-statistic of difference = 3.99). These findings are consistent with Gurliacci, Jeria, and Sofianos (2008), who examine institutional trades that were executed using Goldman Sachs' proprietary algorithms in September 2008 and also report a sharp uptick in trading costs. Similarly, execution risk records a dramatic increase from 1.53 percent in 2007 to 2.59 percent in 2008. Moreover, in 2009, trading costs register a further increase to 0.25 percent while

[13] http://www.bloomberg.com/apps/news?pid=20601103&sid=amB3bwJD1mLM. Electronic communication networks (ECNs) and alternative trading systems such as BATS and DirectEdge dominate trading in U.S. equities.

execution risk registers a small decline to 2.29 percent. Collectively, the findings suggest that institutions experienced a severe liquidity shock during the financial crisis and that equity markets can remain unusually illiquid for extended periods of time.

The sudden increase in trading costs in 2008 cannot be attributed to structural changes in market design, regulation and technology. Notably, the quality of institutional executions that is observed in 2008 is similar to those last observed a decade ago. Thus, the decline in trading costs observed over the last decade is quickly erased during the crash, which emphasizes the magnitude of dislocations in financial markets. He and Krishnamurthy (2010) note that the sudden and dramatic increase in risk premia is a striking feature of financial crises. We present new empirical evidence in the context of liquidity premia.

4.2. A closer look at institutional trading costs during the financial crisis of 2007-09

In Table 2, Panel B, we report trading costs for institutions surrounding key events during the 2007-09 financial crisis. For comparison purposes, we denote January, 2007 to April, 2007 as the pre-crisis benchmark period. The first event that we examine is the 2007 quant-crisis, which has been studied closely by Khandani and Lo (2008). Surrounding the quant-event, we observe a significant increase in execution risk for institutions (t-stat of difference = 5.71) but no increase in trading costs. Surrounding the second event - the acquisition of investment bank, Bear Stearns, by J.P. Morgan in April 2008 - we find that liquidity deteriorates significantly relative to the benchmark period. Specifically, institutional trading costs (execution risk) increase from 0.12 percent (1.27 percent) in the benchmark period to 0.19 percent (2.05 percent) surrounding the sale of Bear Sterns.

Trading costs remain at elevated levels during the summer of 2008 as conditions in credit markets continued to deteriorate (see Figure 1). We examine the months surrounding the collapse of investment bank Lehman Brothers that coincided with several notable market developments: the failure of large financial institutions such as AIG, Washington Mutual, and Wachovia, Troubled Asset Relief Program (TARP) and other initiatives to rescue large financial institutions, and the introduction and repeal of the short sale ban.[14] The deterioration in liquidity conditions for institutions during these months is severe. Trading costs increase from already elevated levels in the summer of 2008 to 0.22 percent in September 2008, 0.30 percent in October 2008 and 0.35 percent in November 2008. Execution risk also increases markedly during these months. Relative to liquidity observed before the crisis, trading costs during the crisis-peak are *almost thrice as large*, emphasizing the large scale liquidity deterioration for institutions.

Trading costs continue to remain at crisis-peak levels during the first quarter and second quarter of 2009. Some signs of recovery in liquidity conditions are observed in the fourth quarter of 2009, where we estimate that trading costs declined to about 0.18 percent from 0.29 percent in the second quarter of 2009 and execution risk declined to 1.64 percent from 2.53 percent in the second quarter. It is remarkable that trading costs almost 14 months after the collapse of Lehman Brothers still *remain almost twice as large* as those observed before the crisis.

The slow patterns of recovery, extending over several months, suggest that market liquidity is not resilient after an extreme shock. These patterns are inconsistent with the presence of arbitrageurs who step in quickly and voluntarily to provide liquidity when there is a significant buy-sell imbalance in the market (e.g., Campbell, Grossman and Wang (1993)). Rather, the patterns in equity market costs are more consistent with He and Krishnamurthy (2010), who observe that recovery patterns in a variety of asset markets following past financial crises tend to be slow. They note that the slow pattern of recovery reflects the slow movement of capital into affected markets.

4.3. The impact of market conditions on trading costs

As described in Section 3.1., execution shortfall is based on a pre-trade benchmark price. Perold (1988) observes that a pre-trade benchmark appropriately captures the price concessions associated with implementation of institutions' trading decisions. While the pre-trade benchmark is conceptually appealing and is widely used in the literature, it is important to note that execution shortfall is affected by

[14] The impact of the short sale ban on security prices, liquidity and return volatility is examined in several recent studies. Boehmer, Jones and Zhang (2009) show that the stocks who are subject to the ban suffered a severe decline in liquidity relative to a control group of non-banned stocks.

the price drift over the trading horizon. Specifically, a downward drift in price, as observed in U.S. equity markets during the financial crisis, would *increase* the cost of sell orders, all else the same. For the same reason, a downward drift in price would *decrease* the cost of buy orders.

We report that the buy dollar volume as a percentage of the total dollar volume is close to 50 percent for all sample years (see Table 1, Panel B) and for each month over the financial crisis period (see Table 2, Panel B). Therefore, we expect that the execution shortfall estimated using both buy and sell transactions is not affected by the market movement. To directly examine these effects, in Figure 1 and Figure 2, we plot execution shortfall and execution risk after adjusting for market movements. For each order, we implement the adjustment in Keim and Madhavan (1995) and subtract the daily return on the S&P 500 index from the order's execution shortfall after accounting for the order's direction. Trends in Figure 1 and Figure 2 are similar to the unadjusted results discussed in Section 4.2.

Figure 3 plots the trading costs for buys and sells over the 2006-2009 period. Consistent with Huang and Wang (2009), we find that sell orders are more expensive to execute than buy orders in a crisis. In fact, execution shortfall for sell orders more than *tripled* during the crisis peak relative to the levels observed in early 2007. In contrast, execution shortfall for buy orders is *negative* during the crisis peak but turns positive during the run-up in equity market prices in April 2009. Thus, the results in Figure 3 suggest that the asymmetry in buy-sell trading costs based on a pre-trade benchmark is sensitive to market movements, consistent with Chiyachantana, Jain, Jiang and Wood (2004) and Hu (2009).

4.4. Trading costs during the crisis, grouped by firm characteristics

Theoretical models predict that liquidity during crisis episodes declines more for firms with risky characteristics (see *Hypothesis II*). In Table 3, we examine whether the financial crisis had a differential impact on the liquidity of portfolios formed on firm size, return volatility and ex-ante liquidity beta. Huang and Wang (2009) predict that liquidity of small stocks will decline more during the crisis while Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) predict that liquidity of more volatile stocks will decline more during the crisis. Cross-sectional difference in liquidity response based on liquidity beta is an important assumption of Acharya and Pedersen's (2005) liquidity-adjusted CAPM. Examining these ideas, trading costs are reported for high and low quintile portfolios formed on (a) firm size in Panel A, (b) return volatility in Panel B, and (c) ex-ante liquidity-beta in Panel C. Similar to Table 2, Panel B, we report on trading costs before the crisis, events during the crisis and post-crisis periods.

In Table 3 Panel A, we note that institutional trading costs are lower for large cap stocks than for small cap stocks before the crisis. The difference in one-way trading costs is around 0.10 percent. Trading costs around the Bear Sterns' event increase for large cap and small cap stocks but the spread between the two portfolios does not change. However, we estimate that the spreads in liquidity costs increase significantly during the crisis-peak. Trading costs for large-cap stocks increase from 0.07 percent before the crisis to 0.28 percent in November 2008. Trading costs increase even more for small cap stocks, from 0.17 percent before the crisis to 0.75 percent in November 2008. Thus, (one-way) trading cost difference between large cap and small cap stocks increases from 0.10 percent before the crisis to 0.47 in November 2008 (t-statistic of diff-of-diff test = 2.69).

These findings provide empirical support for Hypothesis II. The conclusions are similar when we examine market-adjusted trading costs (Figure 1) and execution risk (Figure 2). Particularly striking from Figure 1 is the fact that the gains from structural changes in the last decade were most prominent for small stocks but these gains were lost during the financial crisis. Trading costs remain high for large and small cap stocks even when the stock market rallied during the second quarter of 2009. The spread between large cap and small cap stocks decline from the crisis peak during the last six months of 2009 but continue to remain high relative to the benchmark period before the crisis. Our evidence suggests that large cap stocks are relatively more resilient than small caps stocks.

In Table 3, Panel B, we stratify stocks into volatility quintiles based on the standard deviation of daily returns in calendar year 2006. Returns are based on daily bid-ask closing quote midpoints obtained from CRSP. Only stocks with at least 50 observations are included in the analysis. Results are supportive of the theoretical predictions from Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009). Trading costs for high-volatility stocks increase from 0.18 percent before the crisis to 0.49 percent in

November 2008. Trading costs for low-volatility stocks also increase from 0.07 percent to 0.27 percent but the difference-in-differences tests indicate that the decline in liquidity in November 2008 is larger for high-volatility stocks. The findings are also consistent with evidence in Hameed, Kang and Viswanathan (2010), who find that market declines have a more pronounced impact for high volatility firms.

In Table 3, Panel C, we stratify stocks into liquidity-beta quintiles. We calculate the stock's liquidity beta as the covariance of stock liquidity and the equal-weighted average market liquidity. Specifically, we use daily percentage effective spreads to calculate monthly average percentage effective spreads for each stock.[15] For a stock to be included in a month, we require at least 10 daily observations. For market liquidity, we calculate the equal weighted average of daily effective spreads across stocks and create a monthly average using these daily effective spread estimates. The ex-ante liquidity betas are based on the five years of monthly data (from 1/2002 to 12/2006) preceding the financial crisis.

An important assumption of the liquidity-adjusted CAPM (Acharya and Pederson (2005)) is that stock liquidity declines more during a downturn for stocks with high ex-ante liquidity-beta. We examine whether the behavior of stocks with high ex-ante liquidity-beta is consistent with the model assumption during an episodic event. The difference in trading costs between high and low liquidity beta stocks before the crisis is 0.07 percent. This difference increases to 0.15 percent surrounding the collapse of Bear Sterns. Trading costs for high-liquidity beta stocks increase to 0.38 percent in September 2008, reach a crisis-peak of 0.56 percent in October 2008 and remain at an elevated level (0.39 percent) through the third quarter of 2009. Trading costs for low liquidity-beta firms also increase during the financial crisis but the increase was much smaller than that observed for high liquidity-beta stocks. The crisis-peak level of trading costs is 0.33 percent in November 2009. Notably, by the fourth quarter of 2009, trading costs for low liquidity-beta stocks decline to 0.12 percent while trading costs for high liquidity-beta stocks decline to 0.34 percent. The difference in trading costs is 0.22 percent which is significantly larger than the 0.07 percent difference estimated before the crisis.

[15] We are grateful to Hans Stoll, Christoph Schenzler and the Financial Markets Research Center (FMRC) at Vanderbilt University for providing daily percentage effective spreads for all stocks. The FMRC calculates these measures using TAQ data.

Two observations are noteworthy. First, we conclude that liquidity betas are stable; liquidity betas estimated over a past, non-crisis period can forecast the extent of decline in liquidity during an episodic event. This finding provides empirical support for an important *assumption* of the liquidity-adjusted CAPM model. Second, we conclude that liquidity of stocks with low ex-ante liquidity betas are resilient and exhibit quicker recovery patterns. Thus, liquidity-beta captures two related attributes: (a) sensitivity to episodic events, and (b) resiliency after episodic events. We believe these results contribute to a better understanding of why liquidity betas are priced in asset pricing tests.

4.5. Do institutions alter trading activity during the financial crisis?

In this section, we examine whether institutions alter their trading behavior in response to a liquidity shock. Results in Table 2 suggest that institutional trading costs increased by 66 percent during the financial crisis. If institutions are sensitive to liquidation costs, they would choose to curtail trading activity during the crisis. It is important to understand whether institutions alter their trading behavior during a downturn, since a preference for trading certain assets during an episodic event can provide a link between liquidity and asset prices.

In addition to the increase in overall trading costs, we estimate that the increase in trading costs are more pronounced for smaller, more volatile and higher-liquidity beta stocks. Institutions faced with an exogenous liquidity shock must choose which securities from their portfolio to trade. Brunnermeier (2009) proposes that investors are particularly sensitive to liquidation costs during an episodic event and predicts a *substitution* effect wherein institutions become reluctant to trade illiquid assets and instead choose to trade liquid assets. On the other hand, it is possible that buy-side institutions do not alter their trading activity based on liquidation costs. This is because institutions consider liquidation costs to be of only second-order importance relative to the risk-return attributes of the portfolio. Another possibility is flight-to-liquidity effect that is proposed by Vayanos (2004) wherein institutions reduce their holding in riskier, illiquid securities during bad time periods. A flight-to-liquidity effect has been documented in the Euro sovereign bond market by Beber, Brandt and Kavajecz (2009).

Table 4, Panel A reports results on dollar trading (buying and selling) for institutions. During the benchmark period (January to April 2008), the average monthly dollar trading volume for an institution in the sample is $995 million.[16] We calculate a *relative volume* measure, which is the ratio of each institution's trading in a crisis-month relative to the institution's trading in a non-crisis (benchmark) period. A *relative volume* of 1.0 for an institution indicates that trading activity for the institution is no different during a crisis month than during the non-crisis month. We report the average relative volume across all institutions, and the t-statistic of the test that the average relative volume for a month equals one.

The key finding from Table 4, Panel A is that buy-side institutions reduce their trading activity as the crisis in financial markets becomes more severe. The relative volume stays at similar or higher levels as compared to the benchmark until October 2008, but then drops off sharply to about 75 percent of benchmark volume for the remainder of the sample period.[17] These findings suggest that institutions curtail trading activity as the crisis becomes severe, possibly in response to the high trading costs.

Additional empirical evidence supporting the proposition that institutional trading is sensitive to trading costs can be observed in Table 4, Panel B – D. We report trading activity for NYSE market value quintiles in Panel B, return volatility quintiles in Panel C and liquidity-beta quintiles in Panel D. For each institution, we first calculate the share of dollar volume in a particular NYSE size, volatility, or liquidity beta quintile for each of the first four months of 2008. We average the volume shares to estimate non-crisis trading activity for each quintile for an institution. We then calculate the proportion of dollar volume in a quintile over the crisis month. The *relative proportion* measure is the ratio of the institution's quintile share over a crisis-month relative to institution's quintile share over the non-crisis period. We report the average relative proportion across all institutions and the t-statistic of the test that the average relative volume for a month equals one.

[16] We acknowledge that the financial markets were stressed during this benchmark period due to the bank run on Bear Sterns in March 2008.

[17] The results are similar when we examine trading activity based on selling activity alone. As reported in Table 2, the buy/sell percentages suggest that sell volume did not change relative to buy volume during the crisis period.

Focusing on market value quintiles in Panel B, we estimate that large firms (quintiles 1 and 2) account for 73 percent of trading while small firms (quintile 4 and 5) account for only 14 percent of trading for the average institution during the benchmark period. During the financial crisis, trading activity declines significantly for small firms while trading activity increases for large firms (See Figure 4). The relative proportion measure for small (quintile 1) firms declines as low as 0.31, suggesting that the proportion of trading in small firms during the crisis drops to 31 percent of the proportion of trading during a non-crisis period. Note that our measure explicitly accounts for the possibility that overall trading activity in a crisis-month can differ from those observed during a non-crisis month. The relative proportion measure declines to about 0.71 for firms in quintile 2. In contrast, the relative proportion of institutional trading in large cap firms (quintile 5) is higher than one. The trends are consistent with the idea that institutions reduce (proportionate) trading activity in small stocks, or alternatively, they focus trading activity in the large stocks during the crisis.

The results for volatility quintiles in Panel C are consistent with results observed for market value quintiles in Panel B. We observe a decline in relative proportion for high-volatility quintiles and an increase in the relative proportion measure for low volatility quintiles during the crisis. Recall that high volatility stocks experience a larger increase in trading costs as compared to low volatility stocks during the financial crisis (see table 2). In our analysis of liquidity-beta quintiles in Panel D, we note that the relative proportion measure is higher than one for low liquidity-beta stocks and lower than one for high-liquidity beta stocks. Collectively, these findings are consistent with Hypothesis II that investors alter their trading behavior during an episodic event to account for differential impact on liquidity.

Importantly, as seen in Panel B – D and Figure 4, the deviations for the relative proportion measure from one for firms in the extreme quintiles appear to be temporary. The relative proportion measure averaged across institutions reverts to 1.0 by the fourth quarter of 2009. For example, from Panel B, we observe that relative proportion trading activity in small stocks declines to 30% of its pre-crisis levels in March 2009 but reverts to 97% of its pre-crisis levels in November 2009. Similar trends can be observed for volatile stocks in Panel C and high liquidity-beta stocks in Panel D. Coincidently, as reported in table 3, the trading costs for small stocks recover to about 40% of the crisis-peak levels by the fourth quarter of 2009. These patterns suggest that trading activity slowly reverts to the normal patterns as the liquidity conditions in the underlying markets slowly revert to normal.

Collectively, we present evidence on how certain asset characteristics become important for market participants around episodic events. We find that buy-side institutions defensively tilt their trading activity towards more liquid stocks and away from illiquid stocks in response to a liquidity shock. In other words, institutions are sensitive to liquidation costs and more importantly, ex-ante low liquidity-sensitive stocks serve the role of liquidity hedges for institutions during a crash. Thus, investors' preference for low liquidity beta stocks around episodic events can serve as a mechanism that links liquidity-beta and asset prices. As far as we are aware, there is little evidence directly documenting how institutions alter trading behavior across securities during a crash mainly because crisis events of the magnitude observed in 2007-09 are infrequent. For this reason, the recent financial crisis serves as an excellent laboratory to study institutional response to severe liquidity conditions.

4.6. Does institutional trading respond to trading costs?

Evidence in Table 4 suggests that institutions reduce trading activity in response to an increase in trading costs during a financial crisis. In this section, we examine institutions' trading choice in a multivariate framework. We regress the proportionate share of dollar volume in a NYSE market value quintile *i* in month *t* onto differences in quintile *i*'s trading costs and return measures from their respective cross-sectional averages over month *t*, pooling all the quintiles together, as presented in Equation (2) below –

$$\frac{Dollar\ value\ of\ trades_{\ i,t}}{\sum_{i=1}^{5} Dollar\ value\ of\ trades_{\ i,t}} = \alpha + \beta_1 * [TC_{i,t} - TC_t] + \beta_2 * [R_{i,t} - R_t] \qquad (2)$$

where $TC_{i,t}$ is the value-weighted institutional execution shortfall for stocks in quintile *i* over month *t*, TC_t is the value-weighted execution shortfall across all stocks over month *t*, $R_{i,t}$ is the value weighted portfolio return for quintile *i* over month *t* and R_t is the value-weighted return for CRSP index over month *t*.

The approach of classifying trading costs and return variables as deviations from cross-sectional averages follows the approach in Beber, Brandt and Kavajecz (2010), who investigate flight-to-quality effects in the Euro sovereign bond market. The variable transformation acknowledges that institutions choosing which securities to trade consider the relative liquidity of the assets. The monthly averages serve as anchor points and control for time series variation in the level of trading costs or market returns. Note that the dependent variable, the proportionate volume for a market size quintile, is invariant to the time series variation in total institutional trading activity over the sample period. Thus the regression specification investigates whether there is an association between the time series variations in *relative* institutional trading activity and *relative* trading costs for market value quintiles.

The regressions coefficient based on monthly data on the full sample from January 1, 1999 to December 31, 2009 are presented in Table 5. We standardize each independent variable by deducting the mean and dividing by the standard deviation so that the reported standardized coefficients can be interpreted as the impact on trading costs for a standard deviation change in the explanatory variable. For this reason, the regression intercept, estimated to be 0.20, measures the volume share for a quintile holding the independent variables at their full sample averages. The substitution effect proposed by Brunnermeier (2009) would show up as negative coefficient on trading cost differential.

Table 5 reveals that the regression model has significant explanatory power with adjusted R^2 for the base specification of 26.7%. In Table 5, model (1), we observe a negative and statistically significant coefficient on trading cost differential, consistent with Brunnermeier (2009). The interpretation is that an increase in relative trading costs for some stocks is associated with a decline in institution's share of trading activity. Interestingly, the negative and significant coefficient on relative returns tell a different story – that poor relative returns for a quintile are associated with an increase in institution's share of trading activity. The economic significance of the results is also substantial, for example, the results for trading cost differential suggests that a quintile with average return performance and trading costs one standard deviation above the average is associated with an average market share reduction of 10.4 percent.

We also examine whether the trading activity of institutions points to an increased importance of liquidity during periods of perceived market uncertainty. In model (2), we proxy for market uncertainty based on the TED Spread and interact trading cost differential with the TED Spread. The negative and significant coefficient on the interaction term is consistent with the idea that liquidity concerns become relatively more important for institutions when market uncertainty is high. However, the interaction terms based on the VIX index in model (3) is not significant. In model (4) and (5), we identify periods with high uncertainty as those periods placed in the upper quartile of TED spread and VIX index, respectively and report conditional regression estimates for periods of high market uncertainty. For both models, we estimate that the trading cost differential coefficient is larger and more negative. Collectively, the empirical evidence suggests that institutions are sensitive to trading costs and points to an increased importance of liquidity during periods of higher market uncertainty.

5. An analysis of variations in trading costs across institutional traders

5.1. An analysis of trading costs across institutions

We analyze the extent to which institutions are equally affected by the liquidity decline during the financial crisis. Despite the fact that average execution costs rise markedly and the execution cost risk increases, it is possible that some buy-side institutions benefit from serving as liquidity providers when liquidity is dear. The often-cited example of such an investor is a passive small-cap fund managed by Dimensional Fund Advisors (DFA) which selectively provides liquidity to those trading for non-information based reasons (see Da, Gao and Jagannathan (2010)). Keim (1999) estimates that, over the period 1982-1995, the fund earned an annual premium of 2.2% over a pure indexing strategy.

To identify institutions with different trading styles, we examine trading patterns observed for the institution in a month. We classify a buy order as being *Volume_With* if the stock return for the day is positive and *Volume_Against* if the stock return for the day is negative; the converse for sell orders. For each institution, we calculate a *Style Index* based on the aggregate trading volume with and against the stock return in each month, as follow:

$$Style\ Index = \frac{\sum Volume_{With} - \sum Volume_{Against}}{\sum Volume_{With} + \sum Volume_{Against}}$$

We sort institutions into quintile portfolios based on the Style Index, a simple measure of whether the institution tends to demand liquidity from the market or supply liquidity to the market. We classify institutions in *high Style Index* quintile as liquidity-demanding (Q5 institutions) and institutions in *low Style Index* quintile as liquidity-supplying (Q1 institutions). We find that the average Style Index for Q5 institutions is positive, suggesting a high propensity to trade in the direction of daily return; while the average Style Index for Q1 institutions is negative, suggesting a high propensity to trade against the direction of daily return.[18]

If the Style Index captures systematic patterns in an institution's trading style, the Style Index ranking should forecast relative liquidity demand, and thus trading costs, for the institution in a future month. We calculate the volume-weighted execution shortfall for all of an institution's daily orders in the month following the Style Index ranking. We report the monthly average execution shortfall across all institutions in each Style Index quintile portfolio based on the prior month rankings. Our evidence is consistent with Style Index broadly classifying institutions as liquidity supplying versus demanding. Specifically, the evidence presented in Table 6 and Figure 5 suggests significant cross-sectional difference in trading costs in the month following the Style Index ranking.

Over the sample period, the difference in trading cost between Q1 and Q5 institutions in the month following the Style Index ranking averages 59 basis points. However, this difference changes over time: during 1999-2003, the trading cost spread between Q1 and Q5 institution averages 69 basis points. Following the declining trend in trading costs observed in Figure 1, the spread difference shrinks to 46 basis points in 2004-2007. Evidence also suggests that Q5 institutions are the primary beneficiaries of improved market liquidity during this period. From the 1999-2003 period to the 2004-2007 period, the Q5

[18] We also estimate an alternative Style Index wherein institutions are classified as liquidity demanding (liquidity supplying) if they exhibit a propensity to trade with (against) the stock's daily trade (buy-dell) imbalance from TAQ database. Results are similar to those obtained using the return-based measure and not reported in the interest of brevity.

institutions lower their trading costs by 24 basis points, from 64 basis points to 40 basis points per order. In contrast, Q1 institutions' costs are stable.

These trends are reversed during the financial crisis where we estimate that high Style Index (Q5) institutions experience a sharp increase in average trading costs to 57 basis points per order. In contrast, Q1 institutions marginally improve their performance, despite the increase in average trading cost and execution risk reported in Table 2.

Figure 6 presents the execution risk for Q1 and the Q5 institutions in the month following the Style Index ranking. Execution risk increases significantly over the crisis period for both groups and the movements in risk appear to be synchronized. Thus, the increased execution risk itself does not explain why Q1 institutions obtain lower trading costs while Q5 institutions absorb the brunt of the liquidity shock during the crisis. In a similar vein, we observe from Figure 2 that execution risk for large and small stocks moves together over the sample period. Collectively, these results suggest that fluctuations in execution risk are correlated across assets or among participants in financial markets. Yet, despite this correlated risk, trading costs across institutions are not necessarily correlated.

5.2. An analysis of Institutional Trading Patterns

Figure 5 reveals an abrupt switch in mid-2007 in the long term trend of convergence in the cross-section of institutional trading costs. Despite the fact that average execution costs rise markedly and the execution cost risk for both groups of institutions also increases, the low Style Index institutions (Q1) improve their performance, while the performance of High Style Index institutions (Q5) deteriorates.

We now investigate whether these trends reflect low Style Index institutions providing liquidity and high Style Index institutions demanding liquidity when liquidity is priced at a premium by market participants. One possibility is that the results in Figure 5 simply reflect Q5 institutions selling a disproportionate amount of shares while Q1 institutions buying a disproportionate amount of shares during the crisis. In results not reported in the paper, we do not observe significant differences in the buy and sell volume percentages of Q1 and Q5 institutions during the crisis period. This finding suggests a more complex explanation than high Style Index institutions simply dumping shares into the market.

In Figure 7, we estimate the trading cost of buys and sells separately for Q1 and Q5 institutions over the 2006-2009 period. Specifically, we decompose the total trading costs of an institution into costs of executing buy and sell orders. We calculate the contribution of buy trades to the total execution costs for an institution in a month as the volume weighted execution shortfall for buy trades multiplied by the number of shares bought by an institution divided by the total number of shares traded by the institution in the month. The sum of buy and sell contributions equal the total volume weighted execution shortfall for the institution in the month. We report the equal weighted average across institutions in the high Style Index and low Style Index groups.

The resulting trading cost patterns across the two Style Index groups are markedly different. Before the crisis, Q1 institutions generally receive negative trading costs on buys and sells, suggesting they were responding to order imbalances. However, during the crisis-peak, even Q1 institutions pay positive execution costs for sell orders but earn large negative trading costs for buy trades. In contrast, we note that Q5 institutions pay positive execution costs for both buys and sells, both before and during the crisis, and the difference in trading costs across the two groups in the same month is economically large. Consistent with theoretical prediction by Jiang and Wang (2009), the buy-sell asymmetry for Q1 and Q5 institutions increases sharply during the crisis. Surprisingly, Q5 institutions continue to pay positive trading costs for buy orders even during the crisis-peak. This poor performance occurs at a time when buy trades are executing for negative cost (see Figure 3).

In Figure 8, we examine whether there exists a significant difference in trading costs across Q1 and Q5 institutions for certain types of stocks. We decompose the total execution costs of Q1 and Q5 institutions (in month $M+1$) into the cost associated with each market value quintile. We follow a similar methodology as described above for the buy-sell decomposition for the decomposition by market value quintiles. Consistent with Figure 7, the overall patterns reveal that Q1 institutions tend to get paid for executions in all firm size groups, while Q5 institutions tend to pay for execution across *all* firm size groups. As liquidity became more costly in 2007-09, the spread in trading costs increases.

The results thus far suggest that high Style Index institutions incur higher trading costs than low Style Index institutions. The spread in Q1-Q5 trading costs declines from 1999 until 2007 but experiences an increase during the financial crisis which can be attributed solely to higher trading cost for high Style Index institutions; in fact trading costs for low Style Institutions decline. A notable finding is that despite the dramatic increase in overall trading costs, not all institutions had to pay these higher liquidity costs during the financial crisis. Collectively, the results are consistent with high Style Index institutions demanding liquidity and low Style Index institutions supplying liquidity.

In Table 7, we test this explanation by examining correlations between trading costs for high and low Style Index institutions with the Pastor and Stambaugh (PS, 2003) aggregate market liquidity measures.[19] Low Style Index institutions' trading costs have a positive time-series correlation with PS liquidity measure, suggesting that trading costs for these institutions are higher when markets are liquid and lower when market are illiquid. High Style Index institutions, on the other hand, exhibit a negative correlation implying higher costs in illiquid markets. The correlation of the difference in trading costs with the PS measure suggests that difference widens when markets are relatively illiquid. These findings emphasize the role of liquidity risk management in the portfolios of institutional investors and the risk of higher liquidation costs around episodic events.

In Table 8, we regress monthly trading costs for high and low Style Index institutions estimated in the month following Style Index ranking on market conditions. Similar to Table 5, we proxy for market uncertainty based on the (one-month lagged) VIX Index and funding liquidity of intermediaries based on the (lagged) TED Spread and the (lagged) Net Repos. Net Repos is the cumulative difference in short-term lending by U.S. primary dealers reported by the New York Federal Reserve. We also include a crisis indicator variable that equals one for the period after April 2008 and equals zero otherwise.

[19] We are grateful to Lubos Pastor for providing monthly market liquidity statistics on his website. Our sample period for the analysis ends in December 2008, which is the last month for which data is available.

For the low Style Index (Q1) institutions, the regression model has an explanatory power of 5.5% and the only significant explanatory variable is the TED Spread. The positive coefficient on TED Spread suggests that an increase in (lagged) funding costs is associated with an increase in execution shortfall for Q1 institutions. For the high Style Index (Q5) institutions, the regression model exhibits considerably higher explanatory power (36.6%). Further, while the coefficient on TED spread is positive but statistically insignificant (t-stat=1.61), the coefficients on both VIX and Net Repos are highly significant. The results are similar when we regress the difference in monthly trading costs between high and low Style Index institutions on market conditions. The insignificant coefficient for the crisis indicator variable in all regressions is not surprising, since the crisis period is highly correlated with market conditions.

Overall, the results suggest that the trading costs for high Style Index institutions are particularly sensitive to variations in market conditions, as evidenced by the high explanatory power of the model. Specifically, an increase in market-wide volatility and decrease in primary dealer lending is associated with a significant increase in trading costs for high Style Index institutions. In contrast, the low Style Index institutions appear to be largely insulated from markets conditions, as seen in the low explanatory power of the model. These results are consistent with the trading cost patterns observed in Figure 5 and suggest that high Style Index institutions pay a premium for demanding liquidity during uncertain times and when funding liquidity is scarce.

6. Conclusion

The financial crisis of 2007-09 provides an excellent laboratory to test theoretical predictions on stock liquidity and institutional activity during a market downturn. We examine institutional trading during the 1999 to 2009 period using data compiled by ANcerno Ltd, a consulting firm. We examine institutional trades because institutions execute large orders and are particularly concerned about liquidity risk. This study advances our understanding of the liquidity risk faced by institutional investors, who account for an increasing share of global equity trading volume. We present new evidence on institutional preference for asset characteristics during normal conditions and how preferences are altered within periods of market stress

Institutional trading costs decline in the decade leading to the financial crisis. In 2008, institutions experienced a sharp increase in trading costs and an increase in execution risk. The crisis has a more pronounced impact on the liquidity of smaller, more volatile, and higher ex-ante liquidity beta stocks. Importantly, institutions respond to differential liquidity effects by altering their trading activity. We find that institutions tilt their trading activity away from riskier, illiquid assets and toward larger, liquid assets. Thus, stocks with low liquidity-beta serve as a liquidity hedge for institutions during a downturn. We also find that the liquidity for these stocks are resilient and recovers faster than high liquidity-beta stocks.

Whether an institution demands liquidity or supplies liquidity has a large effect on their trading costs, with most of the variation arising from institutions that demand liquidity. As trading costs declined from 1999-2007 they declined primarily for liquidity-demanding institutions. During the 2008-2009 financial crisis, liquidity-supplying institutions actually improve their performance while the performance of liquidity-demanding institutions worsens. Liquidity demanders and liquidity suppliers have significantly different correlations with aggregate liquidity measures. These correlations suggest different institutions can have different exposures to broad liquidity factors. Our results suggest that some institutions were able to insulate themselves and even earn a premium by providing liquidity during the crisis

Overall, we conclude that the deterioration in equity market liquidity during the financial crisis is severe. In fact, market quality during crisis-peak is comparable to market quality last observed a decade ago, emphasizing the large scale dislocations in financial market surrounding the event. We observe an improvement in liquidity during the last quarter of 2009, suggesting that financial markets are slowly returning to normalcy. We believe that the factors affecting the resiliency of financial markets present an important topic for future research.

References

Acharya, V. and L. H. Pedersen, 2005. Asset pricing with liquidity risk, *Journal of Financial Economics,* 77, 375-410.

Acharya, V. and M. Richardson, 2009. Causes of the Financial Crisis, *Critical Review*, 21 (2-3), 195-210.

Adrian, T., and H.S. Shin, 2009. Liquidity and leverage, *Journal of Financial Intermediation*.

Amihud, Y., 2002. Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets,* 5(1), 31-56.

Anand, A., P. Irvine, A. Puckett and K. Venkataraman, 2010, Performance of institutional trading desks: An analysis of persistence in trading costs, working paper, Southern Methodist University.

Aragon, G., and P.E. Strahan, 2009, Hedge funds as liquidity providers: Evidence from the Lehman bankruptcy, working paper, Arizona State University and Boston College.

Beber, A., M. Brandt and K. Kavajecz, 2009. Flight-to-Liquidity or Flight-to-Quality? Evidence from the Euro-Area bond market, *Review of Financial Studies*, 22, 925-957.

Ben-David, I., F. Franzoni, and R. Moussawi, 2010. Hedge Fund stock trading in the financial crisis or 2007-2008, working paper, The Ohio State University.

Berkowitz, S., D. Logue and E. Noser, 1988. The total cost of transacting on the NYSE, *Journal of Finance,* 43(1), 97-112.

Bernardo, A., and I. Welch, 2003, Liquidity and financial market runs, *Quarterly Journal of Economics* 199, 135-158.

Bessembinder, H., 2003. Trade Execution Costs and Market Quality after Decimalization. *Journal of Financial and Quantitative Analysis*, 38, 747-777.

Boehmer, E., C. Jones, and X. Zhang, 2009, Shackling short sellers: The 2008 shorting ban, working paper, University of Oregon.

Boehmer, E. and E. Kelley, 2009, Institutional Investors and the Informational Efficiency of Prices , *Review of Financial Studies*, 22, 3563-3594.

Boyson, N., J. Helwege, and J. Jindra, Crises, Liquidity Shocks, and Fire Sales at Financial Institutions, http://ssrn.com/abstract=1633042

Brunnermeier M., 2009. Deciphering the 2007-2008 liquidity and credit crunch, *Journal of Economic Perspectives,* 23(1), 77-100.

Brunnermeier M., and L. H. Pedersen, 2009. Market Liquidity and Funding Liquidity, *Review of Financial Studies,* 22, 2201-2238.

Campbell, J, S. Grossman, and J. Wang, 1993. Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics*, 108, 905-939.

Cella, Cristina, Ellul, Andrew and Giannetti, Mariassunta, Investors' Horizons and the Amplification of Market Shocks (September 28, 2010). Available at SSRN: http://ssrn.com/abstract=1678021

Chemmanur, T., S. He, and G. Hu, 2009. The role of institutional investors in seasoned equity offerings, forthcoming, *Journal of Financial Economics*.

Chiyachantana, C., P. Jain, C. Jiang, and R. Wood. 2004. International evidence on institutional trading behavior and the determinants of price impact. *Journal of Finance* 59: 865-894.

Chordia, T., R. Roll and A. Subrahmanyam, 2000. Commonality in Liquidity, *Journal of Financial Economics,* 56, 3-28.

Chordia, T., R. Roll and A. Subrahmanyam, 2008. Liquidity and Market Efficiency, *Journal of Financial Economics,* 87.

Chordia, T., R. Roll and A. Subrahmanyam, 2010. Why has trading volume increased? Working paper, Emory University.

Comerton-Forde, C., T. Hendershott, C.M. Jones, P. Moulton, and A.S. Seasholes, 2010, Time variation in Liquidity: The role of market-maker inventories and revenues, *Journal of Finance*, 65 (1), 295-331.

Conrad, J., K. Johnson and S. Wahal, 2001. Institutional trading and soft dollars, *Journal of Finance,* 46, 397- 416.

Coval, J. and E. Stafford, 2007. Asset fire sales (and purchases) in equity markets, Journal of Financial Economics, 86, 479-512.

Da, Z., P. Gao and R. Jagannathan, 2010. Impatient trading, liquidity provision and stock selection by mutual funds, forthcoming, *Review of Financial Studies*.

Garleanu, N., and L.H. Pedersen, 2007, Liquidity and risk management, *American Economic Review*, 97, 193-197.

Goldstein, M., P. Irvine, and A. Puckett. 2010. Purchasing IPOs with commissions. *Journal of Financial and Quantitative Analysis*, forthcoming.

Goldstein, M., P. Irvine, and E. Kandel and Z. Weiner, 2009. Brokerage commissions and institutional trading patterns, Review of Financial Studies, 22(12),5175-5212.

Griffin, J., J. Harris, T. Shu and S. Topaloglu, 2010. Who Drove and Burst the Tech Bubble? forthcoming, *Journal of Finance*.

Griffin, J., P. Kelly and F. Nardari, 2010. Do market efficiency measures yield correct inferences? A comparison of developed and emerging markets, *Review of Financial Studies,* 23(8), 3225-3277.

Gromb, D., and D. Vayanos, 2002, Equilibrium and welfare in markets with financially constrained arbitrageurs, *Journal of Financial Economics,* 66, 361-407.

Gurliacci, M., Jeria, D., and G. Sofianos, 2008. When the going gets tough, the algos get going, Equity Executions Strategies, Goldman Sachs New York, NY.

Hasbrouck, J, 2009. Trading costs and returns for US equities: Estimating effective costs from daily data, *Journal of Finance,* 64(3), 1445-1477.

Hameed A., W. Kang and S. Viswanathan, 2010. Stock market declines and liquidity, *Journal of Finance*, 65(1), 257-294.

He, Z., and A. Krishnamurthy. 2010. Intermediary Asset Pricing, working paper, Northwestern University.
He, Z., Khang, In Gu and A. Krishnamurthy, Balance Sheet Adjustments in the 2008 Crisis, working paper, Northwestern University.

Hendershott, T., C. Jones and A. Menkveld, 2009. Does Algorithmic trading improve liquidity? Working paper, NYU.
Hu, G., 2009. Measures of Implicit Trading Costs and Buy-Sell Asymmetry, *Journal of Financial Markets*, 12, 418-437.

Huang, J., and J. Wang, 2009. Liquidity and Market Crashes, *Review of Financial Studies*, 22, 2607-2643,

Jones, C., 2006, A century of stock market liquidity and trading costs, WP, Columbia University

Jones, C. and M. Lipson, 2001. Sixteenths: Direct evidence on institutional trading costs, *Journal of Financial Economics,* 59(2), 253-278.

Keim, D. 2009. An analysis of mutual fund design: The case of investing in small-cap stocks, *Journal of Financial Economics*, 51.

Keim, D., and A. Madhavan. 1995. Anatomy of the trading process: Empirical evidence on the behavior of institutional traders. *Journal of Financial Economics* 37: 371-398.

Keim D., and A. Madhavan, 1997. Transactions costs and investment style: An inter-exchange analysis of institutional equity trades, *Journal of Financial Economics*, 46, 265-292.

Khandani, A. E. and A. W. Lo, 2007. What Happened to the Quants in August 2007? Available at SSRN: http://ssrn.com/abstract=1015987.

Krishnamurthy, A., 2010. How debt markets have malfunctioned. *Journal of Economic Perspectives* 24 (1), 3-28.

Kyle, A., and W. Xiong, 2001. Contagion as a wealth effect, *Journal of Finance,* 56(4), 1401-1444.

Madhavan, A., 2002. VWAP strategies, *Transaction Performance*, Spring 2002, 32-38.

Pastor, L., and R. Stambaugh, 2003. Liquidity risk and expected stock returns, *Journal of Political Economy,* 111, 642-685.

Perold, A., 1988. The implementation shortfall: Paper versus reality, *Journal of Portfolio Management*, 14, 4-9.

Puckett, A., and S. Yan. 2010. The interim trading skills of institutional investors. *Journal of Finance,* forthcoming.

Roll, R., and A. Subrahmanyam, Liquidity Skewness, forthcoming, *Journal of Banking and Finance.*

Shleifer, A., and R. Vishny, 1997. The Limits of Arbitrage. *Journal of Finance*, 52, 35-55.

Sofianos, G., 2005. Execution quality benchmarks: I can see clearly now…, Trading and Market Structure Analysis, Goldman Sachs New York, NY.

Vayanos, D., 2004, Flight to quality, flight to liquidity and the pricing of risk, NBER working paper.

Table 1 - Descriptive Statistics

This table reports the descriptive statistics for our sample of institutional trades from ANcerno Ltd. for the period from January 1, 1999 to December, 2009. Our analysis is conducted using institutional daily trade orders. Each order is constructed by institution, stock, side and day. We further restrict the sample to orders where execution shortfall is less than or equal to 10%, executed order volume is less than or equal to the total daily trading volume reported in CRSP, the institution responsible for the order has at least 100 orders during a particular month, and the order is for a common stock listed on NYSE or NASDAQ. We present descriptive statistics for the full sample, as well as by disaggregating the sample based on year and firm size quintiles. Firm size quintile breakpoints are constructed using NYSE quintile breakpoints.

	Number of Institutions	**Number of Stocks**	**Number of daily orders**	**Daily order Size**	**Daily order Size/Average daily volume (30 days)**	**Buy dollar volume/Total dollar volume**
Panel A: Full sample						
	955	8,514	43,293,870	16,165	2.9%	50.7%
Panel B: By year						
1999	324	5,726	2,122,761	14,371	4.8%	51.3%
2000	322	5,502	2,509,332	16,189	3.9%	51.4%
2001	350	4,715	2,754,936	18,672	3.8%	52.0%
2002	380	4,383	3,456,098	19,984	3.7%	51.6%
2003	356	4,320	3,558,992	18,799	3.5%	50.6%
2004	367	4,485	4,497,585	18,658	3.5%	50.9%
2005	336	4,342	3,915,803	16,326	3.1%	50.5%
2006	359	4,321	4,933,460	14,668	2.5%	50.5%
2007	339	4,335	5,013,820	13,733	2.2%	50.0%
2008	296	4,052	5,347,082	14,636	1.8%	49.8%
2009	286	3,938	5,184,001	14,270	1.8%	49.8%
Panel C: Firm size (NYSE market value quintiles)						
Small			4,471,299	11,418	11.1%	53.5%
2			6,064,350	12,402	4.4%	52.9%
3			6,699,324	14,298	2.9%	52.2%
4			8,158,691	17,240	2.0%	50.6%
Large			16,556,470	19,398	0.7%	50.1%

Table 2 – Time-series of institutional trading costs

This table examines the time series of execution costs for ANcerno institutions. The trades in the sample are executed by 955 institutions during the time period from January 1, 1999 to December 31, 2009. Only institutions with 100 or more orders in a month are included in the analysis. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell tickets we multiply by -1). We calculate the volume-weighted average execution shortfall and standard deviation of execution shortfall across all tickets for each month (and day) of the sample period. In Panel A we report the average (equal-weighted) execution shortfall and standard deviation across all months (using monthly averages) for a year. We test for the difference between each year and the prior year using the variation of monthly averages to construct our test statistic. In Panel B we report the average (equal-weighted) execution shortfall and standard deviation across all days (using daily averages) for nine different periods during the 2007 to 2009 time period. *T-statistics*, in parentheses, test for the difference between each period and the benchmark period. All numbers are in percent.

Panel A: Yearly Statistics

	All Years	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Execution Shortfall												
mean	0.186	0.221	0.218	0.199	0.164	0.200	0.160	0.148	0.141	0.130	0.212	0.253
t-stat (diff prev yr)			(-0.24)	(-1.21)	(-2.79)	(3.09)	(-4.64)	(-1.74)	(-0.94)	(-1.00)	(3.99)	(1.43)
median	0.179	0.218	0.196	0.192	0.165	0.201	0.158	0.148	0.143	0.123	0.192	0.220
Standard Deviation												
mean	2.070	2.300	2.844	2.532	2.311	1.815	1.617	1.471	1.469	1.529	2.590	2.288
t-stat (diff prev yr)			(6.27)	(-2.54)	(-1.66)	(-4.88)	(-3.24)	(-3.09)	(-0.04)	(0.59)	(4.91)	(-1.17)
median	2.024	2.252	2.798	2.543	2.233	1.877	1.645	1.453	1.458	1.429	2.421	2.135

Panel B: Crisis Period and after – May 2007 to December 2009

	Benchmark	Quant Crisis	Bear Sale	Lehman Bankruptcy				After the Crash (2009)			
	(1/07 - 4/07)	(7/07 - 8/07)	(2/08 - 4/08)	9/08	10/08	11/08	12/08	Q1	Q2	Q3	Q4
Execution Shortfall											
mean	0.119	0.105	0.187	0.217	0.304	0.350	0.267	0.329	0.290	0.202	0.181
t-stat (diff bench)		(-0.74)	(5.36)	(3.15)	(5.58)	(4.25)	(3.03)	(10.61)	(6.86)	(5.62)	(4.83)
median	0.124	0.118	0.195	0.225	0.319	0.404	0.251	0.323	0.280	0.221	0.184
Standard Deviation											
mean	1.271	1.773	2.052	2.779	3.835	3.500	3.167	2.956	2.527	1.843	1.635
t-stat (diff bench)		(5.71)	(17.33)	(11.69)	(21.93)	(15.52)	(12.69)	(27.68)	(17.72)	(13.27)	(6.97)
median	1.223	1.660	1.987	2.581	3.960	3.291	3.191	2.908	2.432	1.810	1.531
Buy/Sell Percentage											
Buy Percentage	51.16%	49.74%	50.27%	48.59%	49.15%	49.16%	49.98%	51.66%	49.38%	49.89%	48.25%

Table 3 – Financial crisis and the cross-section of institutional trading costs

This table examines the time series of execution costs for ANcerno institutions by firm size, volatility, and liquidity beta. The trades in the sample are executed by 955 institutions from January 1, 2007 to December 31, 2009. Only institutions with 100 or more orders in a month are included in the analysis. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell tickets we multiply by -1). We calculate the average volume weighted execution shortfall and standard deviation of execution shortfall across all tickets for each NYSE size quintile in each month of the sample period. We report the average (equal-weighted) execution shortfall and standard deviation across all days (using daily averages) for each NYSE size quintile in each time period in Panel A, for volatility quintiles in Panel B, and for liquidity beta quintiles in Panel C. *t-statistics*, in parentheses, test for the difference between each time period and the benchmark period. All numbers are in percent.

Panel A: Size Quintiles

	Benchmark	Quant Crisis	Bear Sale	Lehman Bankruptcy				After the Crash (2009)			
	(1/07 - 4/07)	(7/07 - 8/07)	(2/08 - 4/08)	9/08	10/08	11/08	12/08	Q1	Q2	Q3	Q4
Quintile 1 (large)											
Execution Shortfall	0.074	0.081	0.119	0.128	0.234	0.282	0.197	0.242	0.209	0.138	0.103
t-stat (diff bench)		(0.44)	(3.60)	(1.95)	(3.40)	(4.90)	(3.12)	(8.00)	(7.21)	(4.57)	(2.79)
Quintile 5 (small)											
Execution Shortfall	0.175	0.115	0.218	0.368	0.501	0.751	0.337	0.500	0.459	0.339	0.301
t-stat (diff bench)		(-1.34)	(1.07)	(3.91)	(3.80)	(4.23)	(2.12)	(4.46)	(4.26)	(3.92)	(2.92)
Diff. of Difference (Q5 minus Q1)											
Execution Shortfall	0.101	0.033	0.098	0.240	0.266	0.470	0.140	0.258	0.249	0.201	0.198
t-stat (diff bench)		(-1.52)	(-0.06)	(2.42)	(2.85)	(2.69)	(0.52)	(2.05)	(2.27)	(2.27)	(2.28)

Panel B: Volatility Quintiles

	Benchmark	Quant Crisis	Bear Sale	Lehman Bankruptcy				After the Crash (2009)			
	(1/07 - 4/07)	(7/07 - 8/07)	(2/08 - 4/08)	9/08	10/08	11/08	12/08	Q1	Q2	Q3	Q4
Quintile 1 (low)											
Execution Shortfall	0.065	0.051	0.121	0.079	0.180	0.270	0.157	0.242	0.195	0.122	0.094
t-stat (diff bench)		(-0.75)	(3.63)	(0.35)	(2.69)	(4.06)	(2.07)	(8.93)	(6.02)	(3.54)	(2.34)
Quintile 5 (high)											
Execution Shortfall	0.182	0.192	0.257	0.355	0.404	0.487	0.409	0.417	0.432	0.322	0.263
t-stat (diff bench)		(0.27)	(2.43)	(2.90)	(3.57)	(3.25)	(2.36)	(5.75)	(6.45)	(4.88)	(3.03)
Diff. of Difference (Q5 minus Q1)											
Execution Shortfall	0.117	0.141	0.136	0.276	0.224	0.216	0.253	0.176	0.237	0.200	0.169
t-stat (diff bench)		(0.73)	(0.56)	(2.40)	(2.42)	(1.92)	(1.67)	(1.41)	(3.37)	(2.91)	(2.06)

Panel C: Liquidity Beta Quintiles

	Benchmark	Quant Crisis	Bear Sale	Lehman Bankruptcy				After the Crash (2009)			
	(1/07 - 4/07)	(7/07 - 8/07)	(2/08 - 4/08)	9/08	10/08	11/08	12/08	Q1	Q2	Q3	Q4
Quintile 1 (low)											
Execution Shortfall	0.084	0.081	0.136	0.118	0.227	0.326	0.217	0.269	0.219	0.139	0.122
t-stat (diff bench)		(-0.13)	(3.72)	(1.35)	(3.38)	(5.09)	(2.73)	(8.16)	(6.31)	(3.61)	(3.01)
Quintile 5 (high)											
Execution Shortfall	0.155	0.192	0.282	0.382	0.561	0.512	0.432	0.473	0.414	0.391	0.339
t-stat (diff bench)		(0.67)	(3.39)	(3.02)	(5.15)	(3.11)	(3.33)	(5.59)	(4.41)	(5.00)	(4.44)
Diff. of Difference (Q5 minus Q1)											
Execution Shortfall	0.071	0.111	0.146	0.264	0.334	0.186	0.214	0.204	0.196	0.252	0.217
t-stat (diff bench)		(0.85)	(1.90)	(2.49)	(3.23)	(0.98)	(2.92)	(2.27)	(2.33)	(3.85)	(3.56)

Table 4 - Financial crisis and Institutions trading activity

This table presents relative trading activity of institutions over the entire sample and across market value, volatility, and liquidity beta quintiles from September, 2008 to November 2009. Only institutions with 100 or more tickets in a month are included. Panel A presents the average relative dollar volumes traded from 09/2008 to 11/2009 relative to the average trading volume of an institution in the first four months of 2008. Panel B presents the composition of trading activity across NYSE market value quintiles. Panel C presents the composition of trading activity across volatility quintiles. Panel D presents the composition of trading activity across liquidity beta quintiles. We first calculate the proportion of dollar volume in a particular NYSE size, volatility, or liquidity beta quintile for each of the first four months of 2008 for each institution. We average the proportions for the first four months for each institution to form benchmark trading activity for an institution. We then calculate the proportion of dollar trading activity for the institution in crisis-months relative to the benchmark proportions described above. The monthly averages across institutions are presented below. *t-statistics* are presented for tests that the relative values equal one.

	Market Value Quintile	Benchmark period	Relative to Benchmark Period								
		01-04/2008	9/2008	10/2008	11/2008	1/2009	3/2009	5/2009	7/2009	9/2009	11/2009
Panel A. Trading Volume											
Average (monthly volume)		$995,287,999	1.129	1.109	0.727	0.703	0.723	0.793	0.763	0.791	0.682
T-Statistic (test relative volume=1)			*3.01*	*2.64*	*-7.75*	*-7.25*	*-7.49*	*-3.93*	*-3.32*	*-3.68*	*-6.78*
Panel B: Proportion of trading volume in market value quintile											
Proportion of trading volume in quintile	Small	4.08%	0.735	0.683	0.501	0.551	0.312	0.576	0.674	0.918	0.969
T-Statistic (test relative proportion=1)	Small		*-5.37*	*-7.30*	*-11.35*	*-9.96*	*-22.27*	*-10.74*	*-5.35*	*-1.26*	*-0.49*
Proportion of trading volume in quintile	2	10.00%	1.003	0.832	0.752	0.769	0.710	0.858	0.859	1.062	0.879
T-Statistic (test relative proportion=1)	2		*0.07*	*-4.82*	*-6.24*	*-5.63*	*-6.76*	*-3.19*	*-2.69*	*1.05*	*-2.42*
Proportion of trading volume in quintile	3	12.44%	1.026	0.999	1.064	1.026	1.028	1.050	1.166	1.206	1.106
T-Statistic (test relative proportion=1)	3		*0.64*	*-0.02*	*1.36*	*0.54*	*0.66*	*1.09*	*2.80*	*3.44*	*1.99*
Proportion of trading volume in quintile	4	17.03%	0.978	1.005	1.057	1.067	1.012	1.104	1.042	1.093	1.177
T-Statistic (test relative proportion=1)	4		*-0.68*	*0.14*	*1.74*	*1.67*	*0.36*	*2.58*	*1.07*	*2.61*	*3.47*
Proportion of trading volume in quintile	Large	56.45%	1.045	1.071	1.064	1.078	1.140	1.024	1.033	0.966	1.004
T-Statistic (test relative proportion=1)	Large		*1.89*	*2.79*	*2.57*	*3.46*	*5.16*	*0.95*	*1.07*	*-1.40*	*0.13*

	Volatility Quintile	Benchmark period	Relative to Benchmark Period								
		01-04/2008	9/2008	10/2008	11/2008	1/2009	3/2009	5/2009	7/2009	9/2009	11/2009
Panel C: Proportion of trading volume in Volatility quintile											
Proportion of trading volume in quintile	Low	35.03%	1.112	1.225	1.232	1.161	1.110	1.125	1.096	1.077	1.049
T-Statistic (test relative proportion=1)	Low		*4.46*	*10.02*	*8.01*	*5.65*	*3.95*	*4.47*	*3.57*	*2.59*	*1.46*
Proportion of trading volume in quintile	2	25.26%	1.013	1.005	0.999	1.012	1.101	1.001	1.059	1.105	1.098
T-Statistic (test relative proportion=1)	2		*0.62*	*0.27*	*-0.03*	*0.55*	*4.49*	*0.03*	*2.47*	*3.47*	*3.59*
Proportion of trading volume in quintile	3	18.31%	0.934	0.871	0.960	0.962	0.962	0.919	0.967	0.977	0.983
T-Statistic (test relative proportion=1)	3		*-3.05*	*-7.10*	*-1.62*	*-1.27*	*-1.44*	*-3.06*	*-1.14*	*-0.72*	*-0.54*
Proportion of trading volume in quintile	4	11.10%	0.964	0.910	0.831	0.931	0.923	1.064	0.945	0.977	1.070
T-Statistic (test relative proportion=1)	4		*-1.23*	*-3.11*	*-5.20*	*-1.82*	*-2.11*	*1.63*	*-1.60*	*-0.64*	*1.74*
Proportion of trading volume in quintile	High	10.25%	0.970	0.856	0.790	0.851	0.889	0.874	0.927	0.933	0.927
T-Statistic (test relative proportion=1)	High		*-0.97*	*-5.00*	*-7.28*	*-4.86*	*-3.93*	*-3.88*	*-2.06*	*-1.95*	*-2.14*

	Liquidity Beta Quintile	Benchmark period	Relative to Benchmark Period								
		01-04/2008	9/2008	10/2008	11/2008	1/2009	3/2009	5/2009	7/2009	9/2009	11/2009
Panel D: Proportion of trading volume in Liquidity beta quintile											
Proportion of trading volume in quintile	Low	40.06%	1.042	1.083	1.059	1.055	1.062	1.050	1.051	1.024	1.054
T-Statistic (test relative proportion=1)	Low		*2.04*	*4.23*	*2.80*	*2.19*	*2.61*	*2.04*	*1.71*	*0.77*	*1.91*
Proportion of trading volume in quintile	2	37.28%	1.020	1.036	1.047	1.022	1.051	1.040	1.022	1.028	1.016
T-Statistic (test relative proportion=1)	2		*1.36*	*2.27*	*2.75*	*1.25*	*3.25*	*2.14*	*1.12*	*1.40*	*0.73*
Proportion of trading volume in quintile	3	11.72%	1.045	0.973	0.994	0.957	0.989	1.042	1.060	1.129	1.134
T-Statistic (test relative proportion=1)	3		*1.28*	*-0.80*	*-0.16*	*-1.21*	*-0.31*	*1.00*	*1.45*	*2.68*	*2.84*
Proportion of trading volume in quintile	4	6.45%	0.942	0.909	0.916	0.929	1.017	1.048	0.962	0.999	1.064
T-Statistic (test relative proportion=1)	4		*-1.39*	*-2.23*	*-1.82*	*-1.50*	*0.34*	*0.89*	*-0.77*	*-0.02*	*1.33*
Proportion of trading volume in quintile	High	4.48%	0.874	0.785	0.753	0.857	0.683	0.768	0.825	0.973	0.900
T-Statistic (test relative proportion=1)	High		*-2.75*	*-4.47*	*-4.93*	*-2.90*	*-7.06*	*-4.44*	*-3.08*	*-0.46*	*-1.68*

Table 5: Institutional trading activity and trading costs

This table examines what institutions trade. The trades in the sample are executed by 955 institutions from January 1, 1999 to December 31, 2009. Each month we separate all trades by NYSE market value quintile and compute the value-weighted execution shortfall for all trades in each quintile, the total dollar value of trades in each quintile, and the value-weighted returns of the quintile portfolio. We then run the following regression: the dependent variable is the total dollar value of trades for the quintile divided by the total dollar value of all trades during the month. Cost difference is the execution shortfall of the quintile minus the execution shortfall for the entire sample. Return difference is the value-weighted portfolio return for the quintile minus the value-weighted return for the CRSP index during that month. We also interact the TED spread and VIX with the cost difference variable. We standardize all independent variables by deducting the sample mean and dividing by standard deviation. *T-statistics* are presented in parentheses.

	Full Sample			High TED	High VIX
Intercept	0.200	0.200	0.199	0.200	0.200
	(26.57)	(26.59)	(26.16)	(14.00)	(12.16)
Cost Difference	-0.104	-0.106	-0.107	-0.121	-0.113
	(-13.35)	(-13.56)	(-12.54)	(-8.26)	(-6.77)
Return Diff.	-0.034	-0.035	-0.033	-0.041	-0.038
	(-4.36)	(-4.48)	(-4.21)	(-2.77)	(-2.30)
TED*Cost Diff.		-0.020			
		(-2.24)			
VIX*Cost Diff.			0.008		
			(0.88)		
	660	660	660	165	165
	0.267	0.271	0.267	0.348	0.248

Table 6 – Trading costs of high Style Index and low Style Index Institutions, 1999-2009.

This table examines the performance of institutional trading desks classified into High and Low Style Index institutions. The trades in the sample are executed by 955 institutions during January 1, 1999 to December 31, 2009. Only institutions with 100 or more tickets in a month are included in the analysis. Institutions are classified based on trading patterns observed for the institution each month. Specifically we classify a buy (sell) order as being $Volume_{With}$ if the stock return for the day is positive (negative) and $Volume_{Against}$ if the stock return for the day is negative (positive). For each institution, we calculate a Style Index based on the aggregate trading volume with and against the stock return in each month, as follow:

$$Style\ Index = \frac{\sum Volume_{With} - \sum Volume_{Against}}{\sum Volume_{With} + \sum Volume_{Against}}$$

We sort institutions into quintile portfolios based on the Style Index. We classify Q5 institutions as high Style Index and Q1 institutions as low Style Index. We calculate the volume-weighted average execution shortfall across the tickets for each institution in the month following the Style Index ranking. Execution shortfall is presented as a percentage. We report the average (equal-weighted) execution shortfall for these quintiles in the month following portfolio formation. We perform our analysis for four different time periods: 1999-2009, 1999-2003, 2004-2007, and 2008-2009. Numbers in parentheses are p-values.

Current Quarter Quintiles	1999-2009	1999-2003	2004-2007	2008-2009
Q1 Low Style Index	-0.058	-0.053	-0.057	-0.073
Q2	0.134	0.160	0.104	0.129
Q3	0.235	0.272	0.172	0.276
Q4	0.337	0.390	0.251	0.392
Q5 High Style Index	0.536	0.638	0.399	0.573
Q5 – Q1 (Exec. Shortfall)	0.594	0.690	0.456	0.647
	(<0.001)	(<0.001)	(<0.001)	(<0.001)

Table 7 – Style Index and Market Liquidity

This table presents the correlations of low Style Index and high Style Index institutions' execution shortfalls to market liquidity. Market liquidity is measured by Pastor and Stambaugh (2003) aggregate liquidity. Panel A presents the results for the 1999-2008 sample, while Panels B and C present the results for the 1999-2006 and 2007-2008 subsamples.

	Low Style Index institutions Trading Costs	High Style Index institutions Trading Costs	[High-Low] Style Index institutions Trading Costs	PS-Aggregate liquidity
Panel A: Sample period 1999-2008				
Execution shortfall (Low Style Index institutions)	1.00	-0.28	-0.64	0.21
		0.00	*0.00*	*0.02*
Execution shortfall (High Style Index institutions)		1.00	0.92	-0.21
			0.00	*0.02*
Difference in shortfall (High-Low)			1.00	-0.26
				0.00
Panel B: Sample period 1999-2006				
Execution shortfall (Low Style Index institutions)	1.00	-0.34	-0.67	0.13
		0.00	*0.00*	*0.22*
Execution shortfall (High Style Index institutions)		1.00	0.93	-0.19
			0.00	*0.06*
Difference in shortfall (High-Low)			1.00	-0.20
				0.05
Panel C: Sampleperiod 2007-2008				
Execution shortfall (Low Style Index institutions)	1.00	-0.23	-0.61	0.38
		0.29	*0.00*	*0.06*
Execution shortfall (High Style Index institutions)		1.00	0.91	-0.45
			0.00	*0.03*
Difference in shortfall (High-Low)			1.00	-0.53
				0.01

Table 8 – Institution Style Exposure and Market Conditions

This table examines the determinants of execution shortfall for institutions grouped by high and low Style Index. Q1 Execution shortfall is the percentage execution shortfall for the low Style Index institutional quintile calculated as in Equation (2). Q5 Execution shortfall is the percentage execution shortfall for the high Style Index institutional quintile. Crisis is an indicator variable that equals one in the period after April 2008 and equals zero otherwise. The Ted Spread is the percentage Eurodollar:t-bill spread, VIX is the S&P 500 volatility index (in percent) and Net Repos is the cumulative difference in short-term lending by U.S. primary dealers reported by the New York Federal Reserve (in $000's). All regressions control for first degree autocorrelation in the residuals. T-statistics are presented in parentheses below the coefficient estimates.

	Q1 Execution Shortfall	Q5 Execution Shortfall	Q1-Q5 Difference
Intercept	-0.070	0.559	0.650
	(-1.48)	(9.13)	(6.81)
Crisis	-0.050	-0.049	0.015
	(-1.46)	(-1.10)	(-0.36)
Ted Spread (t-1)	4.98	4.31	-1.46
	(2.38)	(1.61)	(-0.36)
VIX (t-1)	-0.045	0.682	0.651
	(-0.28)	(3.40)	(2.13)
Net Repos (t-1)	-0.002	-0.021	-0.019
	(-0.44)	(-4.59)	(-2.68)
N	131	131	131
R-squared	0.055	0.366	0.154

Figure 1 – Institutional trading costs, 1999-2009

This figure shows the time series of institutional trading costs. Orders in the sample are executed by 955 institutions during the time period from January 1, 1999 to December 31, 2009. Only institutions with 100 or more tickets in a month are included in the analysis. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell tickets we multiply by -1). For each order, we follow the market adjustment in Keim and Madhavan (1995) and subtract the daily return on the S&P 500 index from the order's execution shortfall after accounting for the ticket's direction. We calculate the volume-weighted average execution shortfall across all orders for each month, for the overall sample, and for the largest and smallest NYSE size quintile. NYSE size quintiles are formed as of the end of the month prior to the month of ticket execution.

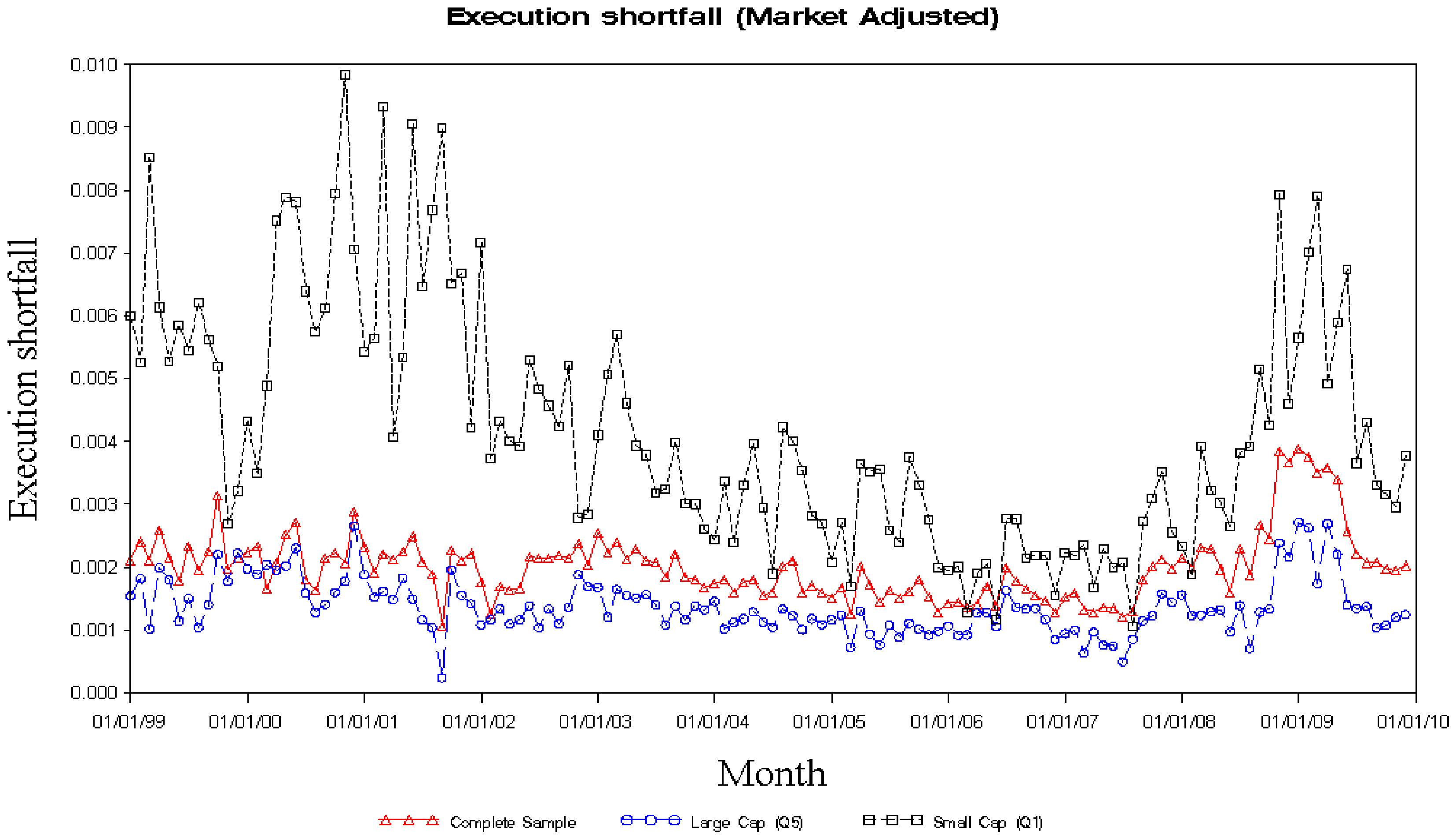


Figure 2 – Institutional execution risk, 1999-2009

This figure shows the time series of execution risk, measured as the standard deviation of execution shortfall. Orders in the sample are executed by 955 institutions during the time period from January 1, 1999 to December 31, 2009. Only institutions with 100 or more tickets in a month are included in the analysis. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell tickets we multiply by -1). For each order, we follow the market adjustment in Keim and Madhavan (1995) and subtract the daily return on the S&P 500 index from the order's execution shortfall after accounting for the ticket's direction. We calculate the standard deviation of execution shortfall across all orders for each month, for the overall sample, and for the largest and smallest NYSE size quintile. NYSE size quintiles are formed as of the end of the month prior to the month of ticket execution.

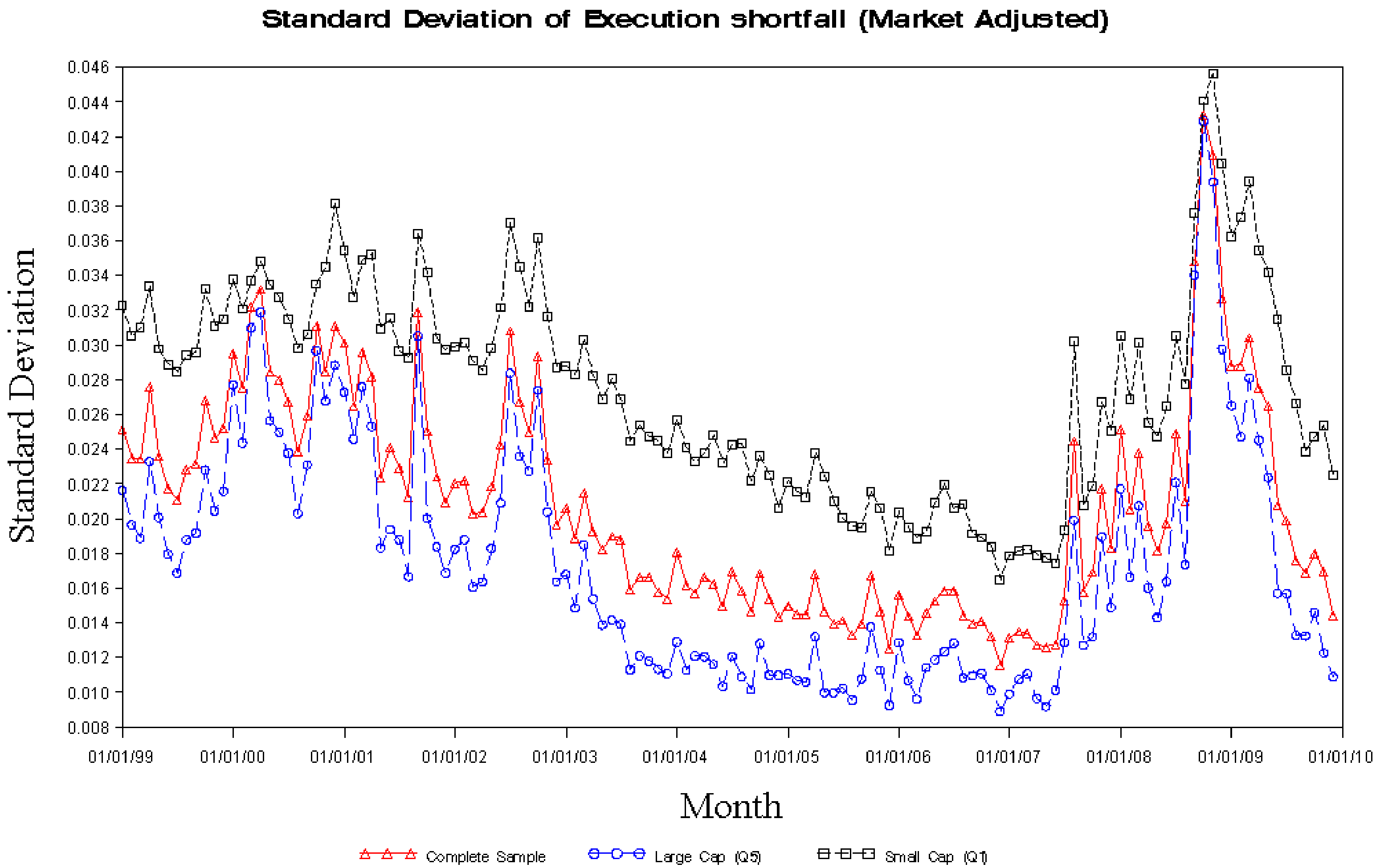


Figure 3 – Institutional trading costs for Buys and Sells 2006-2009

This figure shows the time series of execution shortfall for buys and sells separately. Orders in the sample are executed by 955 institutions during the time period from January 1, 2006 to December 31, 2009. Only institutions with 100 or more tickets in a month are included in the analysis. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell tickets we multiply by -1). We calculate the volume-weighted execution shortfall across all buy tickets and across all sell tickets for each month of the sample period.

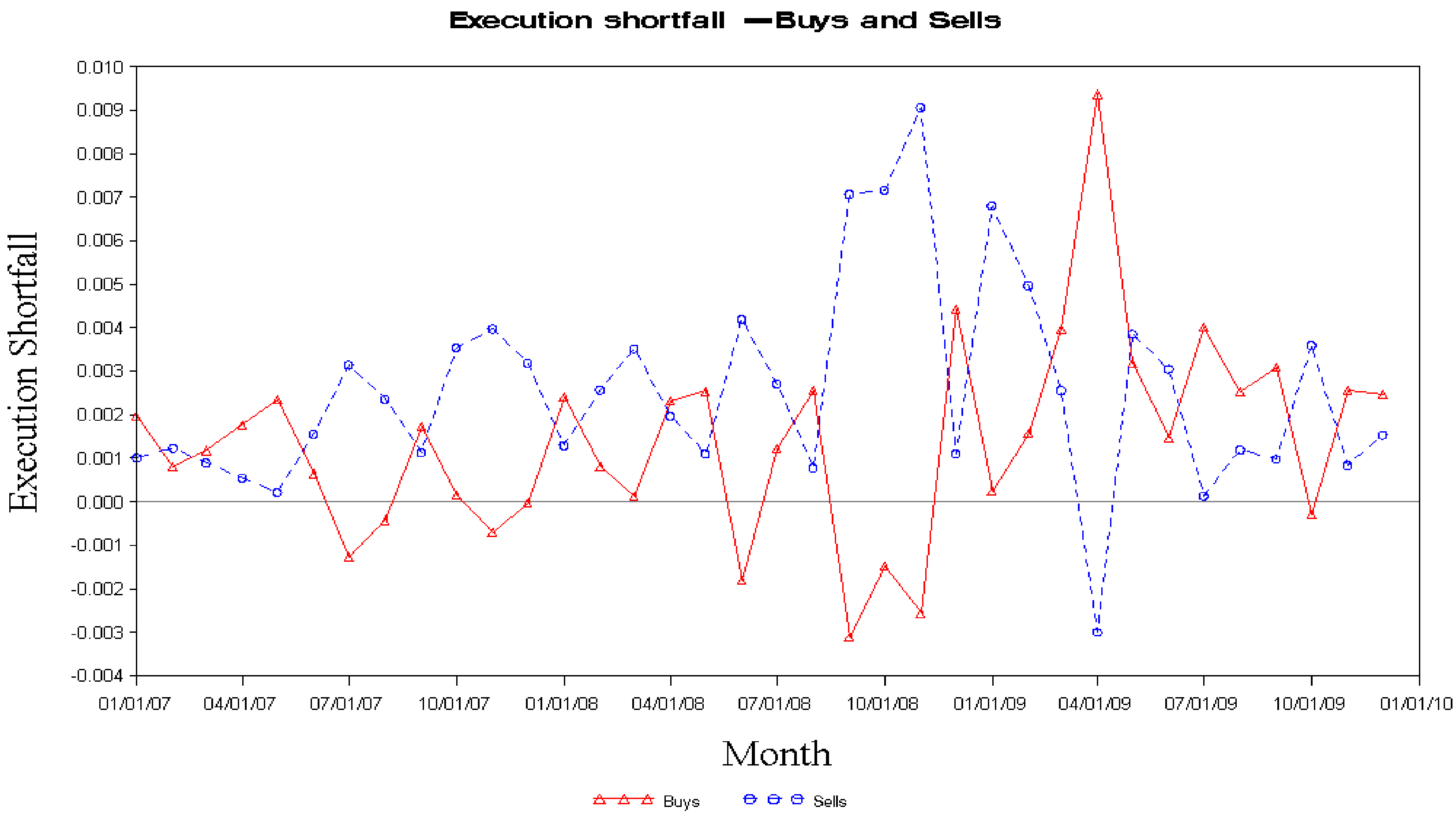


Figure 4 – An analysis of what institutions trade during the financial crisis

This figure shows relative trading activity of institutions for stocks in quintiles of market cap, volatility and liquidity beta from May, 2008 to December, 2009. Only institutions with 100 or more tickets in a month, which trade in at least three of the final four months of 2008, are included. We first calculate the share of trading activity (dollar volume) in a particular quintile for each of the first four months of 2008 for each institution. We average the proportions for the first four months for each institution to form benchmark quintile-share for an institution. We then calculate the share of trading activity for the institution in the remaining months of 2008 and into the fourth quarter of 2009 relative to the benchmark shares. The monthly averages across institutions are plotted below. The observation for April, 2008 represents the average of the first four months and equals one by construction.

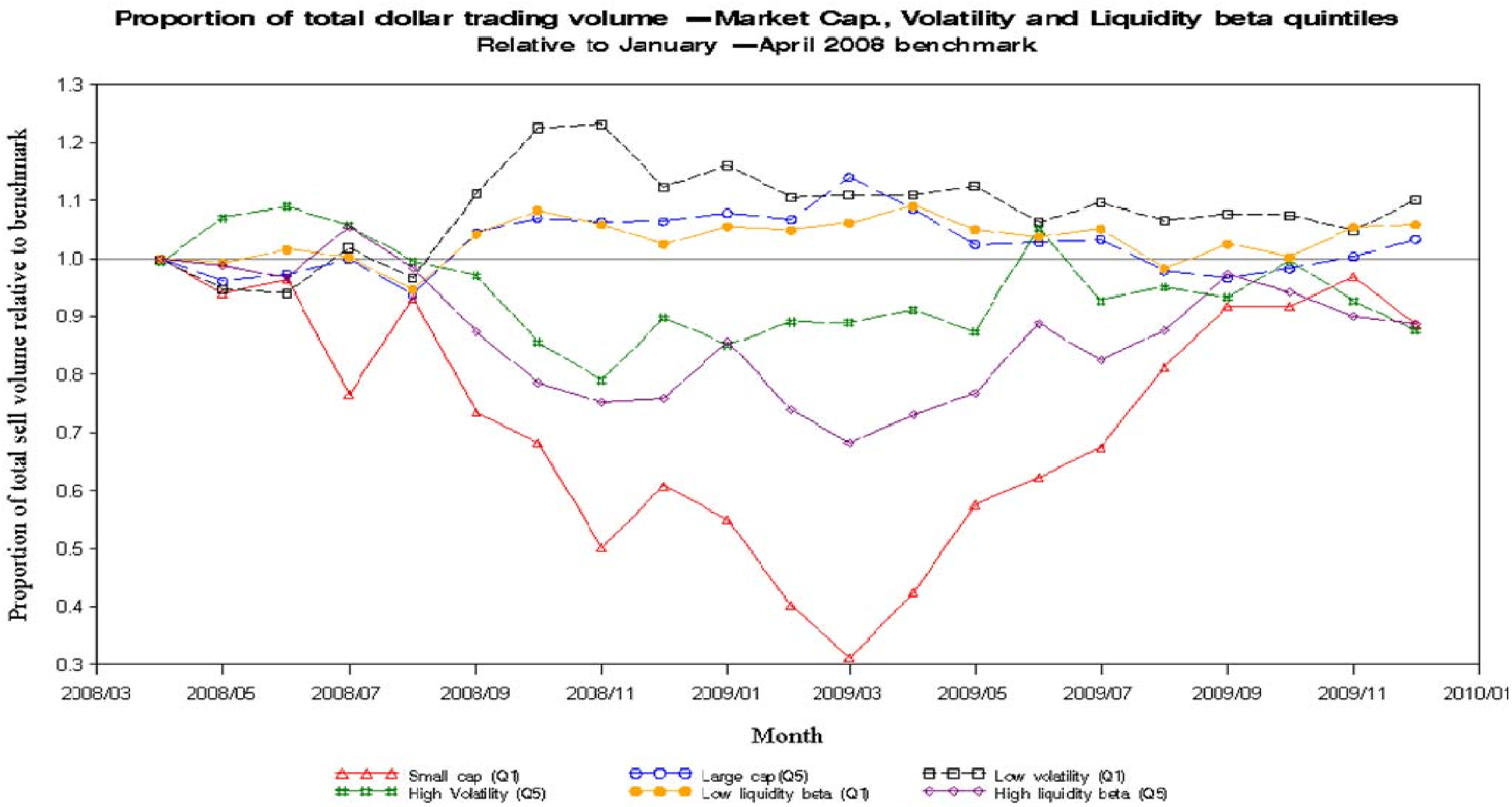


Figure 5 – Institutional trading costs for High Style Index and Low Style Index Institutions

This figure shows the performance of institutional trading desks. Execution shortfall is measured for buy tickets as the execution price minus the market open price on the day of ticket placement divided by the market open price (for sell tickets we multiply by -1). We calculate the share-weighted average execution shortfall across the tickets for each institution each month. Each month, we assign institutions into quintile portfolios based on Style Index for the month. The figure plots the average (equal-weighted) execution shortfall in percentage for Low Style Index (quintiles 1) and High Style Index (quintile 5) in the month *following* the portfolio formation month.

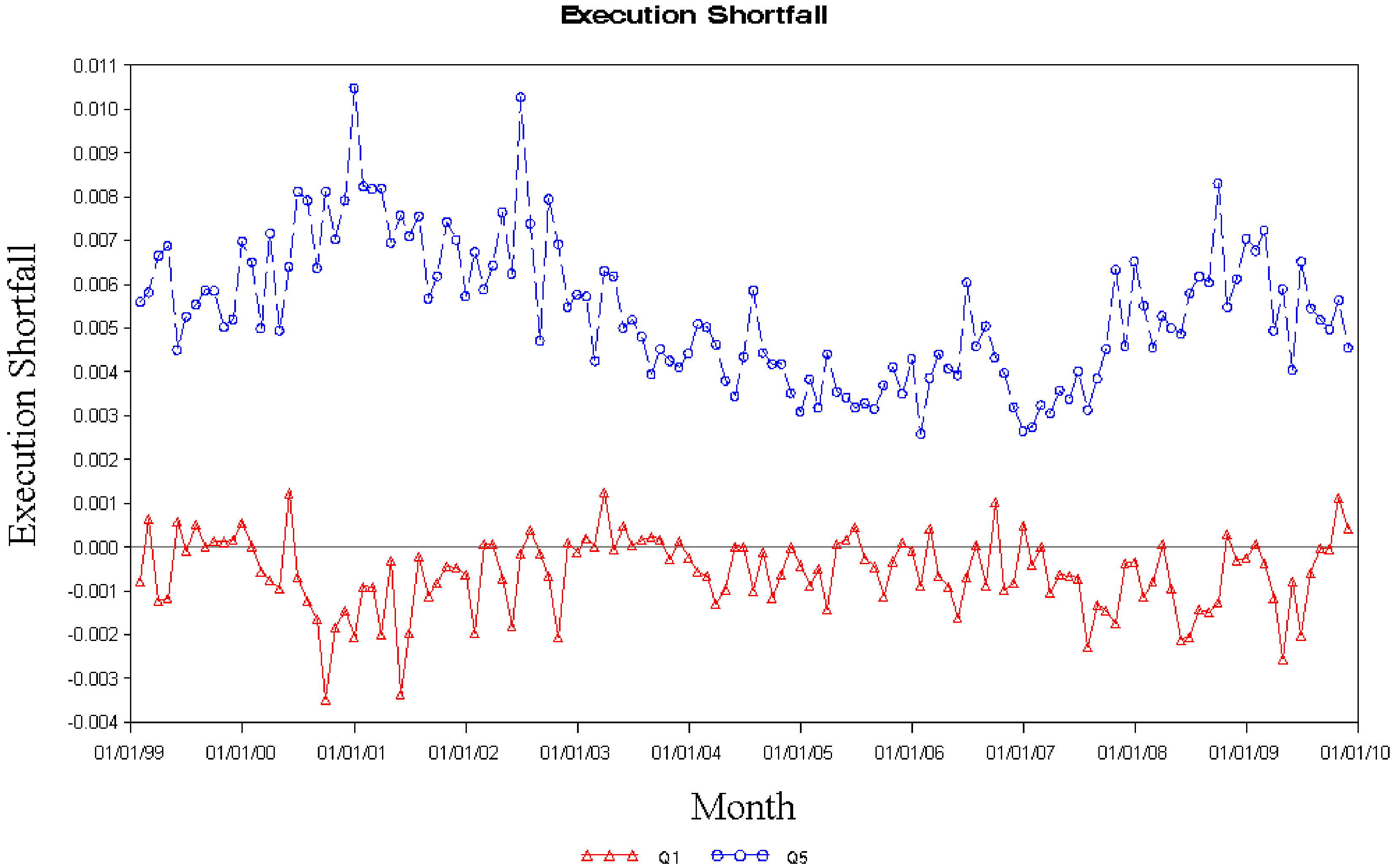


Figure 6 – Institutional execution risk for High Style Index and Low Style Index institutions

This figure shows the time series of the standard deviation of execution shortfall Low Style Index (quintiles 1) and High Style Index (quintile 5) institutional trading desks. Execution shortfall is measured for buy tickets as the execution price minus the market open price on the day of ticket placement divided by the market open price (for sell tickets we multiply by -1). We calculate the volume-weighted average execution shortfall across the tickets for each institution each month. Each month, we assign institutions into quintile portfolios based on Style Index for the month. The figure plots the average (equal-weighted) standard deviation of execution shortfall in percentage for Low Style Index (quintiles 1) and High Style Index (quintile 5) in the month *following* the portfolio formation month.

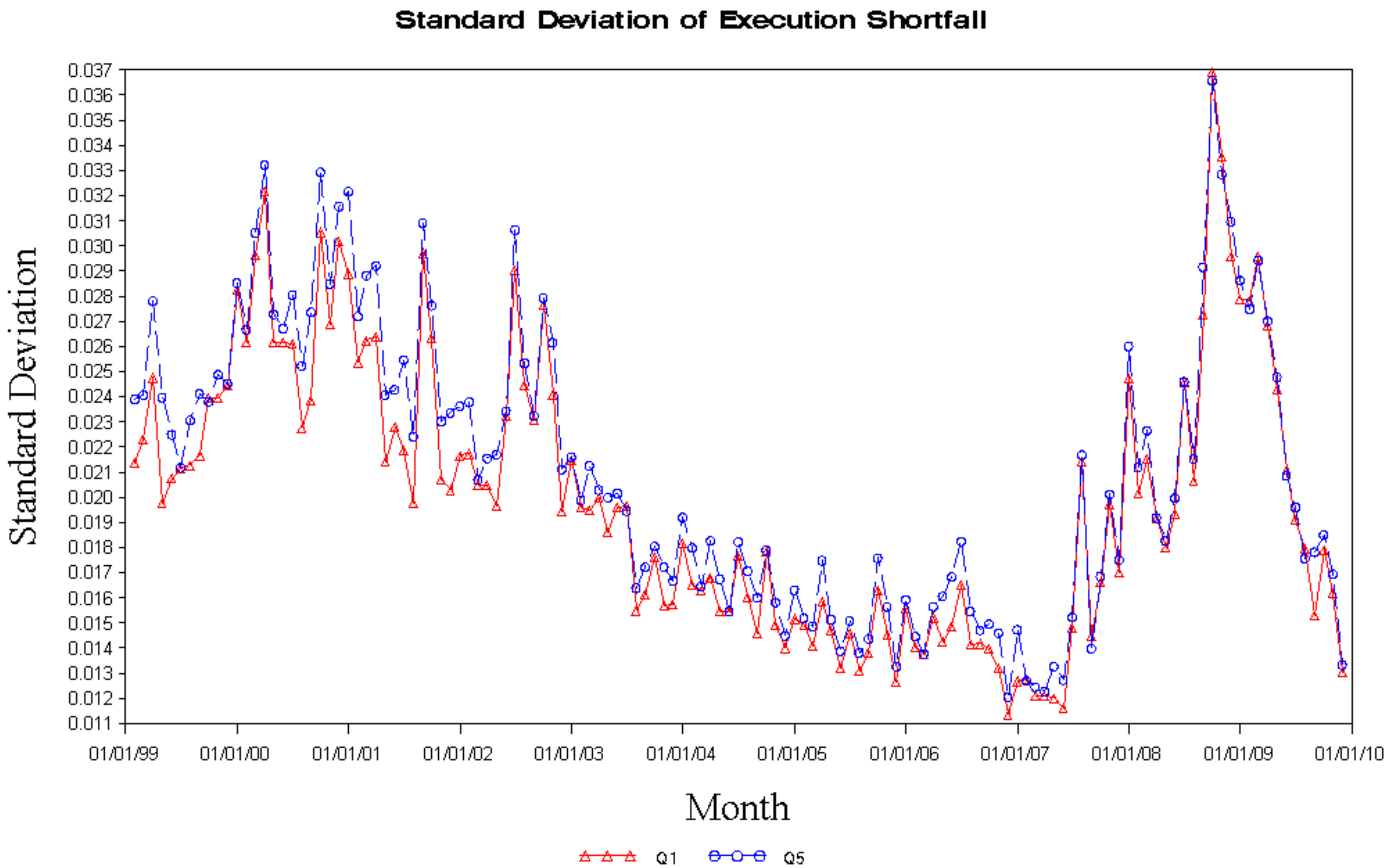
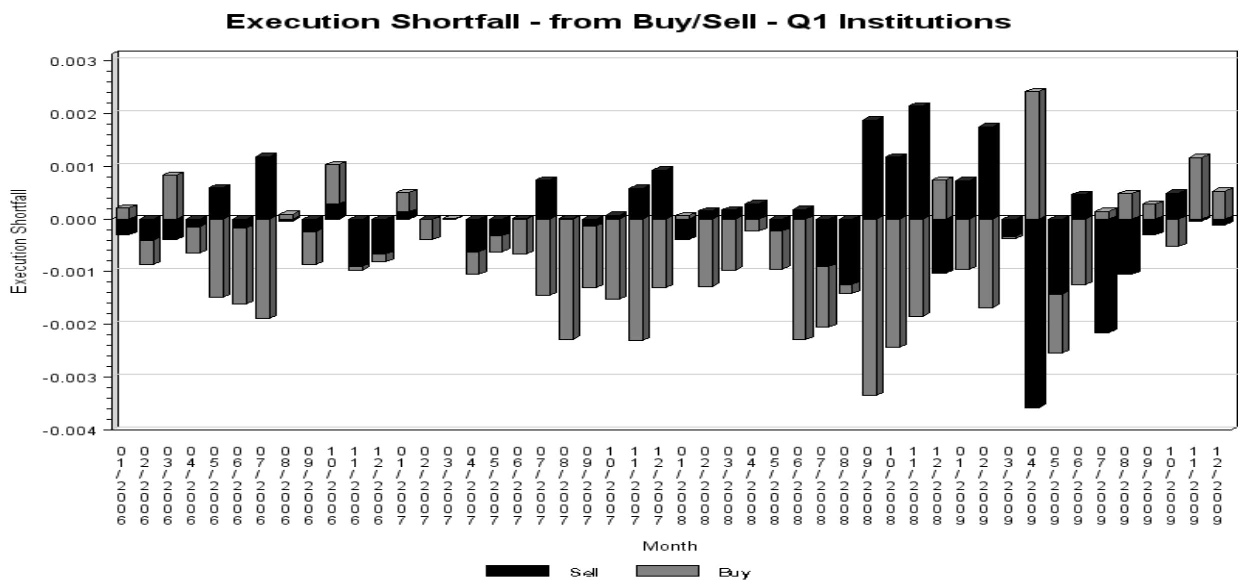


Figure 7 – Institution's Style Index and Buy/Sell Trading Costs

Execution shortfall is measured for buy tickets as the execution price minus the market open price on the day of ticket placement divided by the market open price (for sell tickets we multiply by -1). We calculate the volume-weighted average execution shortfall across the tickets for each institution each month separately for buy and sell trades. The figure plots the average (equal-weighted) execution shortfall for Low Style Index (quintiles 1) and High Style Index (quintile 5) in the month *following* the portfolio formation month. Execution shortfall is presented as a percentage.

Panel A: Low Style Index institutions



Panel B: High Style Index institutions

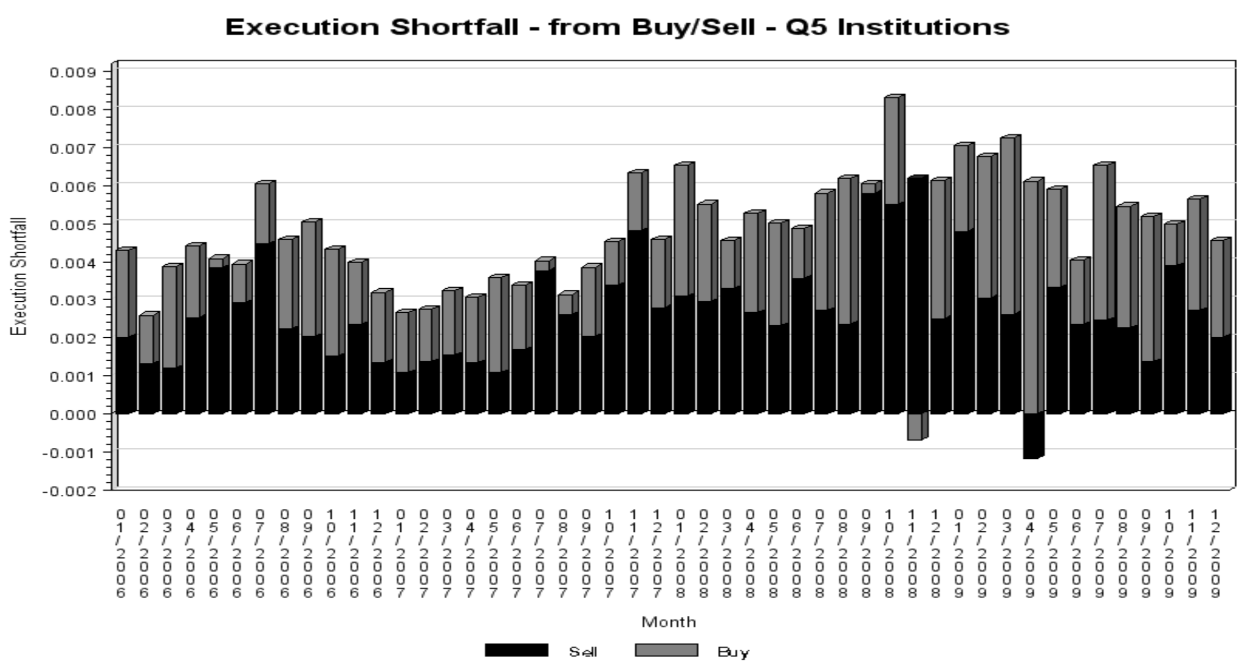
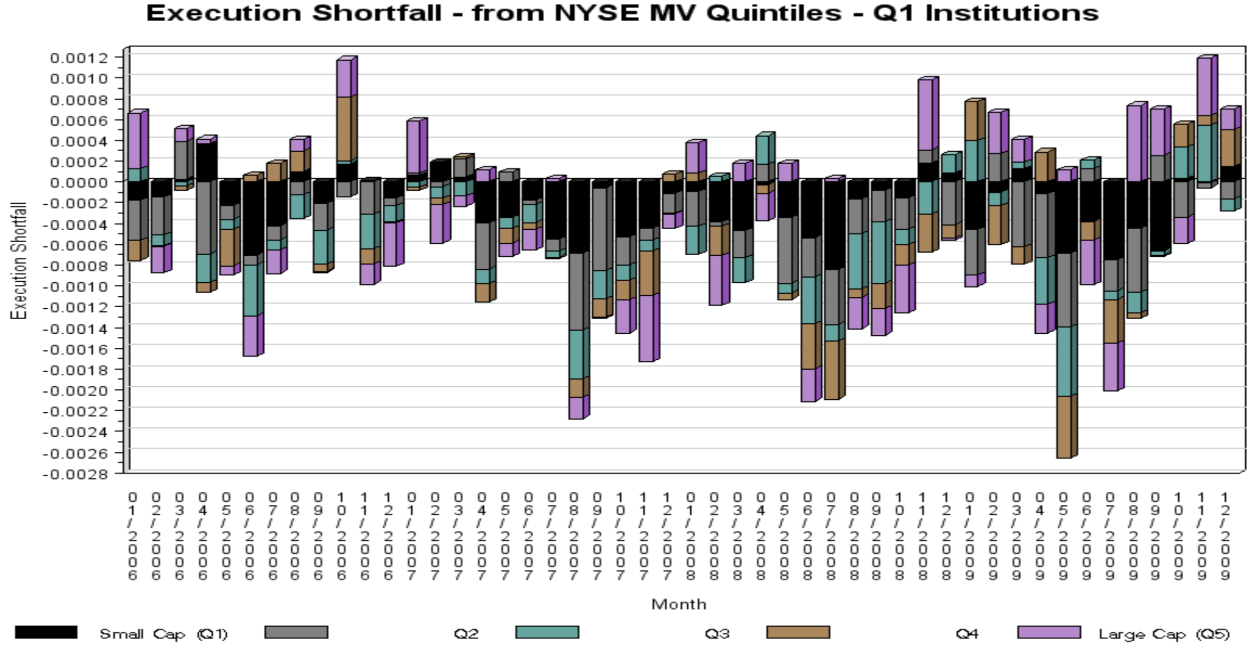


Figure 8 – Institution's Style Index and Buy/Sell Trading Costs by market value

Execution shortfall is measured for buy tickets as the execution price minus the market open price on the day of ticket placement divided by the market open price (for sell tickets we multiply by -1). We calculate the volume-weighted average execution shortfall across the tickets for each institution each month and each NYSE market value quintile of stocks. The figure plots the average (equal-weighted) execution shortfall for Low Style Index (quintiles 1) and High Style Index (quintile 5) in the month *following* the portfolio formation month. Execution shortfall is presented as a percentage.

Panel A: Low Style Index institutions



Panel B: High Style Index institutions