# Market Crashes and Institutional Trading

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This draft: March 2010
First Draft: November 2009

*We thank Viral Acharya, Mike Aitken, Richard Co, Kingsley Fong, Doug Hanna, Marios Panayides, Neal Stoughton, Eric Kelly, Mike Vetsuypens, and seminar participants at the Commodity Futures Trading Commission (CFTC), Securities and Exchange Commission (SEC), Georgia State University, Southern Methodist University, University of Arizona, University of Texas at Dallas and University of New South Wales for comments. We are grateful to ANcerno Ltd., Judy Maiorca, and Allison Keane for institutional trading data, the Chicago Mercantile Exchange (CME) for futures margins data, and the Financial Market Research Center (FMRC) at Vanderbilt Owen Graduate School of Management for daily liquidity measures data.

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## Abstract

This study provides direct evidence on the channel through which liquidity risk can serve as a priced systematic risk factor for asset prices. We examine institutional trading in U.S. equities focusing on the financial crisis of 2007-08 to test several theoretical models on liquidity and trader behavior. Institutional traders experienced a dramatic increase in trading cost and higher uncertainty in execution price during the crisis. Consistent with theoretical predictions, we observe significant variation in the impact of the crisis on individual stock liquidity and a more pronounced impact for smaller, volatile, and high (ex-ante) liquidity beta stocks. Importantly, institutions tilt their selling activity toward less liquidity-sensitive stocks, suggesting such securities serve as a liquidity hedge for institutions in a downturn. We find that funding liquidity, as measured by trader margins, cost of funds, fund flows and market volatility impacts aggregate market liquidity. Remarkably, some institutional traders benefited from market conditions during the crisis. The best trading desks improve their performance while the performance of the worst trading desks deteriorates. Overall, market quality in 2008 is comparable to market quality observed in 1999, suggesting that liquidity improvements achieved over the last decade vanished during the crisis.

## 1. Introduction

The simple idea that liquidity can vary over time, both for individual stocks and for the market as a whole, presents a significant challenge for institutional managers. Market downturns are characterized by a decline in both asset prices and liquidity. For this reason, institutions need to be concerned about not only asset price declines but also their ability to liquidate portfolios at low cost during a downturn.

Building on the idea that individual stock liquidity tends to co-vary positively with market liquidity, Pastor and Stambaugh (2003) and Acharya and Pedersen (2005) develop liquidity-adjusted asset pricing models where the risk premium associated with liquidity risk can be explained by the wealth loss due to illiquidity. Recent theoretical work (e.g., Shleifer and Vishny (1997), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), among others) postulates that the illiquidity risk premium can arise from shocks to funding of leveraged traders. Traders facing funding constraints are reluctant to provide liquidity in risky securities or those with relatively high capital needs. The flight-to-quality effect can increase the liquidity differential between securities in a downturn. To meet liquidity demands, investors choose to sell those securities at low cost whose liquidity is less sensitive to market downturns. Thus, an asset with low sensitivity (or low liquidity beta) acts as a liquidity hedge during a downturn and consequently, theoretical models predict that such securities trade at a price premium relative to securities with high liquidity sensitivity.

Acharya and Pedersen (2005) estimate that the components of liquidity risk, in aggregate, contribute about 4.6% annually to the difference in risk premium between stocks with high and low expected liquidity. They conclude that the economic impact of liquidity on asset returns is large and that liquidity can serve as a priced systematic risk factor. However, there is relatively little empirical work directly testing important predictions from the theoretical models. For example, does the liquidity differential between securities increase during a downturn? Do institutions choose to sell less liquidity sensitivity securities in order to raise cash? Do low sensitivity securities serve as a liquidity hedge in a downturn? This paper contributes to the literature by examining stock liquidity and institutional trading

during a severe market downturn. We provide new direct evidence on the *channel* through which liquidity risk can serve as a priced systematic risk factor for asset prices.

Theoretical models predict that institutions can face a severe liquidity problem during a financial crisis. In the Shleifer and Vishny (1997) model, intermediaries rely on external funds and face the constraint that fund flows are sensitive to recent performance. In a severe market downturn, institutions can experience a fire sale of assets in order to meet broker margin calls and redemption requests from fund investors. In the Kyle and Xiong (2001) model, the high correlation in trading strategies can cause institutions to liquidate positions in risky assets at the same time, leading to excess order imbalances. During the financial crisis of 2007-08, several prime brokers, who serve as counterparties to institutions, sustained large losses in asset-backed portfolios and dramatic erosions in dealer capital. Brunnermeier and Pedersen (2009) model the mechanism by which an erosion in dealer's capital can lower market liquidity and Brunnermeier and Pedersen (2004) show that the risk of predation can cause dealers to undersupply liquidity, thus increasing liquidation costs in periods of high uncertainty.

We focus on the behavior of institutional investors because institutions are more concerned about liquidity risk than retail investors. For example, mutual fund flows can cause exogenous trading demands that can affect prices (Coval and Stafford, 2007). Estimating individual stock liquidity based on institutional executions provides direct evidence on whether securities with high (ex-ante) liquidity beta become illiquid when aggregate liquidity declines, as predicted by Acharya and Pedersen's (2005) liquidity-adjusted CAPM. An examination of institutional activity provides evidence on whether participants choose to avoid trading liquidity-sensitive securities and instead trade other securities in a downturn. Furthermore, institutional investors account for a significant portion of equity ownership and an increasing percentage of global equity trading volume.[1] As a consequence, a better understanding of liquidity risk faced by institutional investors provides an valuable perspective on what types of risks are important in financial markets.

[1] Boehmer and Kelly (2009) establish that institutions are important traders in the markets and contribute to the informational efficiency of prices.

Our paper is related to recent empirical studies that examine the impact of liquidity-suppliers financing constraints on time variations in liquidity. For example, using proprietary data on New York Stock Exchange (NYSE) specialists' inventory positions between 1994 to 2004, Comerton-Forde, Hendershott, Jones, Moulton and Seasholes (2010) show that when specialists lose money on their inventories, effective spreads widen, suggesting that specialists are less willing to provide liquidity. Hameed, Kang and Viswanathan (2010) show that the weekly changes in bid-ask spreads for NYSE stocks over 1988 to 2003 are negatively related to market returns. Their study estimates that the impact is stronger when financial intermediaries are more likely to face funding constraints.

While Comerton-Forde et al. (2010) and Hameed et al. (2010) examine extended time periods when market conditions were relatively normal, the distinguishing feature of our study is that we focus on institutional trading during the 2007-2008 financial crisis. 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 $37 trillion, or about 59 percent. Hedge funds and mutual funds experienced large declines in portfolio values, triggering margin calls, investor withdrawals, and fire sales of assets. Institutions facing an urgent need to raise cash must choose which securities from their portfolio to sell. For this reason, the market turmoil in 2007-08 presents an excellent laboratory to test theoretical models on how institutions trade and stock liquidity behaves when market liquidity dries up. Further, the root of the financial crisis can be tied to developments in the credit markets for financial intermediaries. Our analysis contributes to a better understanding of the link between funding shocks of intermediaries and market liquidity. We also investigate whether some traders benefit from the difficult market conditions observed during the financial crisis. [2]

We examine the proprietary database of institutional investor U.S. equity transactions compiled by ANcerno Ltd. (formerly the Abel/Noser Corporation). Our sample contains approximately 38 million

[2] A related study is Griffin, Harris, Shu and Topaloglu (2009), who examine institutional and individual trading patterns during the technology market bubble and the subsequent crash in 2002. The study focuses on whether institutions exaggerated or ameliorated market movements, which differs from the focus of our study.

order tickets that are initiated by 904 institutional investors over a 10-year period, 1999-2008, representing over $21 trillion in trading volume. The explosive growth in electronic trading has caused institutions to split orders but order splitting strategies are impossible to track using the Trade and Quote (TAQ) database. Our database is distinctive in that it contains a complete trading history of buys and sells for each institution. Further, the dataset contains the complete history of each order initiated by an institution, each typically resulting in multiple executions, and stock identifiers that help obtain relevant data from other sources. Our measure of institutional trading cost, the execution shortfall, accounts for the splitting of a large order by the trading desk into child orders and trading over time.[3]

Institutional trading costs decline from the early part of our sample period (1999-2003) until 2007; consistent with recent research based on bid ask spreads (see for example, Jones (2006), Hasbrouck (2009), Chordia, Roll and Subrahmanyam (2008)). We examine the standard deviation of institutional trading cost as a proxy for execution risk faced by institutions. We find that aggregate execution risk also declined between 2000 and 2007. However, in 2008, institutional trading costs reversed the long-term trend and recorded a sharp increase for every firm size quintile, and particularly so for sell orders. Huang and Wang (2009) present a theoretical model where the increase in investor risk aversion during a crisis exacerbates the selling desire of potential sellers and dampens the buying demand of potential buyers, leading to excess selling pressure. Our findings are supportive of these predictions.

Consistent with liquidity-adjusted CAPM, we document that some securities experience a larger decline in liquidity during down markets that coincide with wealth shocks. Securities that are ex-ante predicted to be liquidity-sensitive (e.g., small, volatile or high liquidity-beta stocks) experienced a severe decline in liquidity during the crisis. Importantly, we document that institutional investors respond by tilting their selling activity away from more liquidity-sensitive securities and toward less liquidity-sensitive securities. This result is noteworthy because the theoretical link between liquidity betas and asset prices is through the liquidation channel; that is, the idea that less liquidity-sensitive securities are

[3] Other studies using the execution shortfall measure include Keim and Madhavan (1997), Jones and Lipson (2001), and Conrad, Johnson and Wahal (2001).

valuable to investors because they can be liquidated at low cost during a severe downturn.[4] As far as we are aware, ours is the first study to provide direct empirical evidence based on institutional trading on the channel by which liquidity risk can serve as a priced systematic risk factor.

We find that institutional trading cost and execution risk are correlated across assets and among participants in financial markets. We use monthly macro-economic data that capture volatility, broker margins, funding costs, and fund flows, to forecast aggregate liquidity in the following month. Liquidity deteriorated sharply around key events during the financial crisis, particularly surrounding the collapse of Lehman Brothers. Liquidity declines when funding liquidity, as measured by T-Bill rate, TED Spread, and broker margins on S&P500 futures contract decreases and when market volatility, as measured by VIX Index, increases. The impact of an increase in broker margin is more significant for volatile securities, suggesting that capital-constrained traders prefer to provide liquidity in less risky securities. Liquidity declines when equity mutual funds, in aggregate, face fund outflows and when the lagged market return is negative. These findings suggest that correlated trading strategies by funds to meet redemption requests or margin calls can lower aggregate market liquidity. Overall, we find support for a link between funding liquidity and market liquidity.

Remarkably, some institutions benefit from market conditions during the financial crisis. We rank the institutions in our sample by *ex ante* trading cost and examine the cross-sectional effects of the financial crisis across low-cost and high-cost institutions. We find that the cross-sectional difference in trading cost is larger when liquidity is expensive. The trading cost increase in 2007-2008 is borne almost entirely by high-cost institutions; the low-cost 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 of low-cost and high-cost institutions reveals only marginal differences in the types of stocks they trade. Thus, the trading cost difference stems from how institutions trade rather than what they trade. Our evidence suggests that some institutions were able to insulate themselves,

[4] Pastor and Stambaugh (2003, page 643) "Liquidation is costlier when liquidity is lower, and these greater costs are especially unwelcome to an investor whose wealth has already dropped."

indeed 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 2007-08 financial crisis and presents the testable predictions regarding trading cost. Our trading cost measures and sample selection are described in Section 3. In Section 4, we present the the determinants of institutional trading costs and the differential impact of the financial crisis on stock liquidity. In Section 5, we investigate whether some trades benefited from the market conditions during the crisis. Section 6 examines how institutions trade during the crisis. Section 7 concludes.

## 2. Hypothesis Development

### 2.1 The Financial Crisis

Brunnermeier (2009) provides an excellent discussion of factors that laid the foundation for the crisis, including the highly leveraged balance sheets of financial institutions and the decline in lending standards that led to a boom in housing prices. Following Brunnermeier (2009) we describe the key events pertaining to the equity markets during the financial market crisis of 2007-08. In August 2007, many quantitative hedge funds suffered heavy losses in credit (structured) products and faced margin calls from brokers. The crisis in credit markets spilled over to equity markets when these institutions sold equities to raise cash (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).[5] During this period, the TED spread, the difference between the LIBOR (London Interbank Offered Rate) and the U.S. Treasury bill rate, increased from about 0.5% to 2.5%. Brunnermeier (2009) notes that, because the LIBOR reflects the interest on interbank (risky) unsecured short term loans, the TED spread typically widens in times of crisis and is a useful measure to gauge the severity of the funding crisis.

During the rest of 2007 and leading into early 2008, financial institutions continued to take large losses on structured products, triggering a large sell-off in equity markets worldwide. The first major

[5] 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. The position rebalancing of convergence traders can lead to increased volatility and reduced market liquidity.

collapse of a large institution occurred in March 2008 when investment bank, Bear Stearns, was acquired by J.P. Morgan in a government orchestrated bailout. Unease among Bear's hedge fund clients and other trading counterparties regarding its large mortgage-backed exposure produced a funding crisis at Bear, leading to its collapse. During the summer of 2008, several large financial institutions, including IndyMac, a large private mortgage broker, Fannie Mae, and Freddie Mac, were taken over by the Federal Deposit Insurance Corporation (FDIC) or were rescued by government guarantees.

The global financial system teetered on the brink of collapse during the last four months of 2008. A significant event during this period was the bankruptcy filing by Lehman Brothers, a large investment bank. Aragon and Strahan (2009) document that hedge fund clients of Lehman failed twice as often after Lehman's collapse as otherwise-similar hedge funds. This is because the accounts of many Lehman clients were frozen, making it impossible for them to trade in response to market conditions.[6] Other financial institutions in vulnerable positions actively solicited suitors to avoid the fate of Lehman. Merrill Lynch sold itself to Bank of America. A week after Lehman's collapse, the Federal Reserve organized a rescue of AIG, a large insurance company with large exposure in credit default swaps (CDS). Several banks were either placed under receivership by the FDIC (e.g., Washington Mutual, Wachovia) or received support from the Federal Reserve (e.g., Citi, Bank of America). After reaching an $81 trillion peak in June 2007, the value of household assets in the United States dropped sharply to $66 trillion by December 2008, emphasizing the magnitude and large-scale repercussions of the financial crisis.

### 2.2. Testable Predictions

Recent theoretical work (e.g., Gromb and Vayanos (2002), Brunnermeier and Pederson (2009)) describes the mechanisms by which an institution's financing constraints can cause a decline in market liquidity. The process of deleveraging in response to a funding shock can cause a number of institutions to sell similar securities at the same time, leading to a decline in security value, and force further fire sales to

[6] The study also identifies a small sample of 27 Lehman-affiliated investment advisors with 13F holdings data. They find that stocks held by these hedge funds experienced a greater decline in market liquidity following Lehman's bankruptcy than other stocks.

meet margin calls. Speculators and arbitragers may be reluctant to correct the mispricing due to funding constraints of their own or in fear of future funding constraints. Huang and Wang (2009) attribute the arbitrageur's reluctance to provide liquidity to an increase in risk aversion. They predict that higher risk aversion can increase the selling interest and decrease the buying interest during a market crash, leading to excess sell imbalances. 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 from risk-averse liquidity providers. Garleanu and Pedersen (2007) propose that tighter risk management by institutions in response to higher volatility in market downturns can lower market liquidity. These discussions support the following hypothesis:

*Hypothesis I: The cost of completing institutional trades increases during a financial crisis. The increase in trading cost is higher for sell orders than for buy orders. Aggregate market liquidity is related to the liquidity-supplier financing constraints.*

When market liquidity declines, theoretical models predict significant differential impact on individual stock liquidity. The liquidity-adjusted CAPM (Acharya and Pederson (2005)) predicts that the impact is more significant for high liquidity beta stocks. Huang and Wang (2009) predict that the selling imbalance during a crisis is more pronounced for less liquid stocks. Vayanos (2004) and Brunnermeier and Pedersen (2009) predict that the liquidity provider's financing constraints can have differential impact on high and low volatility stocks. This is because liquidity providers need to post higher margins for volatile securities and are less willing to do so when facing capital constraints. These discussions support the following hypothesis:

*Hypothesis II: The financial crisis has a more pronounced impact on the liquidity of small, volatile, and high ex-ante liquidity beta stocks.*

Theoretical models predict how investors respond when market liquidity declines. An important prediction from Acharya and Pedersen (2005) is that institutions with an urgent need to raise cash in a downturn choose to sell less liquidity-sensitive (i.e., low liquidity-beta) securities. Brunnermeier (2009) predicts that investors sell liquid assets because selling illiquid assets during a crisis period can be

particularly expensive. Alternatively, an increase in investor's risk aversion can induce a flight-to-quality effect (see Pastor and Stambaugh (2003)) that prompts investors concerned about the overall liquidity of their portfolios to 'flee' small and illiquid stocks and move to stocks with greater liquidity. Finally, if optimal portfolio considerations outweigh liquidity concerns, the investor's selling activity would be unrelated to the liquidity of underlying assets. These discussions lead to the following hypotheses:

*Hypothesis IIIa: Institutions choose to sell securities whose liquidity is less sensitive to market declines (liquidity-adjusted CAPM).*
*Hypothesis IIIb: Institutions choose to 'flee' small and illiquid securities and move to securities with greater liquidity (flight-to-quality effect).*

Over the last decade, technological innovations and regulation have forced stronger integration of fragmented markets such that trading costs of skilled and unskilled traders have converged. However, when market liquidity dries up, the trading desk's skill in responding to market conditions become important.[7] These discussions support the following hypotheses:

*Hypothesis IV: During a financial crisis, the impact of trader skill increases.*

## 3. Execution shortfall measure and descriptive statistics of the sample

### 3.1. Execution shortfall

Our measure of trading cost, the execution shortfall, compares the execution price of a ticket with opening stock price of the day.[8] The choice of a pre-trade benchmark price follows prior literature and relies on the implementation shortfall approach described in Perold (1988).[9] We define execution shortfall

[7] For example, Lauricella (2008) describes the market conditions during the peak of the crisis in October 2008 "So far this month, there have been 10 days where the Dow Jones Industrial Average ricocheted in a range of more than 5%... With that kind of volatility, buying an hour too early or too late can mean the difference between a profit and a loss on the investment."

[8] Results are robust when we use the stock price at placement time as the benckmark. The use of price at placement time fails to account for price movements between decision time and placement time. Execution cost estimates are smaller with the alternative benchmark but our conclusions are unchanged. We acknowledge that neither benchmark can perfectly capture each trading decision but can represent two possible extreme scenarios for accommodating the drift in price.

[9] Some studies (see Berkowitz, Logue and Noser (1988), Hu (2009)) have argued that the execution price should be compared with the volume-weighted average price (VWAP), a popular benchmark among traders. Madhavan (2002) and Sofianos (2005) articulate the limitations of the VWAP benchmark. Among others, the VWAP can be

for a ticket 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 ticket '$t$', $P_0(b,t)$ is price at the open of the day, and $D(b,t)$ is a variable that equals 1 for a buy ticket and equals -1 for a sell ticket. A ticket is defined as the aggregation of all executions by the same institution in the same stock on the same day on the same side (buy/sell). Our approach captures the trading interest of an institution in a particular stock across different brokers during the trading day.

Prior research on liquidity commonality has examined return and volume based measures such as Amihud's (2002) ILLIQ measure (Acharya and Pedersen (2005)) or return reversal (Pastor and Stambaugh (2003)). Return and volume measures are useful for asset pricing tests because the data are available for sufficiently long periods of time. But, as Acharya and Pedersen (2005) note, these measures do not directly measure the implementation cost for institutional investors. The bid-ask spread from TAQ or CRSP databases, used by Chordia, Roll and Subrahmanyam (2000) and Hameed, Kang, and Viswanathan (2010), among others, is an excellent measure of liquidity cost for small orders. However, institutions tend to implement complex strategies involving both demanding and supplying liquidity when executing an order. Our trading cost measure captures the bid-ask spread, the price impact of previous trades by the institution, complex strategies, and the cost of delayed execution, and can directly estimate the trading cost for institutional investors.

### 3.2. Sample descriptive statistics

We obtain data on institutional trades for the period from January 1, 1999 to December 31, 2008 from ANcerno Ltd. (formerly the Abel/Noser Corporation). ANcerno is a widely recognized consulting firm that works with institutional investors to monitor execution costs. ANcerno clients include pension plan sponsors such as CALPERS, the Commonwealth of Virginia, and the YMCA retirement fund, as

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influenced by the transaction that is being evaluated. Further, although an execution may outperform the VWAP, the execution quality is poor when the broker has delayed the trade and the stock price has drifted away.

well as money managers such as Massachusetts Financial Services (MFS), Putman Investments, Lazard Asset Management and Fidelity. Previous academic studies using ANcerno data include Goldstein, Irvine, Kandel and Wiener (2009), Chemmanur, He and Hu (2009), and Lipson and Puckett (2007).

We present the summary statistics for ANcerno data in Table 1. The sample contains a total of 904 institutions, responsible for approximately 38 million tickets in 8,340 stocks over the 10 year sample period.[10] The average ticket size over the sample period is 16,420 shares, which represents 3.0% of the stock's average daily volume. Table I, Panel B shows the trends over time. The number of institutions in the database remains relatively constant. The number of stocks traded has declined from 5,694 in 1999 to 4,041 in 2008. The average ticket size shows an initial increase to 19,961 in 2002 and then a decline to 14,631 in 2008. As a percent of daily volume, the average ticket size has declined markedly from 4.8% in 1999 to 1.8% in 2008.

From Table 1, Panel C, we note that our sample contains a greater number of buys than sells and the average sell ticket tends to be larger than the average buy ticket. In Table 1, Panel D, we assign a stock to a market value quintile based on its market cap prior to the month of ticket execution. Rankings are assigned using NYSE market value quintile cutoffs at the end of prior month. Across NYSE market value quintiles, as expected, trading is concentrated in the largest size quintile. The absolute ticket size is also larger for the largest quintile at 19,490 shares, but the corresponding relative ticket size for this quintile is only 0.7% of the average daily volume. For the smallest size quintile, the average ticket size of 11,565 shares represents 11.2% of the average daily volume, suggesting that institutional executions in small stocks are more difficult.

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, date of execution, execution price, number of shares executed, whether the execution is a buy or sell, and the commissions paid. The institution's identity is restricted to protect the privacy of ANcerno clients; but the unique client

[10] As a point of comparison with studies using Plexus data, Edwards and Wagner (1993) examined 64,000 orders, Chan and Lakonishok (1995) examined 115,000 orders, and Keim and Madhavan (1997) examined 25,732 orders.

code facilitates identification for a researcher.[11] Conversations with ANcerno confirm that the database captures the complete history of all transactions of the portfolio managers.[12] In our sample, ANcerno institutional clients traded approximately 625 billion shares, representing more than $21 trillion worth of stock trades. Thus, while our data represent the trading activities of a subset of pension funds and money managers, they represent a significant fraction of total institutional trading volume.

We calculate aggregate statistics for the full sample and by different characteristic-based quintiles (market value, volatility and ex-ante liquidity beta). Depending on the analysis (full sample, characteristic quintile, institution), we calculate the execution shortfall as the volume-weighted average across tickets in a particular sample. Standard deviation of trading cost is based on the distribution of trading cost across tickets for the sample. We calculate the trading cost statistics on a monthly basis. If reported annually, the statistics are equally weighted averages across the monthly observations in a year. The t-statistics testing for differences across years are based on the standard errors of the monthly estimates for the year. For monthly statistics (Table 2, Panel B and Table 4), test statistics are based on daily estimates, and the standard errors of these estimates. We obtain the market capitalization, stock and market return, trading volume, and exchange information from CRSP.

To minimize observations with errors, we impose the following screens: (1) Delete tickets with execution shortfall greater than an absolute value of 10 percent, (2) Delete tickets with volume greater than the stock's CRSP volume on the execution date, or volume greater than 99th percentile in the ticket's execution month (3) Delete tickets associated with internal allocations or corporate events such as private placements of stock (4) Include common stocks listed on NYSE and NASDAQ, (5) Delete institutions with less than 100 tickets in a month, and (6) Delete all observations where the commission per share for a ticket is $0.10 or greater.

[11] In addition, the database provides summary execution information for each ticket, including the share-weighted execution price and the total shares executed. ANcerno provides a separate broker reference file that permits broker identification.

[12] ANcerno receives trading data directly from the Order Delivery System (ODS) of all money manager clients. The method of data delivery for pension plan sponsors is more heterogeneous.

## 4. Results on institutional trading costs

### 4.1. Trends in institutional trading costs

Table 2, Panel A, reports on institutional trading costs in U.S. equities from 1999 to 2008. Technological changes have dramatically altered the structure of U.S. equity markets during this period. For example, the NYSE's market share of trading volume has declined from over 80 percent in the late-1990s to about 33 percent at the end of 2008.[13] Hendershott, Jones and Menkveld (2009) observe that almost all aspects of the institutional trading process have become more automated in recent years. They report that 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.

We document that institutional trading costs have declined over time (see Figure 1). Annual equity trading cost in the beginning of the sample period is estimated to be 0.22 percent. After the move to decimal trading (2002), trading cost declined to 0.16 percent. Institutional trading costs continued to decline in subsequent years and were 0.13 percent in 2007. Patterns based on median trading costs reflect a similar trend. These trends are similar to those reported by several studies (see, for example, Jones (2006), Hasbrouck (2009), Chordia, Roll and Subrahmanyam (2008)) examining trading costs in the pre-crisis period. Consistent with *Hypothesis I*, we observe a dramatic increase in trading cost during the financial crisis. The cost of completing institutional trades increased from 0.13 percent in 2007 to 0.21 percent in 2008, an increase of 66 percent, which is economically and statistically significant (t-stat = 3.95). Gurliacci, Jeria, and Sofianos (2008), who examine trades executed using Goldman Sachs' algorithms in September 2008, also report a sharp increase in trading costs during the month.

Roll and Subrahmanyam (2009) observe that the variation in trading cost can matter to market participants who trade into and out of positions in a short period of time. We observe a similar trend for the standard deviation of institutional trading cost (or execution risk) (see Figure 2). Execution risk at the beginning of the sample period was 2.30 percent and had declined to 1.53 percent by 2007. In 2008,

[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 increased by over 73 percent from 1.53 percent in 2007 to 2.59 percent in 2008. We note that the trading volume market share of buys and sells are similar during the sample period.

Collectively, these findings suggest that institutional investors experienced a dramatic increase in trading cost and execution risk during the crisis. A striking finding is that market quality in 2008 deteriorated to levels last observed in 1999. Thus the significant improvements in market quality achieved over the last decade in U.S. equity markets, attributed in part to technological innovations and regulatory initiatives (e.g., decimalization, Reg NMS, Reg FD, among others) are eroded.

### 4.2. Institutional trading costs during the financial crisis

Focusing on the crisis period, we report the monthly institutional trading cost from January 2007 to December 2008 in Table 2, Panel B. We treat January, 2007 to April, 2007 as the (pre-crisis) benchmark period and compare the benchmark estimates with monthly trading costs from May, 2007 to December, 2008. No unusual patterns are observed until July, 2007. Surrounding the quant-event of August, 2007, which is examined by Khandani and Lo (2007), we estimate an increase in execution uncertainty but not average trading cost. Trading costs increase from 0.12 percent in early 2007 to 0.18 percent in early 2008 (t-stat of diff = 3.45). An increase in trading cost is also observed in April 2008, surrounding the collapse of Bear Stearns. Trading costs remain at elevated levels during the summer of 2008 as conditions in credit markets continued to deteriorate.

Liquidity conditions deteriorate significantly during the last four months of 2008, coinciding with the collapse of several large intermediaries and the introduction and repeal of the short sale ban.[14] Trading costs increased from already high levels of 0.16 percent in August 2008 to 0.22 percent in September, 0.30 percent in October, 0.35 percent in November and 0.27 percent in December. Execution risk also increased markedly during the last four months of 2008. Note though that the monthly dollar trading volume for buys and sells in our sample is similar through the crisis period.

[14] Several recent studies examine the effect of short sale ban on prices, liquidity and volatility. For example, Boehmer, Jones and Zhang (2009) document that stocks subject to the ban suffered a severe decline in liquidity as compared to a control group of non-banned stocks.

The dramatic increase in trading cost, coinciding with the sharp increase in TED spread is consistent with *Hypothesis I*, and reflects the substantial compensation for liquidity provision during the financial crisis. Figure 3 plots the trading costs for buys and sells over the 2006-2008 period. Consistent with Huang and Wang (2009), we find that sell orders are more expensive to execute than buy orders (*Hypothesis I*). Specifically, execution shortfall for sell orders more than *tripled* during the peak of the financial crisis relative to the level observed in early 2007. In contrast, execution shortfall for buy orders during the peak of the crisis is *negative*, suggesting buyers earned compensation for liquidity provision. We revisit the explanation in Section 5, where we examine cross-sectional differences in performance of institutional trading desks.

### 4.3. Funding constraints and market liquidity

We test several new predictions proposed by theoretical models that link funding constraints and market liquidity. Table 3 presents the correlations between execution cost variables (cost and risk), market variables (VIX, Index return and the T-bill rate) and several measures of leverage, or funding availability in the market. The funding variables include the TED spread (Eurodollar-T-bill), margins on CME futures contracts, net fund flows, broker funding and net Repos.[15] Panel A of Table 3 presents these correlations over the 1999-2006 period and Panel B presents the same correlations over the 2007-2008 crisis period. What is immediately apparent when comparing the two panels is the jump in correlations of almost all the execution, market and funding variable during the crisis period. The correlations between all of the funding variables and execution risk increase dramatically. For example, the correlation between CME Margin and Execution shortfall increases from 0.23 in the 1999-2006 subperiod to 0.78 in the crisis period. This jump in funding and execution cost correlation is evidence that leverage, not normally a significant factor in trading costs, became very important during the crisis period. We also note that the

[15] Net Repos measures Primary Dealer net repos less reverse repos from Federal Reserve Bank of New York Data. Broker Funding represents broker lending activities for 7 leading brokers representing 88% of total broker capital according to SIA figures. Broker funding data is collected from the Commitments and Contingencies footnote to broker 10-Q and 10-K filings with the SEC. This footnote includes broker lending commitments, underwriting commitments, private equity commitments and secured lending commitments. Broadly speaking, we interpret Net Repos as brokerage firms marginal Source of Funds.

correlations between funding variables are particularly high during the crisis period. For example, the correlation between the TED spread and broker funding jumps in magnitude from -0.07 in the 1999-2006 period to -0.76 in the crisis period. This is a useful result for other research on funding liquidity during the liquidity crisis as it indicates that all proxies for funding liquidity are roughly equally useful in capturing leverage effects during the crisis.

Table 4 presents regressions on the determinants of monthly aggregate trading cost (Panel A) and execution risk (Panel B). Our explanatory variables capture the information environment, the aggregate liquidity demand and the cost and supply of funding capital in the previous month. In model (1) of Table 4, we identify the key events for equity markets during the crisis (see section 2.1): the quant event of August 2007, the collapse of Bear Stearns in March 2008, and that of Lehman Brothers in September 2008, using indicator variables that equal one for event months and equal zero otherwise. We include one-month lagged value of the dependent variable to capture persistence and a trend variable to capture any time trend in liquidity.[16] As expected, the lagged dependent variable is positive and significant in all specifications. The negative coefficient on the trend variable suggests that liquidity has improved on average in the last decade. The most significant liquidity event in model (1) is Lehman's collapse (September to November of 2008). The coefficient on the Lehman dummy in Panel A is 0.11 percent, suggesting the liquidity decline coinciding with Lehman's bankruptcy was economically large. Aggregate execution risk (Panel B) increased around the 2007 Quant crisis and Lehman's collapse.

In model (2), we choose to measure the traders' cost of funding using the T-Bill rate and TED spread, as Table 3 indicates that all funding proxies were highly correlated during the crisis period, The TED spread coefficient is positive and highly significant in both panels. Thus, an increase in traders' funding cost for liquidity provision is associated with lower liquidity and higher execution uncertainty.

[16] We test for the presence of heteroskedasticity and autocorrelation in this regression. We fail to reject constant error variance and the Durbin-Watson statistic does not indicate autocorrelated errors. We also compare this specification with one that includes an ARCH(1) parameter and find that the specification without the ARCH(1) parameter outperforms based on the AIC and the SBC criteria.

This evidence provides empirical support for a link between conditions in credit markets and institutional trading costs.

In model (3), we examine the impact of changes in broker margins on liquidity. Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) predict that margin increases can be destabilizing when they force traders to de-lever positions in times of crisis, leading to a liquidity spiral. Alternatively, margins can be stabilizing when financiers know that the price decline is driven by illiquidity and the expected price reversal lowers the funding risk on positions. Since margins are trader- and broker-specific and not reported publicly, we use the dollar exchange margin charged by the CME on each S&P 500 futures contract, normalized by notional dollar value of each futures contract.[17] Since margins are set to protect the financier, we expect individual broker margins to be correlated with CME margins. Regression coefficient on CME margin is positive and highly significant in both panels, suggesting that an increase in trader margins (a supply effect) is associated with decline in liquidity and higher execution uncertainty in subsequent months.

Brunnermeier and Pedersen (2009) further posit that the impact of increased margins is higher for volatile stocks as capital-constrained liquidity providers withdraw from risky securities. In an analysis not reported in the paper, we stratify the sample into quintiles based on return volatility. We regress the execution shortfall (and execution risk) associated with a volatility quintile on the volatility quintile rank (one to five, with five being the high volatility quintile), the CME margin variable described above, and the interaction of volatility quintile rank and CME margin (our variable of interest). We find that stocks with higher return volatility have lower liquidity. Further, an increase in CME margin has a more pronounced impact on liquidity for volatile stocks. These findings are consistent with findings in Comerton-Forde et. al. (2010) that the liquidity of volatile stocks is most sensitive to NYSE specialist's capital constraints.

Brunnermeier and Pedersen (2009) predict that market volatility is a state variable that can affect market liquidity. This is because financiers forecast future stock volatility based on past volatility and

[17] The S&P 500 futures contract has a notional amount equal to the S&P 500 Index level multiplied by $250.

adjust margin levels to protect against defaults. In model (4), we find that the coefficient on VIX index, the proxy for stock volatility, is positive and highly significant. Thus, an increase in market volatility is associated with a subsequent decline in market liquidity.

Traders face funding risk when they make losses on existing positions. Comerton-Forde et. al (2010) report that NYSE specialists are net long over 94% of the time, suggesting that liquidity suppliers are more likely to hit capital constraints in a market downturn (a supply effect). Adrian and Shin (2009) demonstrate that leverage ratios for security broker dealers are strongly procyclical implying that losses on existing positions can weaken balance sheets and lead to greater asset sales (a demand effect), reinforcing the market stress. In model (5), we proxy for the traders' aggregate losses using one-month lagged return on the S&P 500 index. The coefficient on lagged S&P 500 Index return is negative and highly significant in both panels. These findings are along the lines of Chordia, Roll and Subrahmanyam (2001), Chordia, Sarkar and Subrahmanyam (2005) and Hameed, Kang, and Viswanathan (2010), who find that negative market returns decrease aggregate stock market liquidity.

Shleifer and Vishny (1997) note that mutual funds face the risk of large redemptions from fund investors during a market decline, and Coval and Stafford (2007) document significant price pressure arising from these 'fire sales'. A high correlation in selling activity of mutual funds can lead to large trading imbalances and lower liquidity. We proxy for demand side pressures for liquidity from mutual funds using data on the net aggregate monthly flows into mutual funds. We recognize that fund flows have grown over time and are likely to be non-stationary. We standardize the aggregate fund flows by the total market capitalization of all common stocks in CRSP each month. In model (6), the coefficient on the standardized aggregate fund flow variable is negative, suggesting that net outflows from funds are associated with higher institutional trading costs in the next month.

In the interest of completeness, we also report a specification where the variables associated with market volatility, funding costs, funding constraints and liquidity demand are included in the same regression. We note that the coefficient on TED spread is positive and significant in both regressions. The

coefficient on CME margins is positive and significant in the trading cost regression. The coefficients on VIX and lagged S&P 500 Index return are significant in the execution risk regression.

In results not reported in the paper, we examine the economic significance, based on one standard deviation shock to each explanatory variable. A shock of one-standard deviation to TED spread, broker margin, lagged market return, VIX and aggregate fund flows causes the institutional trading cost to change by 0.03 percent, 0.01 percent, 0.01 percent, 0.02 percent, and 0.01 percent, respectively. Overall, the results in Table 4 present evidence on the link between funding cost, liquidity demand and aggregate institutional trading costs.

### 4.4. Institutional trading costs by firm size, return volatility, and liquidity-betas

An important prediction from liquidity-adjusted CAPM is that market-wide downturns have a differential impact on stock liquidity. In Table 5, we examine institutional trading costs for portfolios formed on firm size, return volatility and (ex-ante) liquidity beta (*Hypothesis II*). Huang and Wang (2009) predict that the crisis has a pronounced impact on less liquid stocks. Differential impact on high and low volatility stocks and high and low liquidity beta stocks are predicted by Gromb and Vayanos (2002), Brunnermeier and Pedersen (2009), and Acharya and Pedersen (2005).

In Table 5, we estimate institutional trading costs and execution risk for the extreme (a) firm size quintiles in Panel A, (b) volatility quintiles in Panel B, and (c) liquidity-beta quintiles in Panel C, focusing on benchmark period (Jan to April 2007) and key event months during the financial crisis.

In Panel A, several patterns can be observed. First, institutional trading costs and execution risk for large stocks are lower than those estimated for small stocks. Second, results are consistent with Huang and Wang (2009) predictions that the impact of the crisis is more significant for liquidity of small stocks. Specifically, trading costs in large stocks increased by 0.21 percent during the crisis, from 0.07 percent in benchmark period to 0.28 percent in November, 2008. During the same period, the trading costs for small stocks increased by over 0.58 percent. Remarkably, surrounding Lehman's collapse, trading costs for small stocks are in the range of 0.50 percent to 0.75 percent, highlighting that small stocks experienced

significant liquidity dry-ups during the peak of the financial crisis. Trends in execution risk are similar. Based on the difference-in-difference tests, we conclude that trading cost increases for small stocks during the crisis are statistically larger than trading cost increases for large stocks.

Table 5, Panel B presents the results that are consistent with predictions in Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009). We stratify stocks in our sample into volatility quintiles using the standard deviation of daily bid-ask quote midpoint returns in the calendar year 2006. We obtain the closing bid-ask quotes from CRSP and require a minimum of 50 daily observations for a stock to be included in this analysis. For low-volatility stocks, institutional trading costs increased by 0.20 percent during the crisis, from 0.07 percent in early-2007 to 0.27 percent in November 2008. For high-volatility stocks, the increase in trading cost is 0.31 percent. During the peak of the crisis, the difference-in-difference tests indicate that liquidity deteriorated more for high-volatility stocks than low-volatility stocks, as predicted by theoretical models. These findings are consistent with results reported in Hameed, Kang and Viswanathan (2010), who find that the impact of market decline on liquidity in the pre-crisis period is strongest for high volatility firms.

In Table 5, Panel C, we test theoretical predictions from the liquidity-adjusted CAPM (Acharya and Pedersen (2005)). We calculate the liquidity beta of a stock as the covariance of the 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.[18] For a stock to be included in a month, we require at least 10 daily observations. Similarly, we first construct a daily market liquidity measure as the equal weighted average of effective spreads across stocks, and then create a monthly average of market liquidity using these daily estimates. Finally, we use the 60 monthly observations (from 1/2002 to 12/2006) to calculate the covariance of the stock liquidity and market liquidity, which is our liquidity beta measure. We form quintiles based on these liquidity betas.

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

We find that trading cost increased by 0.24 percent for the portfolio of low liquidity-beta stocks during the crisis. For the portfolio of high liquidity-beta firms, trading costs increased by 0.40 percent, from 0.16 percent in the benchmark period to 0.56 percent in October 2008. The difference-in-difference tests indicate that liquidity deteriorated more for high-beta stocks than low-betas stocks. These findings on liquidity-beta from the financial crisis period are important because they provide empirical validity for using ex-ante liquidity beta estimated over a non-crisis period as a measure of the asset's liquidity-sensitivity during a significant market downturn. Our analysis is particularly interesting because we examine data from the perspective of institutional investors who comprise a significant portion of global equity volume and therefore provides insights on what types of risks are important in financial markets.

**4.5. Institutional selling activity during the financial crisis**

Theory predicts that investors faced with liquidity needs under deteriorating market conditions choose to sell securities with low liquidation cost. For this reason, investors are willing to pay a higher price for securities with low liquidity-sensitivity to market downturns. For example, Brunnermeier (2009) predicts that investors choose not to sell illiquid assets and instead choose to sell liquid assets. Similarly, Acharya and Pedersen (2005) predict that investors choose not to sell high liquidity-beta assets and instead choose to sell other assets in a downturn. Although the liquidation choice is the important channel that links liquidity-beta and asset prices, there is little empirical evidence that directly tests the theoretical predictions. In this section, we examine the selling activity of institutions during the financial crisis. The financial crisis of 2007-08 is particularly well-suited for this investigation as anecdotal evidence suggests that institutions faced urgent needs to liquidate assets during the crisis.

Our evidence thus far suggests that the financial crisis was severe during the last four months of 2008. Evidence from credit markets (for example, the TED spread) supports this conclusion. We focus on selling activity of institutions from May to December 2008, benchmarked against the same institution's

selling activity during January to April 2008 (benchmark period).[19] The average monthly selling volume for institutions in our sample during the benchmark period is $493 million (see Table 6, Panel A). Selling activity stays at similar or higher levels until October, 2008 but drops off significantly to about 75 percent of benchmark volume in November and December 2008.[20]

In Table 6, we examine the proportion of institutional sell dollar volume formed on (a) NYSE market value quintiles in Panel B, (b) return volatility in Panel C, and (c) liquidity-beta in Panel D, during the peak of the financial crisis as compared to proportions observed in the benchmark period. The t-statistic tests are based on the null hypothesis that the proportion of sell volume in a particular quintile in a month is similar to those observed in the benchmark period (i.e., relative proportion=1).

Focusing on firm size quintiles in Panel B, large firms account for approximately 74 percent (two large groups) of institutional selling activity during the benchmark period. Figure 4 plots the institutional selling activity over 2008. During the peak of the financial crisis, institutional selling in large cap firms is similar or higher to the benchmark period; the difference being marginally significant in some months. Importantly, we estimate a significant decline in institutional selling activity in small firms relative to benchmark levels. The proportionate decline in selling activity for small caps stocks is economically large, approximately 30 to 45 percent, and statistically significant.

Focusing on volatility quintiles in Panel C, we estimate that low-volatility stocks account for approximately 60 percent of institutional selling activity during the benchmark period. This result is likely due to the negative correlation between volatility and firm size. Consistent with flight-to-quality demand side effects predicted by Brunnermeier (2009), we observe a statistically significant increase in the relative proportion measure during the peak of the crisis for low-volatility quintile stocks. Further, we observe a decline in the relative proportion measure during this period for high-volatility quintile stocks.

[19] We acknowledge that the financial markets were stressed during the benchmark period, including the bank run on Bear Sterns in March 2008.

[20] The buy/sell percentages reported in Table 2 suggest that sell volume in November and December of 2008 did not decline relative to buy volume, suggesting overall trading volume declined in the last two months of 2008.

Turning to liquidity-beta quintiles in Panel D, we observe that institutional activity is focused on the low liquidity-beta stocks during the benchmark period. This is consistent with Acharya and Pedersen (2005) who document that liquidity-beta and firm size are negatively correlated. Low liquidity-beta groups exhibit an increase in the relative proportion trading volume measure during the peak of the crisis period. In contrast, the relative volumes of the high liquidity-beta groups exhibit a statistically significant decline.

Collectively, these results provide new empirical evidence on the channel by which liquidity risk can serve as a priced systematic risk factor for asset prices. As far as we are aware, there is little empirical evidence directly testing how institutions trade when market liquidity dries up. Our findings provide direct empirical evidence in support of theoretical predictions that institutions tilt their selling activity away from liquidity sensitive stocks and choose to sell less liquidity-sensitive stocks during a market meltdown. In other words, the prediction that ex-ante low liquidity-sensitive stocks serve as a liquidity hedge for institutions during market downturns is borne out by our analysis, thus providing an important piece of supporting empirical evidence for the asset pricing literature.

## 5. Trading skill during a financial crisis

In this section, we analyze whether institutional participants are equally affected by the decline in liquidity. To examine this idea we calculate the volume-weighted execution shortfall for all of an institution's tickets and then sort institutions into quintile portfolios (1-best, 5-worst) based on their monthly execution shortfall during the portfolio formation month (month *M*). Table 7 reports a difference of 129 basis points between the best and worst institutions in month *M*. The best performing institutions execute trades with a negative trading cost of 39 basis points, while the worst performing institutions execute trades with a trading cost of 90 basis points.

Following Anand, et al. (2009), we confirm that our quintile sorts recognize persistent trading cost differences by examining differences in month *M+1*, the month following the portfolio formation month. Much of the idiosyncratic volatility in trading costs noted in month *M* does disappear, but

significant cross-sectional differences persist into Month *M+1*. This evidence in Table 7 and Figure 5 shows that Q1 institutions consistently trade better than Q5 institutions. Over the sample period, the persistent difference in trading cost between Q1 and Q5 institutions averages 67 basis points. However, this difference changes over time: during 1999-2003, the persistent trading cost spread between Q1 and Q5 institution averages 81 basis points. Consistent with overall decline in trading costs presented in Figure 1, this difference shrinks to 54 basis points in 2004-2007. These findings suggest that the benefits of lower trading costs and lower execution risk, attributable to technological improvements, increasing volume, and decimalization accrue primarily to the worst trading institutions. From the 1999-2003 period to the 2004-2007 period, the Q5 institutions lower their month *M+1* trading costs by 25 basis points, from 70 basis points to 45 basis points per trade. In contrast, Q1 institutions' cost advantage deteriorated from a gain of 11 basis points per trade to 9 basis points per trade. Thus, the worst traders are helped the most by the market structure and regulatory changes over the last decade.

Over time, cross-sectional variation in trading costs decreases until the crisis period of 2007-2008. In this period, the best institutions *improve* their performance despite the increase in average trading cost and execution risk reported in Table 2. While the best performing institutions actually improve their performance during the crisis period, adding alpha to their portfolio, the worst performing institutions suffer from the liquidity shock: the execution cost performance of the worst Q5 institutions deteriorates to an average cost of 52 basis points per trade.

Figure 6 presents the execution risk in month (*M+1*) for Q1 and the Q5 institutions. Execution risk is similar for both groups and the change in risk is synchronized. Thus, execution risk does not explain why the best trading desks obtain lower trading cost while the worst trading desks absorb the brunt of the crisis. In a similar vein, we can observe from Figure 2 that execution risk for large cap and small cap stocks moves together over the sample period. Collectively, these results suggest that the fluctuations in execution risk are correlated across assets or among participants in financial markets. Yet, despite this correlated risk, we find that trading costs for institutions are not necessarily correlated.

## 6. Institutional Trading Patterns

Section 5 reveals an abrupt switch in 2008 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 also increases, low-cost institutions (Q1) improve their execution cost performance, while the performance of high-cost institutions (Q5) deteriorates. We examine whether this divergence can be explained by Q1 institutions providing liquidity and Q5 institutions demanding liquidity when liquidity is dear. 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 in the 2006-2008 period. This finding suggests a more complex explanation than Q5 institutions simply dumping shares into the market.

In Figure 7, we present an analysis comparing the trading cost of buys and sells separately for Q1 and Q5 institutions over the 2006-2008 period. Specifically, we decompose the total trading costs of an institution into costs of executing buy and sell trades. For example, 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 these buy and sell contributions equal the total volume weighted execution shortfall for the institution in the month. We then aggregate these contributions within an institution quintile by taking an equal weighted average across institutions.

The resulting trading cost patterns across the institutional types 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 period, even Q1 institutions pay positive trading costs on sells. In contrast, Q5 institutions pay positive execution costs for both buys and sells, both before and during the crisis, and the difference in trading cost across institutional types in the same month is economically large. Consistent with theoretical prediction by Jiang and Wang (2009), the buy-sell asymmetry in trading cost for both Q1 and Q5 institutions increases sharply during the crisis. Q1 institutions also pay higher execution costs for sell orders but earn large negative trading costs for buy

trades (liquidity provision). Surprisingly, Q5 institutions continue to pay positive trading costs for buy orders even during the peak of the financial crisis. This poor performance occurs at a time when buy trades were executing for negative cost and sell trades were extremely expensive (Figure 3).

In Figure 8, 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 2008, the spread in trading costs increases. A notable finding is that despite the dramatic increase in trading costs during the 2008 market downturn, not all institutions had to pay these higher liquidity costs.

We further investigate possible liquidity provision by Q1 institutions in Table 8, where we present correlations between trading cost of Q1 and Q5 institutions with market liquidity. Our proxies for liquidity are the Pastor and Stambaugh (2003) aggregate market liquidity and innovation in liquidity measures.[21] Q1 institutions' trading costs have a positive correlation with Pastor-Stambaugh liquidity measures, suggesting that trading costs of Q1 institutions are higher when markets are liquid and lower when market are less liquid. Q5 institutions, on the other hand, have higher costs in illiquid markets. The difference in trading costs of Q5 and Q1 institutions is negatively correlated with market liquidity, indicating that difference widens when markets are relatively illiquid. These patterns are especially strong in 2007-2008. These results suggest that Q1 institutions are being paid to provide liquidity, while Q5 institutions are paying an increased cost for demanding liquidity when liquidity is scarce.

## 7. Conclusion

The financial crisis of 2007-08 provides an excellent laboratory to test theoretical predictions on stock liquidity and institutional activity during a market downturn. We examine institutional trading

[21] We are grateful to Lubos Pastor for providing monthly market liquidity statistics on his website.

during the 1999 to 2008 period using data compiled by ANcerno Ltd, a consulting firm. The ANcerno dataset on institutional trades can capture order splitting strategies by institutions. We examine institutional trading because institutions execute large orders and are particularly concerned about liquidity risk. Since institutions account for an increasing share of global equity trading volume, our analysis of liquidity risk from the perspective of institutional investors provides valuable insights on what types of risk are priced in financial markets.

We document that institutional trading costs declined in the decade leading to the financial crisis. However, in 2008, institutions experienced a sharp increase in trading costs and a higher price uncertainty on executions. Consistent with theoretical predictions, the impact of the crisis is more pronounced for small stocks, volatile stocks, and stocks with high ex-ante liquidity beta. For example, in the case of small stocks, we estimate that trading costs quadrupled during the last few months of 2008 relative to levels observed before the crisis. Importantly, institutions respond to the differential liquidity impact of the crisis by tilting their selling activity toward stocks with low liquidation cost. In other words, we show that stocks with low liquidity-sensitivity to market downturns serve as a liquidity hedge for institutions during a downturn. These finding provide direct empirical support for the channel described in liquidity-adjusted CAPM model that links liquidity-betas with expected returns.

We document significant cross-sectional variation in performance of institutional desks during the crisis. The best trading desks improve their performance while the performance of the worst trading desks further deteriorates. Our results suggest that some institutions were able to insulate themselves, indeed earn a premium by providing liquidity during the crisis, emphasizing the importance of financial slack for intermediaries. Market liquidity tends to decline when funding liquidity as measured by the T-Bill rate, TED Spread, margins on S&P500 futures contracts, and market volatility, as measured by the VIX Index, deteriorate. Our analysis provides empirical support for a link between credit market conditions and and the secondary market liquidity in equities.

Collectively, the liquidity deterioration during the financial crisis is so severe that market quality in 2008 is comparable to market quality observed in 1999. Thus, the significant improvements in market

quality achieved in U.S. equity markets over the last decade, attributable to several regulatory initiatives (e.g., Decimalization, Regulation NMS), technological innovations, and improvements in market structure have vanished during the crisis.

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## 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 31, 2008. We use a ticket as our level of analysis. Each ticket is constructed by institution, stock, side and day. We further restrict the sample to tickets that are executed by clients with at least 100 tickets during a particular month, as well as to tickets executed on NYSE/NASDAQ stocks. We present the results for the full sample, as well as by disaggregating the sample based on year, order direction, and firm size quintiles. Firm size quintiles are based on the stocks in our sample.

| | Number of Institutions | Number of Stocks | Number of tickets | Ticket Size | Ticket Size/Average daily volume (30 days) |
|---|---|---|---|---|---|
| **Panel A: Full sample** | | | | | |
| | 904 | 8,340 | 38,057,422 | 16,420 | 3.0% |
| **Panel B: By year** | | | | | |
| *1999* | 324 | 5,694 | 2,119,505 | 14,395 | 4.8% |
| *2000* | 322 | 5,456 | 2,504,827 | 16,192 | 3.8% |
| *2001* | 349 | 4,682 | 2,749,396 | 18,629 | 3.8% |
| *2002* | 380 | 4,361 | 3,449,651 | 19,961 | 3.7% |
| *2003* | 356 | 4,292 | 3,554,285 | 18,791 | 3.5% |
| *2004* | 367 | 4,476 | 4,489,924 | 18,661 | 3.5% |
| *2005* | 336 | 4,330 | 3,912,157 | 16,335 | 3.1% |
| *2006* | 359 | 4,308 | 4,928,713 | 14,674 | 2.4% |
| *2007* | 339 | 4,325 | 5,009,688 | 13,738 | 2.2% |
| *2008* | 296 | 4,041 | 5,339,276 | 14,631 | 1.8% |
| **Panel C: Order direction** | | | | | |
| ***Sell*** | | | 17,894,533 | 17,120 | 3.1% |
| ***Buy*** | | | 20,162,889 | 15,798 | 3.0% |
| **Panel D: Firm size (NYSE market value quintiles)** | | | | | |
| ***Small*** | | | 4,090,421 | 11,565 | 11.2% |
| ***2*** | | | 5,449,532 | 12,499 | 4.6% |
| ***3*** | | | 6,036,901 | 14,377 | 3.0% |
| ***4*** | | | 7,405,144 | 17,400 | 2.1% |
| ***Large*** | | | 15,075,262 | 19,490 | 0.7% |

## 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 904 institutions during the time period from January 1, 1999 to December 31, 2008. Only institutions with 100 or more tickets in a month are included in the analysis. 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 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 each month in the 2007-2008 sample period. *t-statistics*, in parentheses, test for the difference between each month and the benchmark period. We also report the proportion of total monthly dollar trading volume for buy (sell) trades in each period. All numbers are in percent.

*Panel A: Yearly Statistics*

| | All Years | 1999 | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **Execution Shortfall** | | | | | | | | | | | |
| *mean* | 0.180 | 0.221 | 0.217 | 0.199 | 0.164 | 0.200 | 0.160 | 0.148 | 0.141 | 0.130 | 0.212 |
| *t-stat (diff prev yr)* | | | (0.25) | (-1.18) | (-2.79) | (3.07) | (-4.62) | (-1.80) | (-0.94) | (-1.00) | (3.95) |
| *median* | 0.173 | 0.218 | 0.196 | 0.193 | 0.166 | 0.201 | 0.158 | 0.149 | 0.143 | 0.123 | 0.191 |
| **Standard Deviation** | | | | | | | | | | | |
| *mean* | 2.050 | 2.301 | 2.846 | 2.533 | 2.312 | 1.816 | 1.618 | 1.471 | 1.469 | 1.529 | 2.589 |
| *t-stat (diff prev yr)* | | | (6.28) | (-2.53) | (-1.66) | (-4.89) | (-3.25) | (-3.10) | (-0.03) | (0.59) | (4.91) |
| *median* | 2.022 | 2.253 | 2.799 | 2.544 | 2.234 | 1.878 | 1.645 | 1.453 | 1.458 | 1.429 | 2.420 |
| **Buy/Sell Percentage** | | | | | | | | | | | |
| *Buy Percentage* | 50.76% | 51.29% | 51.44% | 52.00% | 51.62% | 50.64% | 50.89% | 50.46% | 50.54% | 49.97% | 49.79% |
| *Sell Percentage* | 49.24% | 48.71% | 48.56% | 48.00% | 48.38% | 49.36% | 49.11% | 49.54% | 49.46% | 50.03% | 50.21% |

*Panel B: Crisis Period – May 2007 to December 2008, monthly estimates*

| | Benchmark Period (1/07 to 4/07) | 5/07 | 6/07 | 7/07 | 8/07 | 9/07 | 10/07 | 11/07 | 12/07 |
|---|---|---|---|---|---|---|---|---|---|
| **Execution Shortfall** | | | | | | | | | |
| *mean* | 0.119 | 0.127 | 0.111 | 0.086 | 0.121 | 0.143 | 0.188 | 0.160 | 0.150 |
| *t-stat (diff benchmark)* | | (0.51) | (-0.45) | (-1.85) | (0.07) | (1.67) | (4.13) | (2.18) | (1.63) |
| *median* | 0.122 | 0.124 | 0.109 | 0.106 | 0.155 | 0.143 | 0.189 | 0.180 | 0.179 |
| **Standard Deviation** | | | | | | | | | |
| *mean* | 1.271 | 1.264 | 1.237 | 1.439 | 2.078 | 1.488 | 1.685 | 1.988 | 1.730 |
| *t-stat (diff benchmark)* | | (-0.17) | (-0.85) | (2.20) | (6.67) | (4.49) | (7.42) | (12.03) | (7.33) |
| *median* | 1.223 | 1.250 | 1.201 | 1.353 | 1.935 | 1.397 | 1.657 | 1.951 | 1.704 |
| **Buy/Sell Percentage** | | | | | | | | | |
| *Buy Percentage* | 51.15% | 49.87% | 48.60% | 50.52% | 48.95% | 50.48% | 48.53% | 49.17% | 49.45% |
| *Sell Percentage* | 48.85% | 50.13% | 51.40% | 49.48% | 51.05% | 49.52% | 51.47% | 50.83% | 50.55% |

| | 1/08 | 2/08 | 3/08 | 4/08 | 5/08 | 6/08 | 7/08 | 8/08 | 9/08 | 10/08 | 11/08 | 12/08 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Execution Shortfall** | | | | | | | | | | | | |
| *mean* | 0.184 | 0.167 | 0.175 | 0.214 | 0.178 | 0.112 | 0.195 | 0.163 | 0.216 | 0.303 | 0.351 | 0.267 |
| *t-stat (diff benchmark)* | (3.45) | (2.47) | (3.01) | (6.81) | (3.32) | (-0.37) | (4.01) | (2.45) | (3.14) | (5.56) | (4.29) | (3.01) |
| *median* | 0.199 | 0.169 | 0.191 | 0.214 | 0.171 | 0.141 | 0.207 | 0.168 | 0.225 | 0.316 | 0.422 | 0.252 |
| **Standard Deviation** | | | | | | | | | | | | |
| *mean* | 2.513 | 2.038 | 2.242 | 1.890 | 1.800 | 1.997 | 2.522 | 2.139 | 2.778 | 3.833 | 3.498 | 3.165 |
| *t-stat (diff benchmark)* | (8.83) | (18.55) | (10.18) | (11.45) | (8.32) | (18.28) | (14.77) | (9.09) | (11.68) | (21.90) | (15.49) | (12.67) |
| *median* | 2.294 | 2.016 | 2.168 | 1.835 | 1.704 | 2.038 | 2.489 | 2.120 | 2.579 | 3.958 | 3.289 | 3.189 |
| **Buy/Sell Percentage** | | | | | | | | | | | | |
| *Buy Percentage* | 50.10% | 50.61% | 51.34% | 48.96% | 49.95% | 49.56% | 49.62% | 51.28% | 48.59% | 49.14% | 49.16% | 49.99% |
| *Sell Percentage* | 49.90% | 49.39% | 48.66% | 51.04% | 50.05% | 50.44% | 50.38% | 48.72% | 51.41% | 50.86% | 50.84% | 50.01% |

## Table 3

This table reports correlations of monthly variables used to analyze the link between funding liquidity and market liquidity. The variables include the execution shortfall, the standard deviation of execution shortfall, VIX, Eurodollar-T-bill spread, T-bill rate, lagged S&P 500 return, the average CME futures margin on S&P 500 index futures contract, and the aggregate net monthly flows to mutual funds. Panel A presents the correlations over the 1999-2006 period. Panel B presents the correlations over the 2007-08 period.

*Panel A: 1999-2006*

| | Execution shortfall | S.D. (t) | VIX (t-1) | Ted Spread (t-1) | T-Bill (t-1) | CME Margin (t-1) | S&P Return (t-1) | Net fund flows (t-1) | Broker funding (t-1) | Net Repos (t-1) |
|---|---|---|---|---|---|---|---|---|---|---|
| **Execution shortfall (t)** | 1.000 | 0.585 | 0.587 | 0.319 | 0.231 | 0.232 | -0.023 | 0.033 | -0.605 | -0.675 |
| **S.D. of Execution shortfall (t)** | | 1.000 | 0.728 | 0.324 | 0.419 | 0.246 | -0.265 | -0.152 | -0.786 | -0.820 |
| **VIX (t-1)** | | | 1.000 | -0.019 | -0.012 | 0.647 | -0.324 | -0.427 | -0.762 | -0.720 |
| **Ted Spread (t-1)** | | | | 1.000 | 0.827 | -0.506 | 0.120 | 0.243 | -0.074 | -0.278 |
| **T-Bill (t-1)** | | | | | 1.000 | -0.624 | -0.034 | 0.180 | -0.005 | -0.216 |
| **CME Margin (t-1)** | | | | | | 1.000 | -0.182 | -0.542 | -0.471 | -0.303 |
| **S&P Return (t-1)** | | | | | | | 1.000 | 0.477 | 0.131 | 0.085 |
| **Net fund flows (t-1)** | | | | | | | | 1.000 | 0.046 | -0.015 |
| **Broker funding (t-1)** | | | | | | | | | 1.000 | 0.957 |
| **Net Repos (t-1)** | | | | | | | | | | 1.000 |

*Panel B: 2007-2008*

| | Execution shortfall | S.D. (t) | VIX (t-1) | Ted Spread (t-1) | T-Bill (t-1) | CME Margin (t-1) | S&P Return (t-1) | Net fund flows (t-1) | Broker funding (t-1) | Net Repos (t-1) |
|---|---|---|---|---|---|---|---|---|---|---|
| **Execution shortfall (t)** | 1.000 | 0.865 | 0.858 | 0.906 | -0.797 | 0.783 | -0.663 | -0.842 | -0.837 | -0.457 |
| **S.D. of Execution shortfall (t)** | | 1.000 | 0.831 | 0.808 | -0.796 | 0.742 | -0.729 | -0.778 | -0.829 | -0.445 |
| **VIX (t-1)** | | | 1.000 | 0.895 | -0.732 | 0.884 | -0.816 | -0.884 | -0.738 | -0.625 |
| **Ted Spread (t-1)** | | | | 1.000 | -0.740 | 0.758 | -0.683 | -0.862 | -0.728 | -0.463 |
| **T-Bill (t-1)** | | | | | 1.000 | -0.801 | 0.517 | 0.674 | 0.880 | 0.284 |
| **CME Margin (t-1)** | | | | | | 1.000 | -0.617 | -0.728 | -0.839 | -0.717 |
| **S&P Return (t-1)** | | | | | | | 1.000 | 0.789 | 0.622 | 0.517 |
| **Net fund flows (t-1)** | | | | | | | | 1.000 | 0.712 | 0.495 |
| **Broker funding (t-1)** | | | | | | | | | 1.000 | 0.538 |
| **Net Repos (t-1)** | | | | | | | | | | 1.000 |

## Table 4: Institutional trading cost and funding liquidity

This table reports coefficient estimates from monthly regressions of aggregate trading cost and aggregate execution risk on proxies of aggregate demand for fund and aggregate cost of funds. The model is estimated over the 120 months in our sample. Independent variables include a time trend variable (t), the lagged values of the dependent variable, VIX, Eurodollar-T-bill spread, T-bill rate, S&P 500 return, and the average CME futures margin on S&P 500 index futures contract in the month. We include indicator variables that equal one during the Bear Stearns failure, Lehman Brothers failure, and Quant Crisis, and zero otherwise. Panel A presents the results for aggregate trading cost and Panel B for the aggregate execution risk. We report p-values in italics below the coefficients.

*Panel A: Aggregate Trading Cost*

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| **Intercept** | 0.0011 | 0.0019 | 0.0004 | 0.0007 | 0.0008 | 0.0011 | 0.0012 |
| | *0.00* | *0.00* | *0.06* | *0.00* | *0.00* | *0.00* | *0.00* |
| **Lag(Dependent variable)** | 0.4775 | 0.1859 | 0.4814 | 0.3543 | 0.6060 | 0.5405 | 0.1339 |
| | *0.00* | *0.04* | *0.00* | *0.00* | *0.00* | *0.00* | *0.19* |
| **t** | -0.000004 | -0.000008 | -0.000002 | -0.000002 | -0.000002 | -0.000003 | -0.000006 |
| | *0.00* | *0.00* | *0.05* | *0.03* | *0.04* | *0.00* | *0.00* |
| **Bear Stearns dummy (=1 in 03/2008)** | 0.0003 | | | | | | |
| | *0.42* | | | | | | |
| **Lehman dummy (=1 in 09,10,11/2008)** | 0.0011 | | | | | | |
| | *0.00* | | | | | | |
| **Quant crisis dummy (=1 in 08/2007)** | -0.0002 | | | | | | |
| | *0.62* | | | | | | |
| **Eurodollar-T-Bill Spread (previous month)** | | 0.0437 | | | | | 0.0324 |
| | | *0.00* | | | | | *0.00* |
| **T-Bill rate (previous month)** | | -0.0057 | | | | | -0.0021 |
| | | *0.00* | | | | | *0.39* |
| **CME Margin (previous month)** | | | 0.0118 | | | | 0.0055 |
| | | | *0.00* | | | | *0.33* |
| **VIX (previous month)** | | | | 0.0026 | | | 0.0014 |
| | | | | *0.00* | | | *0.07* |
| **S&P 500 return (previous month)** | | | | | -0.0024 | | -0.00003 |
| | | | | | *0.00* | | *0.97* |
| **Fund flows ($ billion, previous month)** | | | | | | -0.0808 | 0.0267 |
| | | | | | | *0.00* | *0.38* |
| **Adjusted R-squared** | 0.5480 | 0.6072 | 0.4767 | 0.5793 | 0.4897 | 0.4941 | 0.6199 |

*Panel B: Aggregate Execution Risk*

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 | Model 7 |
|---|---|---|---|---|---|---|---|
| **Intercept** | 0.0065 | 0.0071 | 0.0034 | 0.0040 | 0.0050 | 0.0044 | 0.0093 |
| | *0.00* | *0.00* | *0.07* | *0.01* | *0.00* | *0.03* | *0.01* |
| **Lag(Dependent variable)** | 0.7504 | 0.7005 | 0.8888 | 0.6975 | 0.7938 | 0.8274 | 0.6024 |
| | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* | *0.00* |
| **t** | -0.000027 | -0.000033 | -0.000003 | -0.000011 | -0.000013 | -0.000011 | -0.000035 |
| | *0.00* | *0.02* | *0.74* | *0.25* | *0.16* | *0.33* | *0.02* |
| **Bear Stearns dummy (=1 in 03/2008)** | 0.0039 | | | | | | |
| | *0.15* | | | | | | |
| **Lehman dummy (=1 in 09,10,11/2008)** | 0.0087 | | | | | | |
| | *0.00* | | | | | | |
| **Quant crisis dummy (=1 in 08/2007)** | 0.0069 | | | | | | |
| | *0.01* | | | | | | |
| **Eurodollar-T-Bill Spread (previous month)** | | 0.2047 | | | | | 0.1690 |
| | | *0.00* | | | | | *0.02* |
| **T-Bill rate (previous month)** | | -0.0010 | | | | | -0.0001 |
| | | *0.95* | | | | | *1.00* |
| **CME Margin (previous month)** | | | -0.0160 | | | | -0.0384 |
| | | | *0.65* | | | | *0.45* |
| **VIX (previous month)** | | | | 0.0138 | | | 0.0096 |
| | | | | *0.02* | | | *0.23* |
| **S&P 500 return (previous month)** | | | | | -0.0223 | | -0.0213 |
| | | | | | *0.00* | | *0.00* |
| **Fund flows ($ billion, previous month)** | | | | | | -0.2730 | 0.1977 |
| | | | | | | *0.27* | *0.49* |
| **Adjusted R-squared** | 0.7975 | 0.7661 | 0.7484 | 0.7599 | 0.7716 | 0.7506 | 0.7854 |

## Table 5 – 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 904 institutions during the time period from January 1, 1999 to December 31, 2008. Only institutions with 100 or more tickets in a month are included in the analysis. 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 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 month 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 month and the benchmark period. All numbers are in percent.

*Panel A: Size Quintiles*

| | Benchmark | Quant Crisis | | Bear Sale | | | Lehman Bankruptcy | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1/07 to 4/07) | 7/07 | 8/07 | 2/08 | 3/08 | 4/08 | 9/08 | 10/08 | 11/08 | 12/08 |
| **Quintile 1 (Large)** | | | | | | | | | | |
| Execution Shortfall | 0.074 | 0.063 | 0.096 | 0.098 | 0.119 | 0.136 | 0.128 | 0.234 | 0.282 | 0.198 |
| *t-stat (diff benchmark)* | | (-0.77) | (1.29) | (1.09) | (2.11) | (4.08) | (1.95) | (3.39) | (4.90) | (3.12) |
| Standard Deviation | 0.940 | 1.132 | 1.523 | 1.574 | 1.805 | 1.435 | 2.524 | 3.576 | 3.006 | 2.553 |
| *t-stat (diff benchmark)* | | (2.96) | (7.71) | (15.18) | (8.24) | (11.92) | (10.80) | (20.03) | (13.67) | (9.92) |
| **Quintile 5 (Small)** | | | | | | | | | | |
| Execution Shortfall | 0.176 | 0.106 | 0.123 | 0.163 | 0.231 | 0.256 | 0.368 | 0.501 | 0.755 | 0.338 |
| *t-stat (diff benchmark)* | | (-1.61) | (-0.99) | (-0.27) | (1.08) | (1.62) | (3.91) | (5.59) | (7.54) | (2.97) |
| Standard Deviation | 1.792 | 1.891 | 2.753 | 2.685 | 2.946 | 2.505 | 3.255 | 4.123 | 4.303 | 4.125 |
| *t-stat (diff benchmark)* | | (1.25) | (6.19) | (17.96) | (13.70) | (13.52) | (13.40) | (24.32) | (25.40) | (22.18) |
| **Diff. of Difference (Q5 minus Q1)** | | | | | | | | | | |
| Execution Shortfall | 0.101 | 0.042 | 0.026 | 0.065 | 0.112 | 0.119 | 0.240 | 0.267 | 0.473 | 0.140 |
| *t-stat (diff benchmark)* | | (-1.49) | (-1.02) | (-0.63) | (0.21) | (0.38) | (2.41) | (2.86) | (4.98) | (0.76) |
| Standard Deviation | 0.851 | 0.759 | 1.230 | 1.111 | 1.141 | 1.070 | 0.731 | 0.547 | 1.297 | 1.572 |
| *t-stat (diff benchmark)* | | (-2.46) | (3.82) | (5.05) | (5.19) | (5.06) | (-1.22) | (-3.62) | (4.71) | (6.65) |

*Panel B: Volatility Quintiles*

| | Benchmark | Quant Crisis | | Bear Sale | | | Lehman Bankruptcy | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1/07 to 4/07) | 7/07 | 8/07 | 2/08 | 3/08 | 4/08 | 9/08 | 10/08 | 11/08 | 12/08 |
| **Quintile 1 (Low Volt.)** | | | | | | | | | | |
| Execution Shortfall | 0.065 | 0.044 | 0.059 | 0.107 | 0.096 | 0.155 | 0.077 | 0.180 | 0.265 | 0.157 |
| *t-stat (diff benchmark)* | | (-1.44) | (-0.31) | (2.22) | (1.66) | (5.17) | (0.49) | (4.44) | (7.16) | (3.55) |
| Standard Deviation | 0.815 | 1.070 | 1.576 | 1.490 | 1.693 | 1.437 | 2.427 | 3.385 | 3.001 | 2.562 |
| *t-stat (diff benchmark)* | | (3.45) | (7.47) | (14.07) | (9.95) | (10.79) | (12.22) | (21.69) | (16.33) | (11.54) |
| **Quintile 5 (High Volt.)** | | | | | | | | | | |
| Execution Shortfall | 0.182 | 0.170 | 0.214 | 0.253 | 0.230 | 0.287 | 0.356 | 0.403 | 0.490 | 0.411 |
| *t-stat (diff benchmark)* | | (-0.32) | (0.69) | (1.66) | (1.13) | (2.76) | (3.87) | (4.88) | (5.39) | (3.85) |
| Standard Deviation | 1.717 | 1.769 | 2.469 | 2.396 | 2.621 | 2.207 | 3.189 | 4.192 | 3.840 | 3.587 |
| *t-stat (diff benchmark)* | | (0.62) | (5.55) | (12.24) | (7.23) | (7.92) | (10.07) | (19.22) | (14.67) | (11.72) |
| **Diff. of Difference (Q5 minus Q1)** | | | | | | | | | | |
| Execution Shortfall | 0.117 | 0.126 | 0.155 | 0.147 | 0.134 | 0.132 | 0.279 | 0.224 | 0.225 | 0.254 |
| *t-stat (diff benchmark)* | | (0.28) | (0.95) | (0.73) | (0.42) | (0.38) | (3.64) | (2.43) | (2.07) | (2.65) |
| Standard Deviation | 0.902 | 0.699 | 0.894 | 0.906 | 0.928 | 0.770 | 0.761 | 0.807 | 0.838 | 1.025 |
| *t-stat (diff benchmark)* | | (-4.80) | (-0.19) | (0.07) | (0.41) | (-3.21) | (-1.36) | (-1.10) | (-1.28) | (2.17) |

*Panel C: Liquidity Beta Quintiles*

| | Benchmark | Quant Crisis | | Bear Sale | | | Lehman Bankruptcy | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | (1/07 to 4/07) | 7/07 | 8/07 | 2/08 | 3/08 | 4/08 | 9/08 | 10/08 | 11/08 | 12/08 |
| **Quintile 1 (Low LB)** | | | | | | | | | | |
| Execution Shortfall | 0.083 | 0.068 | 0.092 | 0.121 | 0.118 | 0.165 | 0.119 | 0.225 | 0.327 | 0.218 |
| *t-stat (diff benchmark)* | | (-1.01) | (0.43) | (2.05) | (1.95) | (5.40) | (1.91) | (3.33) | (5.10) | (2.73) |
| Standard Deviation | 1.026 | 1.234 | 1.770 | 1.736 | 1.944 | 1.659 | 2.635 | 3.663 | 3.215 | 2.824 |
| *t-stat (diff benchmark)* | | (2.97) | (7.79) | (15.21) | (10.52) | (11.50) | (12.02) | (22.05) | (15.00) | (12.21) |
| **Quintile 5 (High LB)** | | | | | | | | | | |
| Execution Shortfall | 0.156 | 0.138 | 0.242 | 0.308 | 0.299 | 0.243 | 0.382 | 0.561 | 0.512 | 0.432 |
| *t-stat (diff benchmark)* | | (-0.34) | (0.96) | (2.98) | (2.60) | (1.75) | (3.98) | (5.14) | (3.10) | (3.31) |
| Standard Deviation | 1.716 | 1.804 | 2.543 | 2.491 | 2.711 | 2.292 | 3.085 | 4.121 | 3.923 | 3.690 |
| *t-stat (diff benchmark)* | | (1.09) | (5.46) | (12.63) | (9.40) | (10.03) | (11.17) | (21.00) | (16.39) | (13.73) |
| **Diff. of Difference (Q5 minus Q1)** | | | | | | | | | | |
| Execution Shortfall | 0.072 | 0.070 | 0.149 | 0.187 | 0.181 | 0.078 | 0.263 | 0.335 | 0.185 | 0.214 |
| *t-stat (diff benchmark)* | | (-0.05) | (1.46) | (2.39) | (2.00) | (0.13) | (3.49) | (4.67) | (1.63) | (2.91) |
| Standard Deviation | 0.689 | 0.570 | 0.772 | 0.754 | 0.767 | 0.633 | 0.450 | 0.458 | 0.708 | 0.865 |
| *t-stat (diff benchmark)* | | (-3.14) | (1.70) | (1.52) | (1.82) | (-1.50) | (-3.55) | (-3.33) | (0.42) | (3.11) |

## Table 6: Financial crisis and Institutions selling activity

This table presents relative selling activity of institutions over the entire sample and across market value, volatility, and liquidity beta quintiles from May, 2008 to December, 2008. 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. Panel A presents the average relative dollar volumes traded from 05/2008 to 12/2008 relative to the average trading volume of an institution in the first four months of 2008. Panel B presents the composition of selling activity across NYSE market value quintiles. Panel C presents the composition of selling activity across volatility quintiles. Panel D presents the composition of selling activity across liquidity beta quintiles. We first calculate the proportion of sell 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 selling activity for an institution. We then calculate the proportion of dollar selling activity for the institution in months five through 12 of 2008 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 | 05/2008 | 06/2008 | 07/2008 | 08/2008 | 09/2008 | 10/2008 | 11/2008 | 12/2008 |
| **Panel A. Sell Volume** | | | | | | | | | | |
| Average (monthly volume) | | $493,499,200.3 | 1.003 | 1.066 | 1.165 | 0.923 | 1.164 | 1.080 | 0.738 | 0.750 |
| T-Statistic (test relative volume=1) | | | *0.05* | *1.38* | *3.69* | *-1.58* | *3.17* | *1.73* | *-6.31* | *-4.07* |
| **Panel B: Proportion of sell volume in market value quintile** | | | | | | | | | | |
| Proportion of sell volume in quintile | Small cap. | 4.34% | 0.954 | 0.916 | 0.868 | 0.974 | 0.695 | 0.775 | 0.559 | 0.643 |
| T-Statistic (test relative proportion=1) | Small cap. | | *-0.73* | *-1.32* | *-2.14* | *-0.37* | *-6.25* | *-4.05* | *-8.02* | *-6.52* |
| Proportion of sell volume in quintile | 2 | 9.56% | 1.038 | 1.030 | 0.903 | 1.152 | 1.096 | 0.999 | 0.839 | 0.863 |
| T-Statistic (test relative proportion=1) | 2 | | *0.66* | *0.51* | *-1.96* | *2.59* | *1.71* | *-0.02* | *-3.44* | *-2.67* |
| Proportion of sell volume in quintile | 3 | 11.68% | 1.173 | 1.118 | 1.129 | 1.262 | 1.062 | 1.121 | 1.141 | 1.244 |
| T-Statistic (test relative proportion=1) | 3 | | *3.42* | *2.28* | *2.68* | *4.10* | *1.14* | *2.26* | *2.28* | *4.13* |
| Proportion of sell volume in quintile | 4 | 17.09% | 1.126 | 1.148 | 1.225 | 1.095 | 0.950 | 1.014 | 1.072 | 0.989 |
| T-Statistic (test relative proportion=1) | 4 | | *3.17* | *3.31* | *4.47* | *2.43* | *-1.20* | *0.33* | *1.63* | *-0.27* |
| Proportion of sell volume in quintile | Large cap. | 57.34% | 0.951 | 0.999 | 0.975 | 0.899 | 1.055 | 1.031 | 1.057 | 1.044 |
| T-Statistic (test relative proportion=1) | Large cap. | | *-2.36* | *-0.04* | *-1.17* | *-4.80* | *1.94* | *1.12* | *1.76* | *1.28* |

*Panel C: Proportion of sell volume in volatility quintile*

| | Volatility Quintile | Benchmark period | Relative to Benchmark Period | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 01-04/2008 | 05/2008 | 06/2008 | 07/2008 | 08/2008 | 09/2008 | 10/2008 | 11/2008 | 12/2008 |
| Proportion of sell volume in quintile | Low | 37.31% | 0.944 | 0.995 | 1.015 | 0.992 | 1.083 | 1.171 | 1.293 | 1.193 |
| T-Statistic (test relative proportion=1) | Low | | *-2.21* | *-0.14* | *0.53* | *-0.28* | *2.66* | *6.43* | *7.63* | *5.73* |
| Proportion of sell volume in quintile | 2 | 24.06% | 1.094 | 1.023 | 1.099 | 1.118 | 1.072 | 1.043 | 0.996 | 1.011 |
| T-Statistic (test relative proportion=1) | 2 | | *3.37* | *0.81* | *3.56* | *2.97* | *2.30* | *1.37* | *-0.15* | *0.37* |
| Proportion of sell volume in quintile | 3 | 17.32% | 1.116 | 1.058 | 1.043 | 1.077 | 1.012 | 0.908 | 0.954 | 1.000 |
| T-Statistic (test relative proportion=1) | 3 | | *2.91* | *1.59* | *1.21* | *2.03* | *0.35* | *-2.60* | *-1.17* | *-0.01* |
| Proportion of sell volume in quintile | 4 | 11.67% | 1.052 | 1.125 | 0.997 | 1.095 | 0.996 | 0.969 | 0.824 | 0.850 |
| T-Statistic (test relative proportion=1) | 4 | | *1.04* | *2.58* | *-0.07* | *1.82* | *-0.08* | *-0.70* | *-4.08* | *-3.74* |
| Proportion of sell volume in quintile | High | 9.64% | 1.168 | 1.123 | 1.134 | 1.032 | 1.003 | 0.892 | 0.798 | 0.917 |
| T-Statistic (test relative proportion=1) | High | | *3.03* | *2.54* | *2.79* | *0.61* | *0.07* | *-2.13* | *-4.61* | *-2.05* |

*Panel D: Proportion of sell volume in Liquidity beta quintile*

| | **Liquidity Beta Quintile** | **Benchmark period** | **Relative to Benchmark Period** | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | 01-04/2008 | 05/2008 | 06/2008 | 07/2008 | 08/2008 | 09/2008 | 10/2008 | 11/2008 | 12/2008 |
| Proportion of sell volume in quintile | Low | 40.43% | 0.997 | 1.029 | 0.968 | 0.960 | 1.022 | 1.067 | 1.042 | 1.016 |
| T-Statistic (test relative proportion=1) | Low | | *-0.11* | *0.95* | *-1.17* | *-1.50* | *0.74* | *2.54* | *1.80* | *0.50* |
| Proportion of sell volume in quintile | 2 | 36.85% | 1.027 | 1.020 | 1.055 | 1.018 | 1.084 | 1.063 | 1.063 | 1.040 |
| T-Statistic (test relative proportion=1) | 2 | | *1.21* | *0.95* | *2.49* | *0.71* | *3.35* | *2.23* | *3.02* | *1.88* |
| Proportion of sell volume in quintile | 3 | 11.60% | 1.172 | 1.182 | 1.234 | 1.379 | 1.047 | 1.073 | 1.054 | 1.056 |
| T-Statistic (test relative proportion=1) | 3 | | *3.35* | *3.32* | *4.59* | *6.10* | *1.00* | *1.41* | *1.00* | *1.11* |
| Proportion of sell volume in quintile | 4 | 6.39% | 1.195 | 1.133 | 1.012 | 1.047 | 0.930 | 1.003 | 0.949 | 1.035 |
| T-Statistic (test relative proportion=1) | 4 | | *2.95* | *2.20* | *0.21* | *0.81* | *-1.33* | *0.05* | *-0.89* | *0.56* |
| Proportion of sell volume in quintile | High | 4.73% | 0.836 | 0.896 | 1.028 | 0.929 | 0.997 | 0.794 | 0.678 | 0.849 |
| T-Statistic (test relative proportion=1) | High | | *-2.95* | *-1.64* | *0.46* | *-1.25* | *-0.05* | *-3.56* | *-6.06* | *-2.40* |

## Table 7 - Persistence in institutional trading costs

This table examines the performance persistence of institutional trading desks. The trades in the sample are executed by 904 institutions during the time period from January 1, 1999 to December 31, 2008. Only institutions with 100 or more tickets in a month are included in the analysis. 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. At the end of each month, we form institutions into quintile portfolios based on execution shortfall for the month. We report the average (equal-weighted) execution shortfall for these quintiles in the portfolio formation month and the next month. Execution shortfall is presented as a percentage. We perform our analysis for four different time periods: 1999-2008, 1999-2003, 2004-2007, and 2007-2008. Numbers in parentheses are p-values.

| | 1999-2008 | | 1999-2003 | | 2004-2007 | | 2007-2008 | |
|---|---|---|---|---|---|---|---|---|
| Current Quarter Performance Quintiles | Portfolio Formation Month | M+1 | Portfolio Formation Month | M+1 | Portfolio Formation Month | M+1 | Portfolio Formation Month | M+1 |
| Q1 Exec. Shortfall (%) | -0.392 | -0.103 | -0.440 | -0.106 | -0.304 | -0.091 | -0.420 | -0.128 |
| Q2 Exec. Shortfall (%) | 0.017 | 0.116 | 0.022 | 0.131 | 0.015 | 0.098 | 0.007 | 0.101 |
| Q3 Exec. Shortfall (%) | 0.220 | 0.228 | 0.263 | 0.268 | 0.161 | 0.170 | 0.201 | 0.219 |
| Q4 Exec. Shortfall (%) | 0.433 | 0.339 | 0.518 | 0.405 | 0.315 | 0.251 | 0.389 | 0.306 |
| Q5 Exec. Shortfall (%) | 0.898 | 0.591 | 1.049 | 0.703 | 0.687 | 0.451 | 0.819 | 0.516 |
| Q5 – Q1 (Exec. Shortfall) | 1.29 (<0.001) | 0.67 (<0.001) | 1.49 (<0.001) | 0.81 (<0.001) | 0.99 (<0.001) | 0.54 (<0.001) | 1.24 (<0.001) | 0.64 (<0.001) |

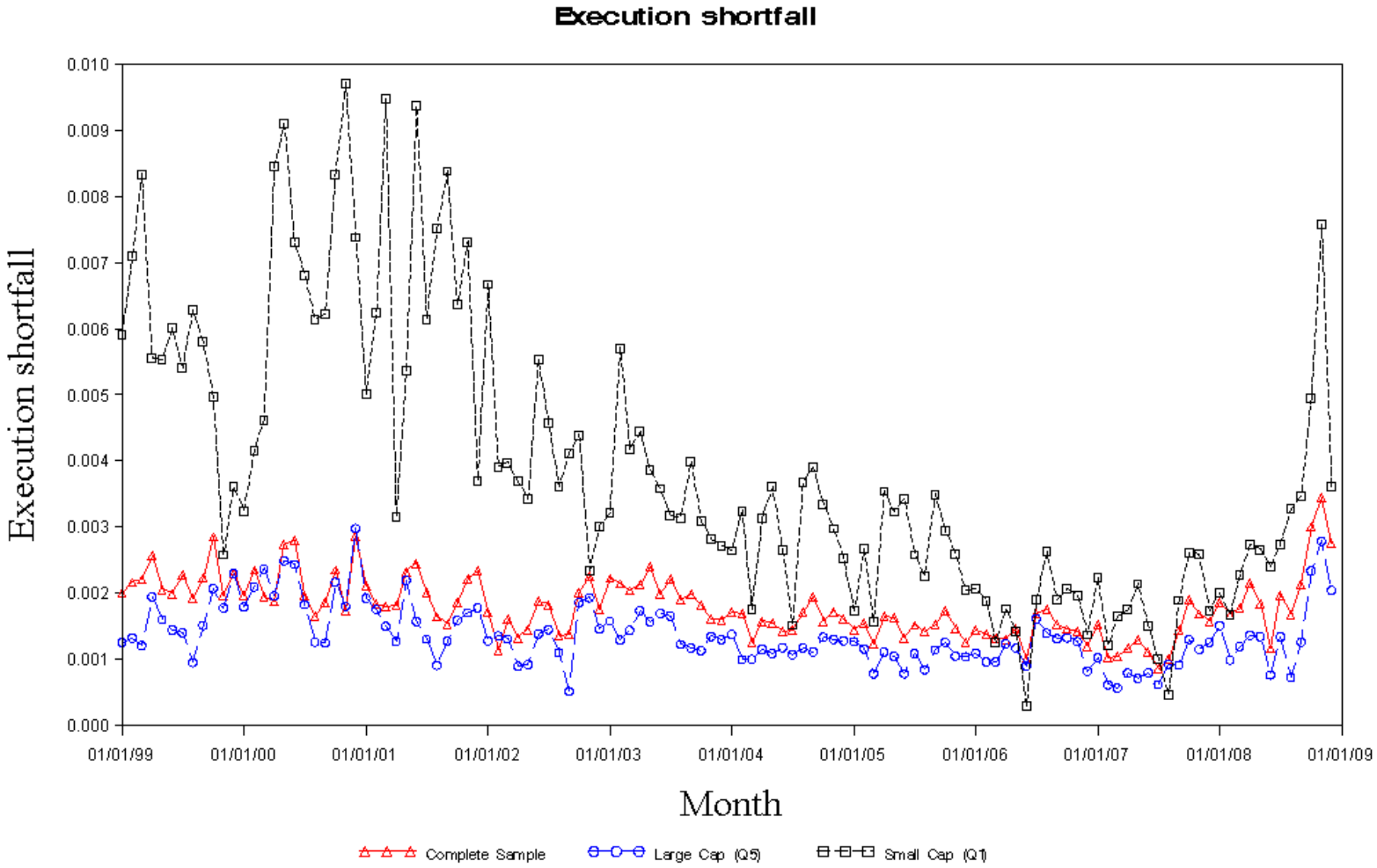
## Table 8

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

| | Q1 Shortfall | Q5 Shortfall | Q5-Q1 | PS-Aggregate liquidity | PS-Innovation in liquidity |
|---|---|---|---|---|---|
| **Panel A: Sample: 1999-2008** | | | | | |
| ***Execution shortfall (low cost (Q1) institutions)*** | 1.00 | -0.28 | -0.63 | 0.26 | 0.21 |
| | | *0.00* | *0.00* | *0.00* | *0.02* |
| ***Execution shortfall (high cost (Q5) institutions)*** | | 1.00 | 0.92 | -0.15 | -0.03 |
| | | | *0.00* | *0.10* | *0.73* |
| ***Difference in shortfall (Q5-Q1)*** | | | 1.00 | -0.23 | -0.11 |
| | | | | *0.01* | *0.23* |
| **Panel B: Sample: 1999-2006** | | | | | |
| ***Execution shortfall (low cost (Q1) institutions)*** | 1.00 | -0.35 | -0.67 | 0.19 | 0.06 |
| | | *0.00* | *0.00* | *0.07* | *0.53* |
| ***Execution shortfall (high cost (Q5) institutions)*** | | 1.00 | 0.93 | -0.12 | -0.03 |
| | | | *0.00* | *0.24* | *0.78* |
| ***Difference in shortfall (Q5-Q1)*** | | | 1.00 | -0.17 | -0.05 |
| | | | | *0.10* | *0.64* |
| **Panel C: Sample: 2007-2008** | | | | | |
| ***Execution shortfall (low cost (Q1) institutions)*** | 1.00 | -0.14 | -0.60 | 0.43 | 0.63 |
| | | *0.51* | *0.00* | *0.04* | *0.00* |
| ***Execution shortfall (high cost (Q5) institutions)*** | | 1.00 | 0.87 | -0.49 | -0.22 |
| | | | *0.00* | *0.01* | *0.30* |
| ***Difference in shortfall (Q5-Q1)*** | | | 1.00 | -0.61 | -0.49 |
| | | | | *0.00* | *0.02* |

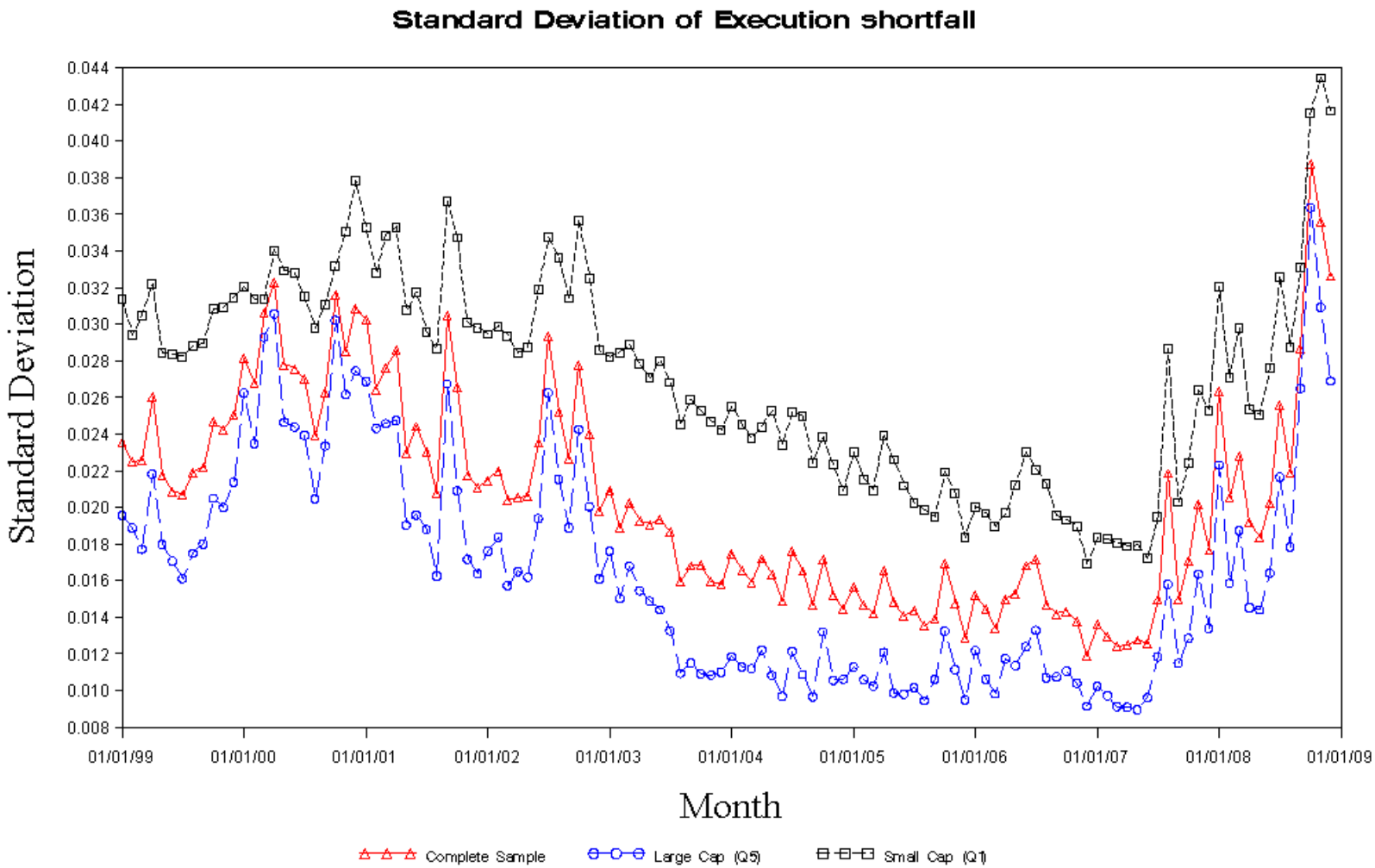
## Figure 1 – Monthly institutional trading costs 1999-2008

This figure shows the time series of execution shortfalls. The tickets in the sample are executed by 904 institutions during the time period from January 1, 1999 to December 31, 2008. Only institutions with 100 or more tickets in a month are included in the analysis. 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 all tickets for each month, for the overall sample, and for the largest and smallest NYSE size quintile in each month of the sample period. NYSE size quintiles are formed as of the end of the month prior to the month of ticket execution.



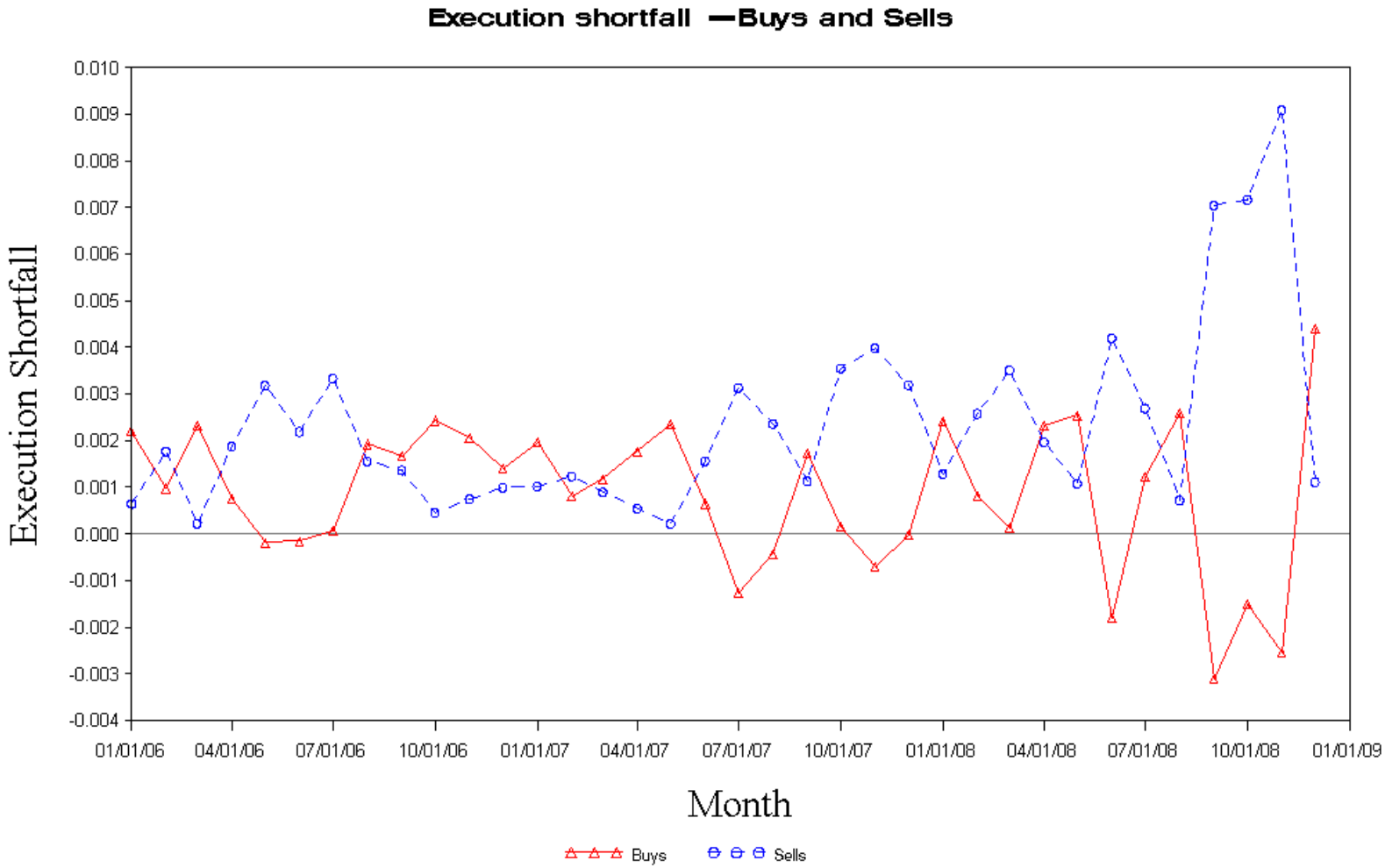
## Figure 2 – Institutional execution risk 1999-2008

This figure shows the time series of the standard deviation of execution shortfall. The trades in the sample are executed by 904 institutions during the time period from January 1, 1999 to December 31, 2008. Only institutions with 100 or more tickets in a month are included in the analysis. 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 standard deviation of execution shortfall across all tickets for each month and for the largest and smallest NYSE size quintile in each month of the sample period. 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 2006-2008

This figure shows the time series of execution shortfall for buys and sells separately from January 1, 2006 to December 31, 2008. The trades in the sample are executed by 904 institutions during the time period from January 1, 1999 to December 31, 2008. Only institutions with 100 or more tickets in a month are included in the analysis. 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 all buy tickets and across all sell tickets for each month of the sample period.



## Figure 4 – Institutional selling activity

This figure shows relative selling activity of institutions for extreme quintiles (market cap, volatility and liquidity beta) from May, 2008 to December, 2008. 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 proportion of sell 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 selling activity for an institution. We then calculate the proportion of dollar selling activity for the institution in months five through 12 of 2008 relative to the benchmark proportions described above. The monthly averages across institutions are plotted in the graph below. The observation for April, 2008 represents the average of the first four months and equals one by construction.

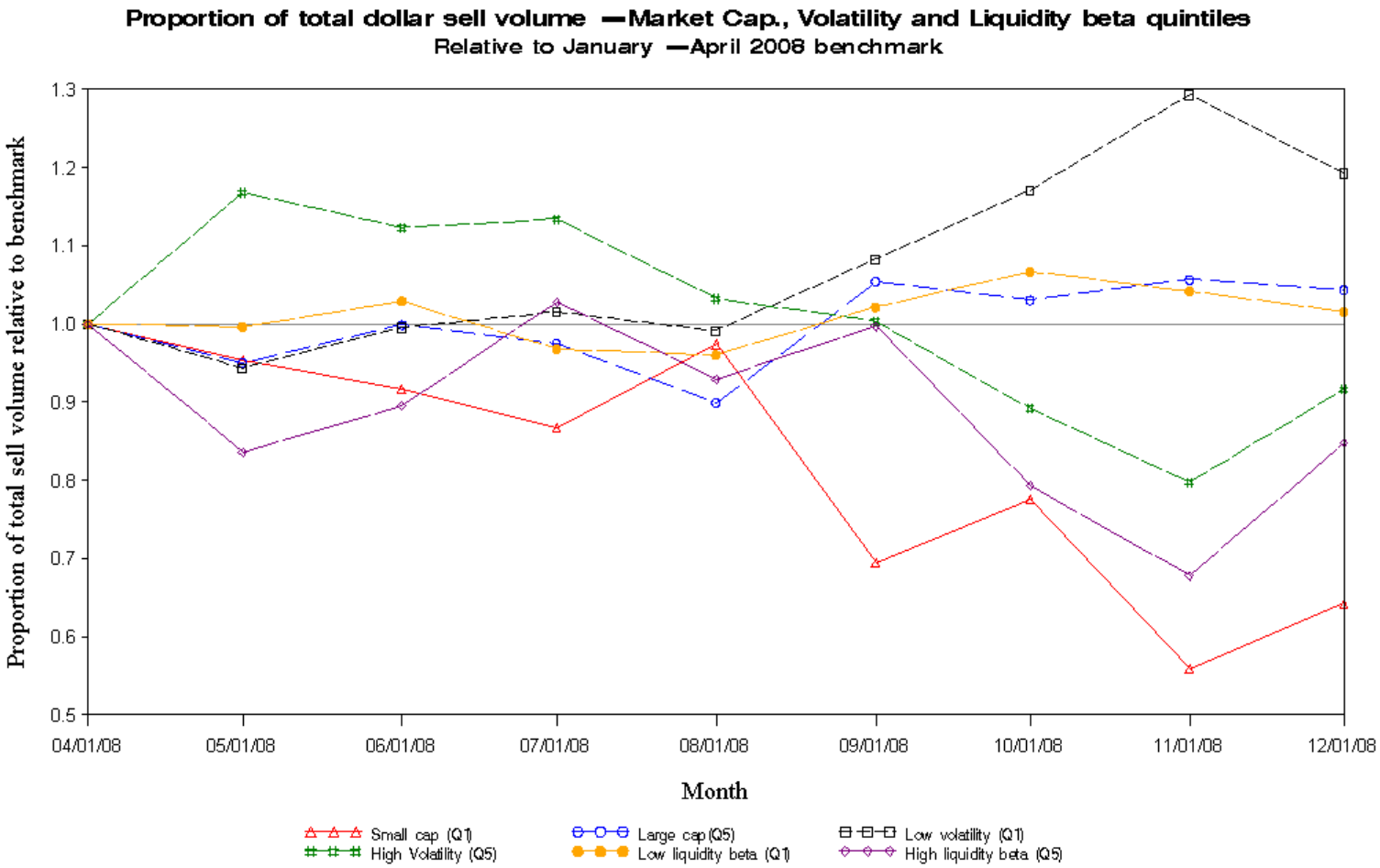
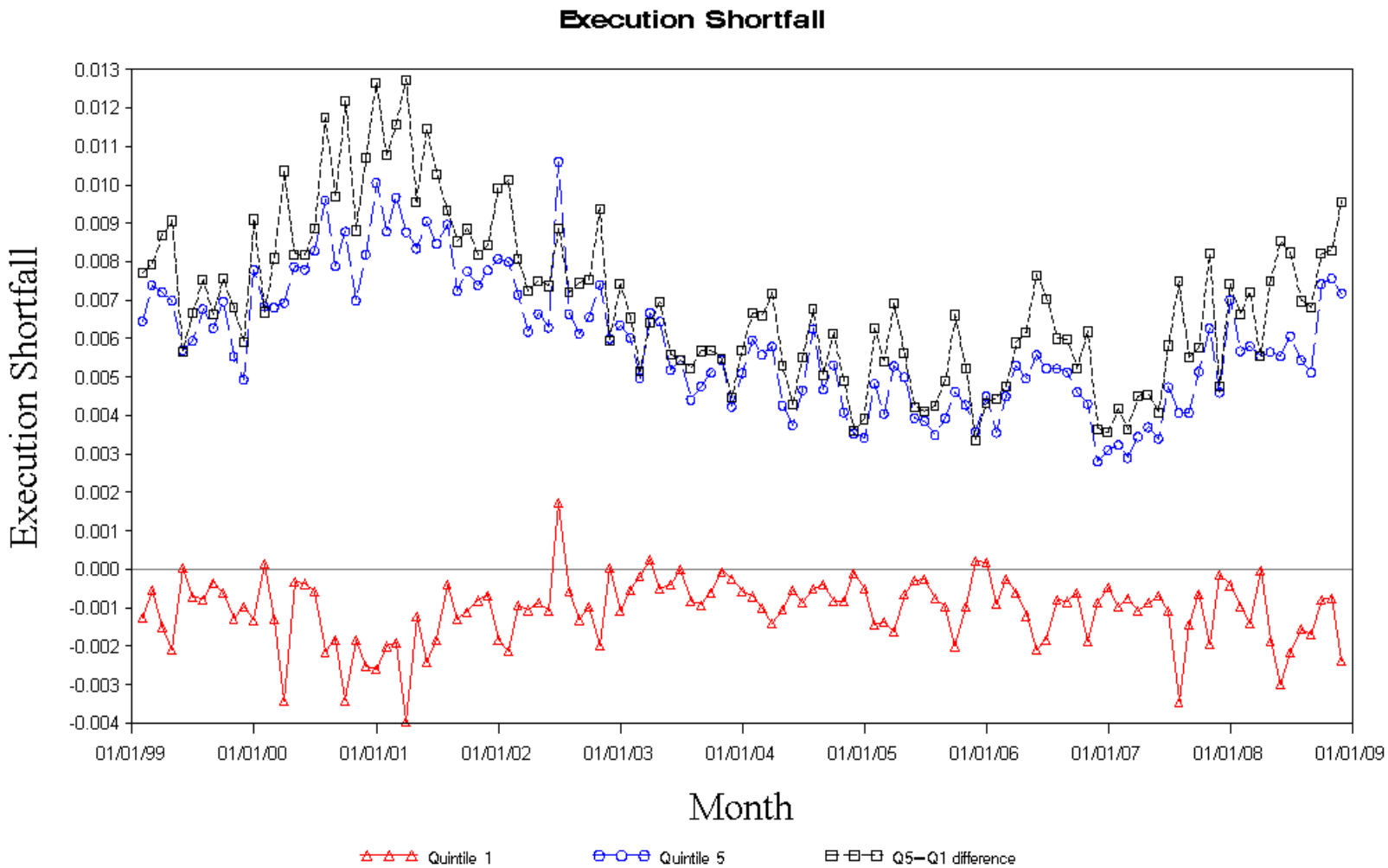


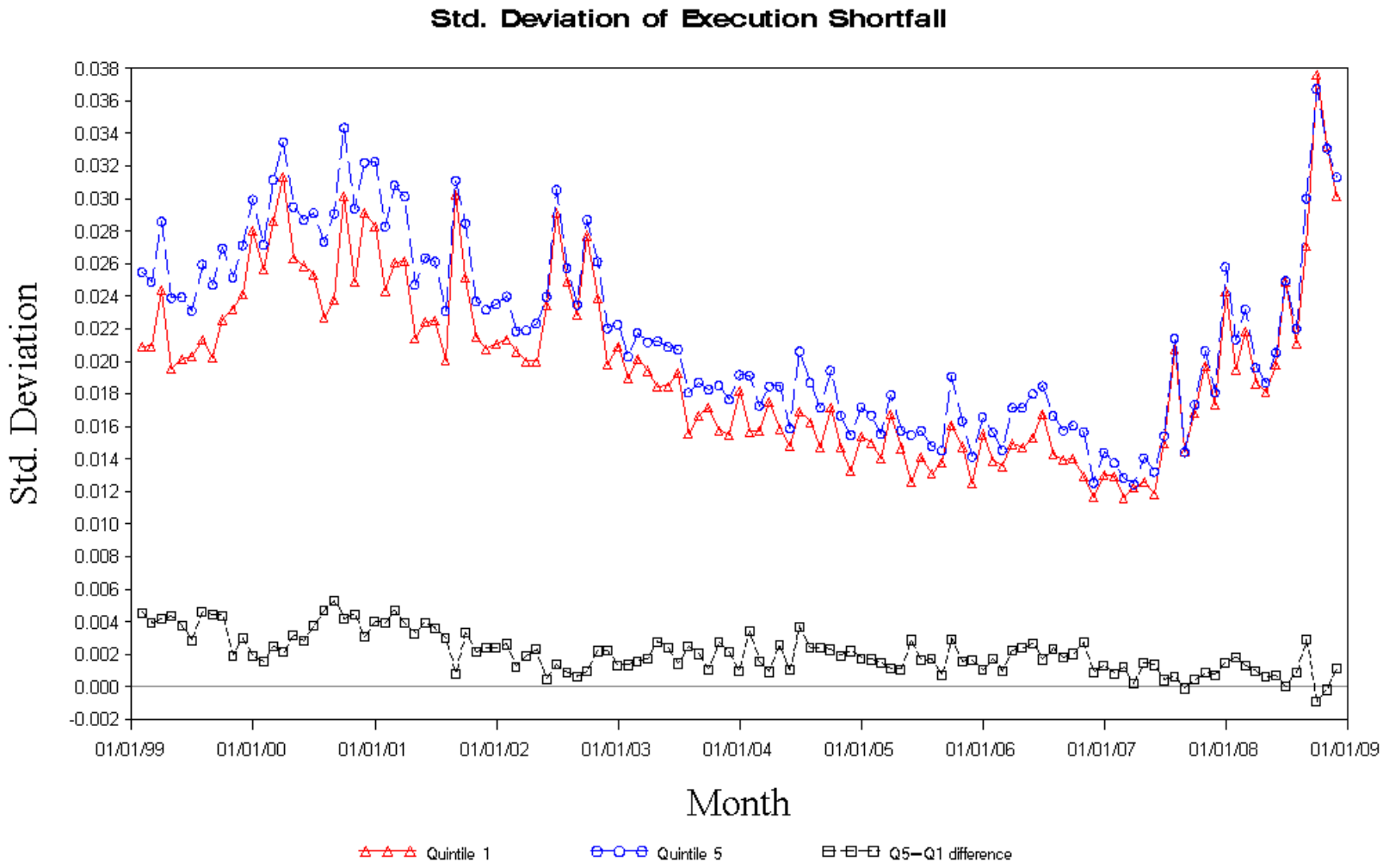
**Figure 5 – Institutional trading costs in month M+1 for Q1 and Q5 institutions**

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 execution shortfall for the month. The figure plots the average (equal-weighted) execution shortfall for quintiles 1 (lowest cost) and 5 (highest cost) in the month *following* the portfolio formation month. Execution shortfall is presented as a percentage.



## Figure 6 – Institutional execution risk in month M+1 for Q1 and Q5 institutions

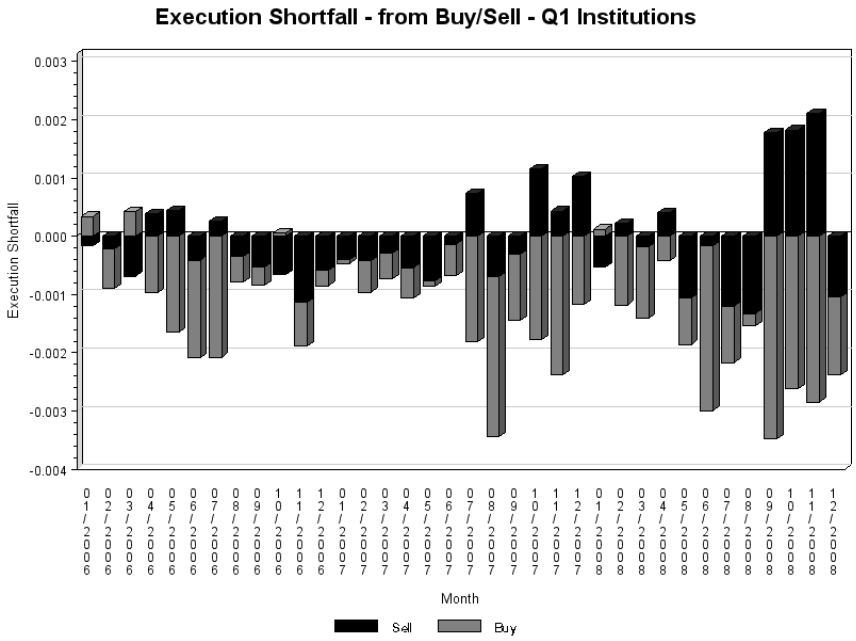
This figure shows the time series of the standard deviation of execution shortfall of quintile 5 (highest cost) and quintile 1 (lowest cost) institutional trading desks. Execution shortfall is measured for buy tickets as the execution price minus the market open price on the day of ticket placement divided 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 execution shortfall for the month. The figure plots the average (equal-weighted) standard deviation of execution shortfall for quintiles 1 (lowest cost) and 5 (highest cost) portfolios in the month *following* the portfolio formation month. Standard deviation of execution shortfall is presented as a percentage.



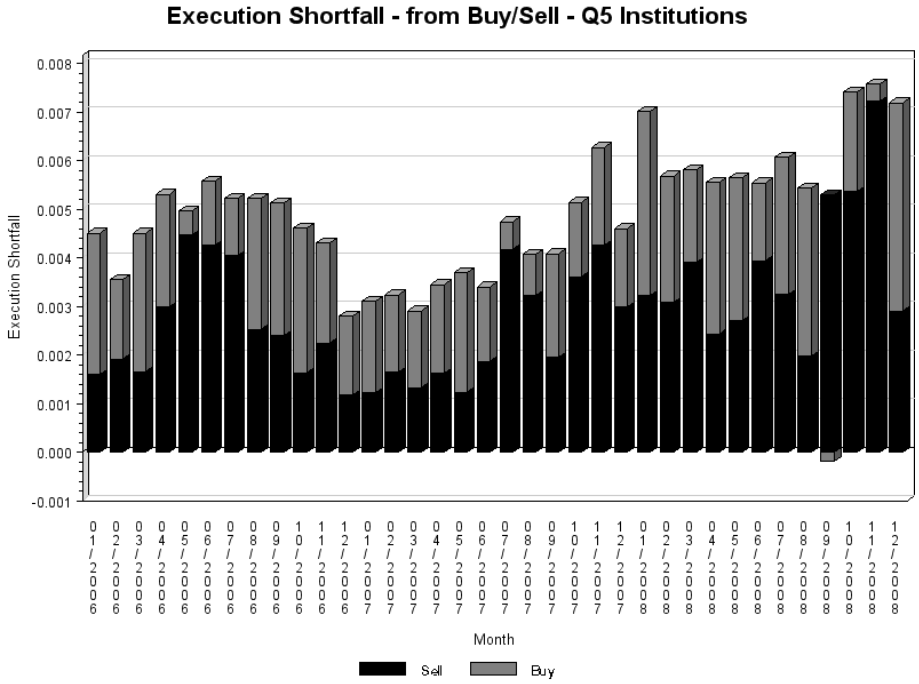
## Figure 7 – Institutional Performance and Buy/Sell executions

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 separately for buy and sell trades. The figure plots the average (equal-weighted) execution shortfall for quintiles 1 (lowest cost) and 5 (highest cost) in the month *following* the portfolio formation month. Execution shortfall is presented as a percentage.

*Panel A: Low-cost Institutions*



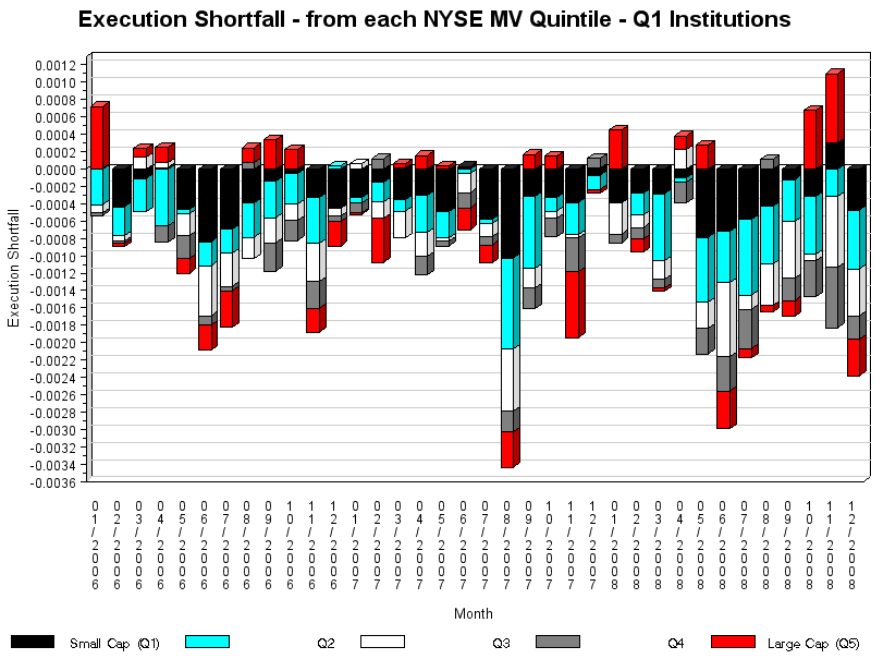

*Panel B: High-cost Institutions*



## Figure 8 –Institutional performance and stock 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 quintiles 1 (lowest cost) and 5 (highest cost) in the month *following* the portfolio formation month. Execution shortfall is presented as a percentage.

*Panel A: Low-cost Institutions*




*Panel B: High-cost Institutions*