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Institutional trading and stock resiliency: Evidence from the 2007–2009 financial crisis ☆

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ABSTRACT

We examine the impact of institutional trading on stock resiliency during the financial crisis of 2007–2009. We show that buy-side institutions have different exposure to liquidity factors based on their trading style. Liquidity supplying institutions absorb the long-term order imbalances in the market and are critical to recovery patterns after a liquidity shock. We show that these liquidity suppliers withdraw from risky securities during the crisis and their participation does not recover for an extended period of time. The illiquidity of specific stocks is significantly affected by institutional trading patterns; participation by liquidity supplying institutions can ameliorate illiquidity, while participation by liquidity demanding institutions can exacerbate illiquidity. Our results provide guidance on why some stocks take longer to recover in a crisis.
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1. Introduction

Resiliency is an important attribute of market quality. A resilient market is defined as one where prices recover quickly after a liquidity shock (see Black, 1971; Kyle, 1985). Much of the existing empirical work examines resiliency over a short horizon, focusing on order submission strategies and the evolution of the limit order book in

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the seconds or minutes subsequent to an order flow shock (e.g., Biais, Hillion, and Spatt, 1995; Coppejans, Domowitz, and Madhavan, 2003; Kempf, Mayston, and Yadav, 2009). While short-horizon recovery patterns and bid-ask spread dynamics deserve attention, the recent financial crisis highlights that liquidity dry-ups can persist over a long horizon, spanning several months, or even years.

We focus on unanswered questions relating to why financial markets stayed illiquid over an extended period during the 2007–09 financial crisis. In particular, we investigate whether, and to what extent, traditional buy-side institutions, such as mutual funds and pension funds, which tend to be buy-and-hold investors, play a role in increasing or ameliorating illiquidity. Recent theoretical and empirical work focuses on the role of financial intermediaries such as banks, broker-dealers, or other traders like hedge funds that serve as arbitrageurs and provide liquidity in different markets. The theoretical models attribute episodes of liquidity dry-ups to either panic selling by market participants or capital constraints faced by financial intermediaries. However, the enduring puzzle in the recent crisis is why did illiquidity persist over a long period, and why did not long-horizon investors with new capital enter the market? The empirical literature focuses on short-horizon resiliency and therefore does not answer whether long-horizon investors influence recovery patterns in a crisis. We posit that buy-side institutions have different exposure to broad liquidity factors based, at least in part, on their trading style, and that a subset of institutions serve as long-term suppliers of liquidity. By studying the behavior of these institutions during the 2007–09 financial crisis, we are able to provide new evidence on the determinants of long-run resiliency after a market crash, thus answering an important empirical question and providing some guidance to the theoretical literature.

We view the market intermediation process as one involving three important parties. Some buy-side institutions take/demand liquidity while other institutions make/supply liquidity. Institutions that demand liquidity trade with market intermediaries (such as specialists, broker-dealers, and high-frequency traders) who are short-run suppliers of liquidity.[1] These market intermediaries in turn trade with another set of buy-side institutions who are the long-run suppliers of liquidity. Hence, the long-run resiliency of financial markets depends critically on the behavior of institutions that supply liquidity to market intermediaries to allow them to offset their short-term positions. We study how these institutions trade during normal conditions, how preferences are altered during periods of market stress, and how such altered preferences affect the speed of recovery in equity markets.

In this paper, we examine a proprietary database of buy-side institutional investors' U.S. equity transactions compiled by Abel Noser Solutions (formerly ANcerno Ltd. and the Abel/Noser Corporation). To provide some context on trading costs in the financial crisis, we first examine the time series of institutional trading costs in U.S. equities from 1999 to 2010. For the full sample, we observe a secular decline in trading costs from 1999 to 2007 but a dramatic increase around October 2008 when trading costs almost triple from pre-crisis levels. Institutional trading costs continue to remain at crisis-peak levels for several months in 2009. While these average liquidity patterns are noteworthy, they do not fully represent the reality of transaction costs incurred by the cross-section of institutions.

Consistent with our framework, we calculate a Trading style (TS) for each institution in our sample based on the prior month percentage of monthly trading volume in the same direction as the contemporaneous daily returns of the stocks that they trade. Institutions with high TS trade more often with the market and are classified as Liquidity demanders (LD), while institutions with low TS trade more often against the market and are classified as Liquidity suppliers (LS). We show that TS classifications are persistent over future periods, indicating that TS captures an important facet of an institution's trading behavior. Our approach to classifying institutions based on the trading style is supported by discussions in the popular press. For example, "Paying for liquidity," *Traders Magazine*, July 27, 2011, quotes a fund manager as

> "*Good liquidity always demands a premium. And we are happy to pay for liquidity. Our trading style tends to be more liquidity taking than providing, and we understand that there are costs associated with this style.*"

Dimensional Fund Advisors (DFA) is an often-cited example of an institutional investor who acts as a liquidity provider. A *Pension & Investments* article ("Face to face with DFA's Eduardo Repetto," September 17, 2007) quotes Eduardo Repetto, DFA's Chief Investment Officer, as

> "*We really like to act as a liquidity provider. In some sense we have an advantage over a market maker since we do not have inventory costs. We want to hold the securities that we buy for our portfolios. Our ability to profit from others trying to be liquidity seekers, while we are liquidity providers, could count quite a lot in the future.*"

The observed patterns in trading costs for LD and LS institutions are strongly consistent with the liquidity supplying or demanding classification. The cross-sectional difference in trading costs between LD and LS institutions in the month following the Trading Style assignment is considerably larger when liquidity is more expensive. The trading cost shock in 2008–2009 is borne almost entirely by LD institutions, whose cost patterns closely track those observed for traditional liquidity measures, such as effective spread, Amihud's (2002) ILLIQ, and Pastor-Stambaugh (2003) measures. In contrast, LS institutions often obtain better executions when markets are less liquid. We show that LD institutions pay more to complete executions while LS institutions get paid more for liquidity provision when funding liquidity is scarce. These results suggest that liquidity suppliers demand higher compensation to offset the higher funding cost or increased risk of supplying liquidity in periods of market stress.[2]

An important theme of our paper is the heterogeneity in buy-side institutions' trading style and the implications of this heterogeneity for the post-crisis recovery patterns in a stock. One theoretical paper that highlights the heterogeneity of institutions' response to the crisis is Acharya and Viswanathan (2011). In their model, institutions facing financing constraints reduce leverage by selling assets to other institutions with financial slack. These less-constrained institutions raise short-term debt to finance the asset purchases. However, due to the risk-shifting moral hazard, lenders ration financing based on the adverse information about the asset's future prospects. The credit rationing by lenders creates a link between the supply of capital and the institution's ability to supply liquidity in an asset. Recent theoretical models provide other explanations for liquidity dry-ups during a severe downturn. In Kyle and Xiong (2001), the liquidity provider's logarithmic utility function implies that their preferences for trading in risky assets decline following market downturns. Other models predict that higher volatility during a market downturn increases the investor's risk aversion (Huang and Wang, 2009), or tightens risk management by institutions (Garleanu and Pedersen, 2007), thereby decreasing liquidity provision. Brunnermeier and Pedersen (2009) emphasize the spiraling effect of a drop in collateral value, funding liquidity, and market liquidity.

The discussions thus far lead to the prediction that post-crisis recovery patterns are slower when liquidity providers reduce participation in an asset. In examining this link between liquidity supply and stock resiliency, we build on the important empirical work by Hameed, Kang, and Viswanathan (2010). Hameed, Kang, and Viswanathan (2010) examine a sample of NYSE stocks between 1988 and 2003 and show that large negative market returns, which proxy for losses suffered by liquidity suppliers, are associated with large weekly increases in bid-ask spreads. The increases in bid-ask spreads last for approximately two weeks and then reverse in subsequent weeks. We extend their work with a detailed analysis of how liquidity suppliers behave in the 2007–09 financial crisis. Brunnermeier (2009) classifies the 2007–09 crisis as the most severe since the Great Depression, characterized by large declines in portfolio values, margin calls, liquidity dry-ups, and fire sales of assets. From the market peak in October 2007 to the low point in March 2009, global equity markets fell by $37 trillion, or about 59%. For these reasons, the market turmoil in 2007–09 presents a unique laboratory to study why liquidity takes so long to recover after a crisis. A key distinction of our study is the institution-specific trade-by-trade data that capture the heterogeneity in institutional investors. The detailed data set allows a closer examination of institutional trading in periods of market stress and the extent to which long-horizon liquidity suppliers affect stock resiliency.

Many theoretical papers offer guidance on the preferences of financially constrained liquidity providers in periods of market stress. For example, Vayanos (2004) and Brunnermeier and Pedersen (2009) predict that liquidity providers are less willing to make markets in volatile, illiquid securities due to the higher collateral or margin requirements. Gromb and Vayanos (2012) contend that arbitrage opportunities that require greater capital commitments from liquidity providers are less attractive and therefore the securities underlying the arbitrage are more illiquid.

We find strong empirical support for these theoretical predictions. We first establish that, although liquidity supplying buy-side institutions continue to provide liquidity in the crisis, they reduce trading activity in small stocks, volatile stocks, and stocks with higher sensitivity to arbitrage capital (Hu, Pan, and Wang, forthcoming). To be specific, LS institutions' relative trading activity in small stocks (measured as a dollar volume proportion of their total trading) in November 2008 is only 35% of their relative trading activity in a pre-crisis benchmark period. Further, we show that LS institutions slowly increase participation in riskier stocks over a period of several months after the crisis peak such that participation reverts to near pre-crisis levels by the fourth quarter of 2009. Specifically, the relative trading activity of LS institutions in small stocks (relative to the pre-crisis benchmark) increases from 35% in November 2008 to 83% by November 2009.

We then focus on the trading cost recovery patterns observed for the cross-section of stocks once the crisis has impaired liquidity. We find that smaller, more volatile stocks experience more significant liquidity declines in the crisis. For example, (one-way) trading costs for large stocks increase from 13 basis points (bps) before the crisis to 26 bps in November 2008 while those for small stocks increase from 23 bps before the crisis to 73 bps in November 2008. While trading costs recover within a month in previous downturns (see Hameed, Kang, and Viswanathan (2010)), we find that liquidity for many stocks does not recover to pre-crisis levels even one year after the crisis-peak. Notably, stocks with reduced participation by LS institutions are associated with slower post-crisis recovery patterns in trading costs.

We construct a stock-specific model-free resiliency measure that captures the percentage of crisis-months when a stock's trading costs exceed a two-sigma threshold relative to its trading costs in a pre-crisis benchmark period. We model the cross-sectional determinants of post-crisis recovery in liquidity. The explanatory variables include stock characteristics that are predicted by theory, the stock's liquidity sensitivity to funding liquidity, and the stock's LS and LD participation. Institutional participation captures the aggregate impact of omitted stock characteristics and market conditions that influence liquidity supply and demand

[1] The Securities Exchange Commission (SEC) (2010) reports that while many high-frequency trading firms do provide liquidity, they tend to have very short horizons and a strong desire to end the day with a flat inventory position. Panayides (2009) shows that other intermediaries, such as the NYSE specialist, have slightly longer holding periods but rebalance their inventories over a multiday horizon.

[2] The clearest example of how aggregate funding liquidity shocks can increase the funding risk of buy-side institutions is via its impact on investor withdrawals. This is because mutual funds are a relatively liquid source of capital for investors facing broker margin calls or other demands on capital.

in the cross-section. We also estimate a panel regression where the dependent variable takes the value of one when the stock's trading costs exceed the two-sigma threshold in a crisis-month, and equals zero otherwise. The panel-data estimation allows us to confirm and elaborate on the conclusions of the cross-sectional estimation.

In both the cross-sectional and panel specifications, we find that smaller and volatile stocks are less resilient and associated with slower recovery patterns after a crisis. The cross-sectional specification shows that stocks with higher liquidity sensitivity to funding liquidity are associated with slower recovery patterns. The panel regression elaborates on this result by showing that funding levels affect overall resiliency and not just resiliency for highly sensitive securities. In both specifications, institutional participation has significant incremental influence on stock resiliency after controlling for stock characteristics and funding liquidity effects. Consistent with contemporary work on fire-sale effects on market quality, we show that stocks subject to more interest from LD institutions are less resilient after the market crash. After controlling for the impact of trading by LD institutions, we find evidence of supply-side effects in equity markets. To be specific, stocks are less resilient when LS institutions withdraw participation and more resilient when LS institutions increase participation in the stock. Overall, the results support that buy-side institutions, who serve as long-run providers of liquidity, influence the resiliency of the market after a stress event.

The remainder of the paper is organized as follows: Section 2 describes the related literature and Section 3 describes trading cost measures and the data. Section 4 presents the time series of trading costs and classifies institutions based on trading style. Section 5 examines the trading behavior of institutions in the crisis and Section 6 presents evidence on the determinants of long-horizon stock resiliency. Section 7 concludes the paper.

2. Related literature

The recent financial crisis highlights the role of intermediary capital in the functioning of financial markets. Two recent papers empirically examine the impact of financing constraints faced by NYSE specialists on liquidity. As discussed earlier, Hameed, Kang, and Viswanathan (2010) show that the bid-ask spreads for NYSE stocks are higher when market returns are lower in the prior period. Using proprietary data on inventory positions of NYSE-specialist firms, Comerton-Forde, Hendershott, Jones, Moulton, and Seasholes (2010) find that specialists are less willing to provide liquidity when they lose money on inventories.

Separately, empirical work on the role of institutional traders in the propagation of the 2007–09 financial crisis is building. Several recent studies examine the impact of the liquidation decisions of institutions (i.e., 'fire sales') who face investor withdrawals or margin calls. Cella, Ellul, and Giannetti (2011) show that investors with short holding periods amplify the effects of market-wide shocks on stock prices. Manconi, Massa, and Yasuda (2012) show that mutual funds with heavy exposure to illiquid securitized bonds sold their holdings of liquid assets, such as corporate bonds, and played a role in propagating the crisis from securitized bonds to corporate bonds. Ben-David, Franzoni, and Moussawi (2012) provide evidence consistent with large-scale equity selloffs by hedge funds. He, Khang, and Krishnamurthy (2010) examine flow-of-funds and SEC filings data and document large-scale selloffs of securitized assets by hedge funds and broker/dealers. They show that these assets were purchased by commercial banks and largely funded by government-backed debt issued by the banks. In contrast, Boyson, Helwege, and Jindra (2010), who also examine activities of commercial banks, investment banks, and hedge funds, conclude that these institutions avoid fire sales by relying on other sources of funding. Aragon and Strahan (2012) examine the portfolio holdings of hedge fund clients of Lehman Brothers, whose accounts were frozen following Lehman's bankruptcy. They document that stocks held by these hedge funds experience a greater decline in liquidity than other stocks, suggesting hedge funds were de facto liquidity providers for these stocks.

Our primary contribution to this existing literature comes in illustrating the heterogeneity in institutional trading and the importance of buy-side liquidity provision for the long-horizon market resiliency. In this context, buy-side institutions are important since they tend to be buy-and-hold investors and account for a majority of equity ownership in financial markets. Our study is the first, as far as we are aware, to construct an institution-specific trading style, which captures an institution's propensity to demand versus supply liquidity and consequently, the institution's exposure to broad liquidity factors.

Our study also contributes by studying institutional trading, trading costs, and resiliency using Abel Noser Solutions' detailed transaction-level data (as compared to quarterly institution holdings data). The sample contains approximately 47 million orders initiated by 982 institutional investors over a 12-year period, 1999–2010, representing over $24 trillion in trading volume. The explosive growth in electronic trading has led institutions to split orders, leading to a large increase in the number of trades, accompanied by a substantial decline in average trade sizes, as reflected in publicly available databases such as the Trade and Quote (TAQ) database. However, the TAQ database does not contain information on the orders that give rise to trades. The Abel Noser Solutions database is distinctive in that it contains a complete history of trading activity by each institution. The detailed order data are particularly well suited for examining how institutions trade in non-crisis periods, how trading preferences are altered in crisis episodes, and whether institutional preferences explain why some stocks remain illiquid for an extended period of time.

3. Data and methodology

3.1. Measuring transactions cost

The asset pricing literature relies extensively on volume-based liquidity measures such as Amihud's (2002) ILLIQ, or return-reversal measures such as Pastor and Stambaugh (2003). These measures do not directly estimate trading costs but they are useful for asset pricing tests because the data necessary to estimate these measures are available over long periods. Other studies use the bid-ask spread from TAQ or Center for Research in Security Prices (CRSP) databases (e.g., Chordia, Roll, and Subrahmanyam, 2011; Hameed, Kang, and Viswanathan, 2010) to measure liquidity. The bid-ask spread is a direct measure of the round-trip liquidity cost for investors placing small orders. However, when executing large orders, the price impact of an earlier trade can influence the price received on subsequent trades. To minimize price impact, institutions break up large orders, use multiple brokers, and implement complex strategies that both demand (through market orders) and supply (through limit orders) liquidity.

Unlike the Abel Noser Solutions database, most publicly available databases, such as the TAQ database, do not identify the traders involved in the transaction. Further, there is no information on the series of transactions that are associated with an institutional order. It is therefore not possible to observe institutional trading strategies or estimate institutional trading costs using standard databases. In this study we use the Abel Noser Solutions database to measure institutional trading costs based on the execution shortfall. The execution shortfall measure compares the execution price of an order with the opening price of the stock for the day, defined as

$$\text{Execution shortfall}(t) = [(P_1(t) - P_0(t))/P_0(t)]D(t) \quad (1)$$

where $P_1(t)$ measures the volume-weighted execution price of order 't', P_0 (t) is the price at the open of the day, and $D(t)$ is a variable that equals one for a buy order and equals -1 for a sell order.[3] The choice of a pre-trade benchmark price follows a well-established approach in the literature.[4]

We define a daily trade order (henceforth, order) as the aggregation of all executions by an institution in the same stock on the same side (buy/sell) on the same day. Our approach 'stitches' or aggregates the institution's trading in a stock across many brokers and also accounts for canceled orders that are resubmitted with another broker on the same day.[5] Execution shortfall captures several dimensions of institutional trading including the bid-ask spread, price impact, slippage costs due to delayed executions, and order-splitting strategies. Unlike the bid-ask spread, which is always positive, execution shortfall can be positive or negative, depending on market conditions and the extent to which an order demands or supplies liquidity. Since execution shortfall captures the one-way trading cost, the measure should be multiplied by two for comparison with the bid-ask spread.

3.2. Data

We obtain data on institutional trades for the period from January 1, 1999 to September 30, 2010 from Abel Noser Solutions. Abel Noser Solutions is a well-known consulting firm that works with institutions to monitor their trading costs. Abel Noser Solutions' clients include pension plan sponsors, such as California Public Employees' Retirement System (CalPERS), the Commonwealth of Virginia, and the Young Men's Christian Association (YMCA) retirement fund, and money managers, such as Massachusetts Financial Services (MFS), Putman Investments, Lazard Asset Management, and Fidelity. Academic studies using Abel Noser Solutions data include Goldstein, Irvine, Kandel, and Weiner (2009), Chemmanur, He, and Hu (2009), Goldstein, Irvine, and Puckett (2011), and Puckett and Yan (2011).

For each execution, the database reports identity codes for the institution and the broker involved in each trade, the CUSIP and ticker for the stock, the stock price at placement time with the broker, the date of execution, the execution price, the number of shares executed, whether the execution is a buy or sell, and the commissions paid on the execution. The institution's identity is restricted to protect the privacy of Abel Noser Solutions' clients, but the unique client code facilitates identification of an institution both in the cross-section and through time.[6]

To minimize observations with errors and to obtain the necessary data for our empirical analysis, we impose the following screens: (1) Delete orders with execution shortfall greater than an absolute value of 10%. (2) Delete orders with order volume greater than the stock's CRSP volume on the execution date, or with an order size greater than the 99th percentile of order sizes in the month. (3) Delete orders associated with internal allocations or corporate events such as private placements of stock. (4) Include common stocks listed on NYSE or Nasdaq with data available on CRSP and TAQ databases. (5) Delete institutions with less than one hundred orders in a month. We obtain data on market capitalization, return, trading volume, and exchange listing from CRSP, and the daily order imbalance from TAQ.

[3] Alternatively, we define P_0 as the stock price when an institution sends a portion of a large order to each broker. Execution shortfall using this approach does not account for the price drift between the decision time (open) and the order placement time with a broker. Estimates based on this measure are smaller but the main results are unchanged. We acknowledge that it is difficult to perfectly capture all dimensions of the trading decision and our approaches represent different ways to account for slippage cost of an adverse price move.

[4] Other studies using the execution shortfall measure include Keim and Madhavan (1997), Jones and Lipson (2001), Conrad, Johnson, and Wahal (2001), and Anand, Irvine, Puckett, and Venkataraman (2012).

[5] The Abel Noser Solutions data set does not provide information on fill rates. Keim and Madhavan (1997), using Plexus data with information on fill rates, conclude "it is rare that an order is not entirely filled." Chiyachantana, Jain, Jiang, and Wood (2004) report average fill rates for their sample of institutional orders exceeding 95% for all sample years. We follow the approach in Keim and Madhavan (1997) and do not assign a cost to the unfilled portion of the order. Our trading cost estimates are understated to the extent that institutions cancel orders when prices move in an unfavorable direction (see Obizhaeva (2010) for a related discussion).

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

Table 1
Data description.
This table reports the descriptive statistics for the sample of institutional trades from Abel Noser Solutions for the period from January 1, 1999 to September 30, 2010. The unit of analysis is an institutional daily trade order. Each order is constructed by institution, stock, side, and day. We further restrict the sample to orders where execution shortfall is less than or equal to an absolute value of 10%, executed order volume is less than or equal to the total daily trading volume reported in CRSP, the institution responsible for the order has at least one hundred orders during a particular month, and the order is for a common stock listed on NYSE or Nasdaq. We present descriptive statistics for the full sample, as well as by disaggregating the sample based on year and firm-size quintiles. Firm-size quintile breakpoints are constructed using NYSE quintile breakpoints.

	Number of institutions	Number of stocks	Number of orders	Order size	Order size/average daily volume (30 days) (%)	Buy dollar volume/total dollar volume (%)	Number of executions per order
Panel A: Full sample							
	982	8,630	47,122,271	15,806	2.8	50.7	3.78
Panel B: By year							
1999	324	5,726	2,122,761	14,371	4.8	51.3	2.05
2000	322	5,502	2,509,332	16,189	3.9	51.4	2.34
2001	350	4,715	2,754,936	18,672	3.8	52.0	2.58
2002	380	4,383	3,456,098	19,984	3.7	51.6	2.63
2003	356	4,320	3,558,992	18,799	3.5	50.6	2.85
2004	367	4,485	4,497,585	18,658	3.5	50.9	3.75
2005	336	4,342	3,915,803	16,326	3.1	50.5	3.63
2006	359	4,321	4,933,460	14,668	2.5	50.5	4.49
2007	339	4,335	5,013,820	13,733	2.2	50.0	5.38
2008	296	4,052	5,347,082	14,636	1.8	49.8	4.53
2009	286	3,938	5,184,001	14,270	1.8	49.8	3.86
2010#	266	3,637	3,828,401	11,750	1.5	50.3	4.48
Panel C: Firm size (NYSE market-value quintiles)							
Small			5,034,163	11,127	10.6	53.5	2.90
2			6,836,989	12,136	4.2	52.9	3.15
3			7,552,682	13,917	2.7	52.1	3.25
4			9,206,414	16,570	1.8	50.5	3.48
Large			18,491,851	18,828	0.7	50.1	4.62

We present the summary statistics for the Abel Noser Solutions data in Table 1. The sample contains a total of 982 buy-side institutions, responsible for approximately 47 million orders in 8,630 U.S. stocks over the 12-year sample period. Conversations with Abel Noser Solutions officials confirm that the database captures the entire buying and selling activity for their institutional clients. The typical order size is 15,806 shares, which represents 2.8% of the stock's average daily volume (ADV) over the previous 30 trading days. As a percent of daily volume, order size trends downwards, from 4.8% in 1999 to 1.5% in 2010 (see Panel B). The number of institutions in the database remains relatively constant from year to year while the number of stocks traded declines from 5,726 in 1999 to 3,637 in 2010. Buy dollar volume as a percentage of total institutional trading volume is close to 50% in all years. As expected, buy-side institutions are more active in large-cap stocks, where stock classifications in Panel C are based on NYSE market-cap quintile cutoffs. For large stocks, the average institutional order size is 0.7% of ADV, while for small stocks, the average order represents almost 11% of ADV, suggesting that institutions have more difficulty filling orders in small stocks.

4. The cross-section of institutional trading costs

4.1. Trends in trading costs 1999–2010

Fig. 1 plots the quoted bid-ask spread, effective spread, Amihud's (2002) ILLIQ, and institutional trading costs in U.S. equities from 1999 to 2010. All measures exhibit a pattern of improving liquidity from the beginning of sample period (1999) to the beginning of the financial crisis (2007). A pattern of declining trading costs is consistent with those reported in several recent studies on U.S. equities (see Hasbrouck, 2009; Chordia, Roll, and Subrahmanyam, 2011) and equity markets outside the United States. For example, Griffin, Kelly, and Nardari (2010) examine data from 28 emerging markets and 28 developed markets and estimate trading cost declines of around 60% between 1994 and 2005. The decline in trading costs can be attributed to several factors including market design (e.g., decimalization), regulation (e.g., Regulation National Market System (NMS)), and technology (e.g., Electronic Communication Networks (ECNs), online brokerage accounts). In particular, Hendershott, Jones, and Menkveld (2011) report that algorithmic trading, defined as the use of computer algorithms to manage the trading process, accounts for about a third of the trading volume in U.S. equities in 2007.

A striking result in Fig. 1 is the sudden and dramatic increase in institutional trading costs from the onset of the crisis (mid-2007) to the peak of the financial crisis. Traditional measures of market quality also exhibit a similar pattern.[7] This reversal of the long-term trend cannot be attributed to a change in market design, regulation, or technology. Notably, trading costs observed in the crisis-peak are as large as those observed almost a decade ago, emphasizing the severity of the liquidity dislocation during the crisis.[8]

[7] In unreported work, we find that execution shortfall contains significant incremental information (relative to effective and quoted spreads) about buy-side heterogeneity and buy-side exposure to funding liquidity.

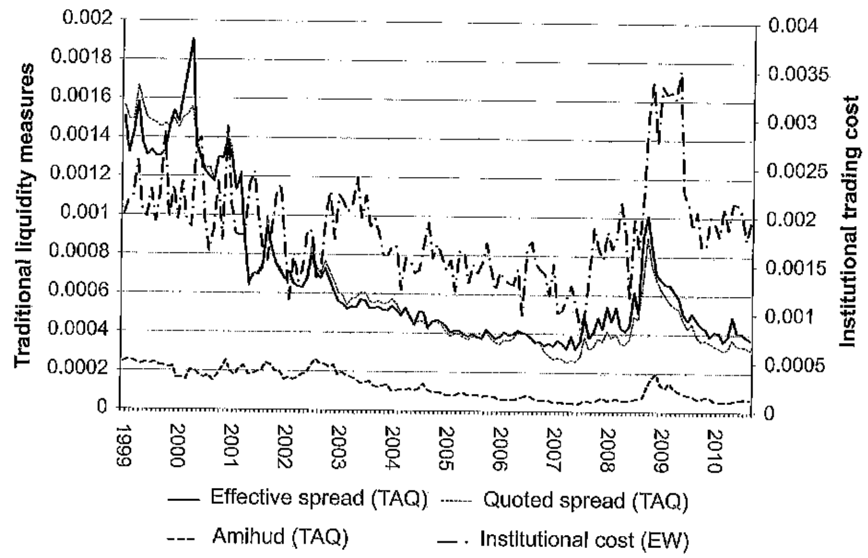

Fig. 1. Institutional trading costs versus traditional liquidity measures. The figure plots the patterns in execution shortfall, quoted bid-ask spreads, effective spreads, and ILLIQ measure. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell orders, we multiply by −1). Execution shortfall is a measure of institutional trading costs. Quoted spread is the difference between the ask and the bid price divided by the quote-midpoint, where the quotes are the national best bid and offer (NBBO). Effective spread for a buy order is the difference between the transaction price and the quote-midpoint at the time of the trade divided by the quote-midpoint (for sell orders, we multiply by −1). TAQ trades are signed based on the modified Lee and Ready (1991) algorithm. ILLIQ is measured as the absolute value of daily return for the stock divided by the dollar trading volume for the day in the stock and is multiplied by 10 million.

4.2. Trading costs during the financial crisis of 2007–09

In Table 2, we report institutional trading costs as well as several traditional liquidity measures—quoted bid-ask spread, effective spread, and ILLIQ—during the months surrounding key events in the financial crisis. For each liquidity measure, we calculate a daily volume-weighted average across all stocks and report the equally weighted daily average and standard deviation of daily averages across specified monthly and multi-monthly periods. For comparison purposes, we denote January 2007–April 2007 as the pre-crisis benchmark period. Similar to the methodology employed by Corwin and Lipson (2004) and Irvine, Lipson, and Puckett (2007), we compare the average daily trading cost during specified "crisis" event periods to the benchmark level using the standard deviation of daily trading costs in both the benchmark and event periods to construct our test statistic. In the interest of brevity, we will focus our discussion on patterns in execution shortfall reported in Panel A, but patterns for traditional liquidity measures reported in Panel B are similar.

Execution shortfall increases significantly from 12 basis points (bps) in the benchmark period to 19 bps in April 2008, when J.P. Morgan acquired the distressed investment bank Bear Stearns. Trading costs remain at elevated levels through the summer of 2008 as conditions in credit markets deteriorate and increase further to 22 bps in September 2008, 30 bps in October 2008, and to 35 bps in November 2008. Trading costs in November 2008 are almost thrice as large as those observed before the crisis. The peak of the financial crisis coincides with the failure of large institutions, such as Lehman Brothers, American International Group (AIG), Washington Mutual, and Wachovia, and the response from market regulators, including the Troubled Asset Relief Program and the short-sale ban.

A remarkable pattern in the 2007–09 crisis is that financial markets remain illiquid for an extended period of time. Specifically, in the first two quarters of 2009, trading costs stay near crisis-peak levels at about 30 bps. Some signs of recovery are observed in the last two quarters of 2009 when trading costs decline to about 20 bps. Nonetheless, almost 14 months after the collapse of Lehman Brothers, trading costs remain almost one and a half times as large as those observed before the crisis. The slow patterns of recovery are not consistent with the daily return mean-reversion patterns observed in normal periods or the relatively fast (two-week) liquidity recovery observed in prior downturns (see Hameed, Kang, and Viswanathan (2010)). Campbell, Grossman, and Wang (1993) attribute these recoveries to the quick arrival of investors who earn a premium for accommodating the liquidity demand of others. The enduring puzzle in the recent crisis is why did illiquidity persist over a long period, and what role did liquidity providers play in the dislocation and recovery?

In the rest of the paper, we identify a set of buy-side institutions whose trading style is broadly consistent with

[8] As an alternative measure, we control for market movements by subtracting the daily Standard & Poor's (S&P) 500 Index return from an institutional trade's execution shortfall adjusting for the trade's direction (see Keim and Madhavan, 1995). Trends in market-adjusted execution shortfall are similar to the unadjusted results discussed here.

Table 2
Time series of institutional trading costs.
This table reports the time series of trading costs. Panel A reports the time-series average execution shortfall for Abel Noser Solutions institutions. The sample consists of 446 institutions during the time period from January 1, 2007 to December 31, 2009. Our sample includes institutions with one hundred or more orders in a month. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell orders, we multiply by −1). We calculate the volume-weighted average execution shortfall and standard deviation of execution shortfall across all orders for each day of the sample period. In Panel A we report the average (equal-weighted) execution shortfall and standard deviation across specified monthly and multi-monthly periods (using daily averages). We test for the difference between each event period and the benchmark period using the variation of daily averages in both periods to construct our test statistic. Panel B reports the time-series average of trading cost measures obtained from either TAQ or CRSP–effective spread, quoted spread, or Amihud's (2002) illiquidity measure. Each cost measure is constructed for each stock on each trading day. We calculate the volume-weighted (dollar trading volume) average effective spread, quoted spread, or Amihud's (2002) illiquidity measure and standard deviation of each across all stocks for each day of the sample period. In Panel B we report the average (equal-weighted) effective spread, quoted spread, or Amihud's (2002) illiquidity measure and standard deviation across specified monthly and multi-monthly periods (using daily averages). Amihud's (2002) Illiq measure is multiplied by 10 million. We test for the difference between each event period and the benchmark period using the variation of daily averages to construct our test statistic. p-values, in parentheses, test for the difference between each period and the benchmark period. All numbers are in percent.

	Benchmark	Quant crisis	Bear sale	Lehman bankruptcy				After the crisis (2009)			
	(1/07–4/07)	(7/07–8/07)	(2/08–4/08)	9/08	10/08	11/08	12/08	Q1	Q2	Q3	Q4
Panel A: Execution shortfal—January 2007 to December 2009											
Execution shortfall											
Mean	0.119	0.105	0.187	0.217	0.304	0.350	0.267	0.329	0.290	0.202	0.181
p-value (diff bench)		(0.74)	(< 0.01)	(0.005)	(< 0.01)	(< 0.01)	(0.006)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
Median	0.124	0.118	0.195	0.225	0.319	0.404	0.251	0.323	0.280	0.221	0.184
Standard deviation											
Mean	1.271	1.773	2.052	2.779	3.835	3.500	3.167	2.956	2.527	1.843	1.635
p-value (diff bench)		(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
Median	1.223	1.660	1.987	2.581	3.960	3.291	3.191	2.908	2.432	1.810	1.531
Buy/sell percentage											
Buy percentage (%)	51.16	49.74	50.27	48.59	49.15	49.16	49.98	51.66	49.38	49.89	48.25
Panel B: Trading cost measures from TAQ and CRSP—January 200–December 2009											
Effective spreads											
Mean	0.0345	0.0425	0.0477	0.0895	0.1009	0.0848	0.0711	0.0663	0.0567	0.0483	0.0419
p-value (diff bench)		(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
Median	0.0333	0.0415	0.0459	0.0739	0.0945	0.0812	0.0705	0.0649	0.0570	0.0474	0.0406
Quoted spreads											
Mean	0.0267	0.0334	0.0378	0.0660	0.0898	0.0752	0.0682	0.0596	0.0513	0.0424	0.0363
p-value (diff bench)		(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
Median	0.0264	0.0331	0.0374	0.0657	0.0859	0.0739	0.0682	0.0595	0.0519	0.0423	0.0352
Amihud's illiquidity											
Mean	0.0046	0.0051	0.0063	0.0075	0.0132	0.0175	0.0197	0.0139	0.0106	0.0080	0.0074
p-value (diff bench)		(0.008)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)	(< 0.01)
Median	0.0045	0.0050	0.0060	0.0073	0.0125	0.0163	0.0178	0.0129	0.0100	0.0077	0.0068

liquidity provision. We examine whether these institutions alter trading behavior during the crisis and to what extent altered preferences can explain the post-crisis recovery patterns in liquidity.

4.3. *Identifying liquidity supplying institutions*

Are all institutions equally affected by the financial crisis? We propose that buy-side institutions differ in their trading style. The cross-section includes those institutions that tend to demand liquidity as well as those that absorb the aggregate order imbalance of other traders and act as liquidity providers. For example, an investment strategy based on short-term trend following can lead to a liquidity demanding trading style. An often-cited example of a liquidity supplying institution is a passive small-cap fund managed by Dimensional Fund Advisors (see Da, Gao, and Jagannathan, 2011). Keim (1999) estimates that, over the period 1982–1995, the fund earned an annual premium of 2.2% over a pure indexing strategy.

We separate institutions into liquidity supplying and liquidity demanding category based on their trading style. Our measure of an institution's trading style is the institution's propensity to trade in the direction of the daily return in the stock. Specifically, we classify a buy order as being *Volume_With* if the stock return for the day is positive and *Volume_Against* if the stock return for the day is negative; the converse for sell orders. For each institution, we calculate a *Trading style* based on the aggregate dollar trading volume with and against the contemporaneous daily stock return in each month, as

$$\text{Trading style} = \frac{\sum Volume_{With} - \sum Volume_{Against}}{\sum Volume_{With} + \sum Volume_{Against}} \tag{2}$$

Each month, we sort institutions into quintile portfolios based on Trading style (TS), a simple measure of whether the institution exhibits a proclivity to trade with or against the direction of the stock's return.[9] In Table 3, Panel A, we report the equally weighted average of TS

[9] We also define TS using daily order imbalances from TAQ data, rather than daily stock returns, and obtain similar results. These results are not reported for brevity but are available from the authors.

Table 3
Institutional trading style persistence and execution shortfall 1999–2010.
This table reports the persistence in Trading style (TS) and the execution shortfall trading costs for institutions classified as High and Low TS. The sample is based on trades from 982 institutions during January 1999–September 2010. Our sample includes institutions with one hundred or more orders in a month. Institutions are classified based on trading patterns observed for the institution each month. Specifically, we classify a buy (sell) order as being $Volume_{With}$ if the stock return for the day is positive (negative) and $Volume_{Against}$ if the stock return for the day is negative (positive). For each institution, we calculate a TS based on the aggregate dollar trading volume with and against the stock return in each month, as follows: Trading style=$[\Sigma Volume_{With} - \Sigma volume_{Against}]/[\Sigma Volume_{With} + \Sigma volume_{Against}]$. We sort institutions into quintile portfolios based on the TS. We classify Q5 institutions as Liquidity demanding (LD) TS and Q1 institutions as Liquidity supplying (LS) TS. In Panel A, we report the average TS measure across institutions in each quintile in the 12-month period following portfolio formation. In Panel B, we calculate the volume-weighted average execution shortfall (in percentage) across the orders for each institution in the month following the TS ranking and report the average (equal-weighted) execution shortfall for institutions in the quintiles. We perform our analysis for four time periods: 1999–2006, 2007–2008, 2008–2009, and 2009–2010. Numbers in parentheses are p-values, which are computed based on two-way clustered standard errors.

Panel A: Trading style persistence

	Trading style						
Current quarter performance quintiles	Portfolio formation month	M+1	M+2	M+3	M+6	M+9	M+12
Q1 *Liquidity supplying style*	−0.197	−0.059	−0.060	−0.055	−0.051	−0.046	−0.043
Q2	−0.017	0.025	0.030	0.029	0.028	0.032	0.031
Q3	0.066	0.065	0.065	0.067	0.066	0.063	0.067
Q4	0.147	0.103	0.103	0.099	0.101	0.099	0.096
Q5 *Liquidity demanding style*	0.301	0.167	0.163	0.161	0.156	0.151	0.144
Q5 − Q1	0.498	0.226	0.223	0.216	0.207	0.197	0.187
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)

Panel B: Institutional trading costs by trading style

	Execution shortfall			
	1999–2006	1/2007–8/2008 (pre-crisis)	9/2008–3/2009 (crisis)	4/2009–9/2010 (post-crisis)
Q1 *Liquidity supplying style*	−0.051	−0.092	−0.048	−0.037
Q2	0.139	0.098	0.178	0.119
Q3	0.236	0.174	0.360	0.244
Q4	0.337	0.283	0.470	0.334
Q5 *Liquidity demanding style*	0.547	0.442	0.671	0.500
Q5 − Q1 (Exec. shortfall)	0.598	0.535	0.719	0.538
	(< 0.001)	(< 0.001)	(< 0.001)	(< 0.001)

across all institutions in each quintile. The average TS for institutions in the highest TS quintile (Q5 institutions) is positive suggesting that these institutions have a tendency to trade in the same direction as daily returns; the converse is true for institutions in the lowest TS quintile (Q1 institutions).

In Table 3, Panel A shows that TS is highly persistent. We report the average TS in future months $M+1$ through $M+12$ for institutions sorted into TS quintiles in month M. We note that TS increases monotonically from quintile 1 to quintile 5 in all future months. Importantly, the TS for Q1 institutions continues to be negative, the TS for Q5 institutions continues to be positive, and the Q5−Q1 difference is statistically significant in all future months. To account for possible dependencies across institutions and through time, we calculate the test statistic for the Q5−Q1 difference based on two-way clustered standard errors (see Moulton, 1986; Thompson, 2011). These results suggest that trading style captures an important dimension of the institution's trading behavior. For ease of exposition, we classify Q5 institutions, which trade more often with the market, as liquidity demanding (LD) and Q1 institutions, which trade more often against the market, as liquidity supplying (LS).

In Table 3, Panel B shows the monthly execution shortfall for different subperiods by TS. Specifically, we calculate a volume-weighted execution shortfall for each institution in each month and assign each institution to a TS quintile based on prior month TS. We then compute a simple average execution shortfall across all institutions in each TS quintile and test for differences between Q5 and Q1 using a methodology identical to that employed in Table 3, Panel A. Across all sample subperiods, LS institutions have negative trading costs while LD institutions have positive trading costs and the Q5−Q1 difference in trading costs in the month following quintile formation is statistically significant. Additionally, the patterns in Fig. 2 indicate that the difference changes over time. LD institutions are the primary beneficiaries of improved liquidity over 1999–2007 while LS institutions' costs are relatively unchanged.

The trading cost spread between LD and LS institutions in 1999–2006 averages 60 bps (Table 3, Panel B). The spread declines to 54 bps between January 2007 and August 2008.[10] However, the long-term trend in declining spread is reversed with an increase to 72 bps in the crisis-peak (September 2008–March 2009). We show that LD

[10] Fig. 2 aggregates costs across all institutions in a quintile-month, while Table 3, Panel B first aggregates for each institution and then across institutions in a month. Both methodologies yield similar inferences.

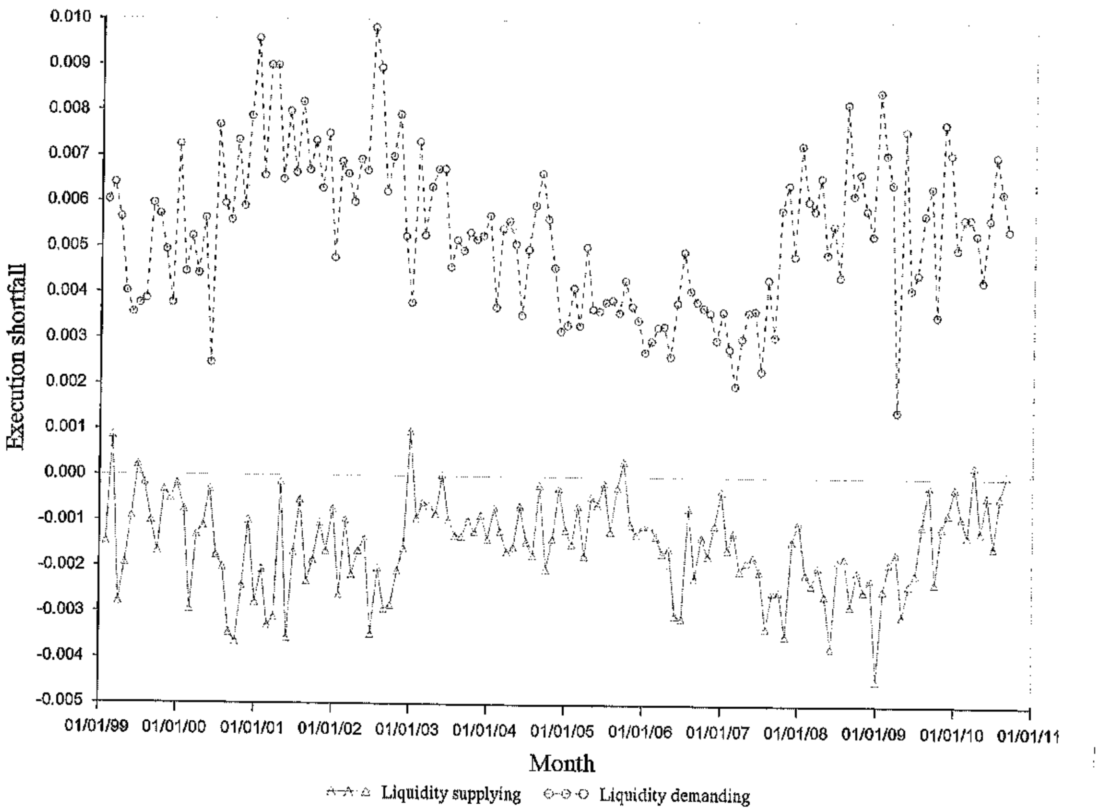

Fig. 2. Trading cost patterns for LS and LD institutions 1999–2010. This figure shows Execution shortfall for institutions classified as liquidity demanding (LD) and liquidity supplying (LS) institutions. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell orders, we multiply by −1). Each month, we assign institutions into quintile portfolios based on Trading style for the prior month. We calculate the trade volume-weighted average execution shortfall across all orders for each institution quintile. The figure plots the trade volume-weighted average execution shortfall in percentage for LS (Quintile 1) and LD (Quintile 5) institutions.

institutions experience a sharp increase in trading costs, from 44 bps before the crisis to 67 bps in the crisis-peak that then declines to 50 bps after the crisis-peak (April 2009–September 2010). In contrast, LS institutions are relatively insulated from market conditions during the crisis.

Table 3 and Fig. 2 show that the liquidity patterns in Table 2 do not represent the reality of transaction costs incurred by the cross-section of institutions. We identify a subset of institutions that are relatively insulated and in fact appear to be better off during the peak of the financial crisis. What can explain the differences across institutions? One possibility is that the results in Fig. 2 simply reflect that LD institutions are selling a disproportionate amount of shares while LS institutions are buying a disproportionate amount of shares during the crisis. In results not reported in the paper, we do not observe significant differences in the buy and sell volume percentages of LS and LD institutions in the crisis months. Thus, the results point to a more complex explanation than LD institutions simply dumping shares at fire-sale prices.

In Fig. 3, we plot the trading cost of buys and sells separately for LS and LD institutions over the 2006–2010 period. Specifically, 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 the buy and sell contributions equals the total (volume-weighted) execution shortfall for the institution in the month. We report the volume-weighted average in the two groups. Trading cost patterns are markedly different for the two groups. Before the crisis, LS institutions generally receive negative trading costs on buys and sells, suggesting they were responding to buy-sell imbalances. However, during the crisis-peak, even LS institutions pay positive execution costs for sell orders but earn large negative trading costs for buy trades. In contrast, LD institutions pay positive execution costs for both buys and sells and additionally, the costs for buy orders remain positive even during the peak of the financial crisis.

In our analyses of the trading behavior of LS and LD institutions, we find certain patterns that buttress the role of LS institutions as liquidity suppliers. During the crisis period, these institutions supply more liquidity with their buy trading and they are more likely to trade against a stock's return. Furthermore, LS institutions supply liquidity with their buy trades in stocks that experience large negative returns on adjacent days, thus providing liquidity to stocks under considerable selling pressure. By supplying liquidity at these times, LS institutions earn a significant liquidity premium. In contrast, LD institutions tend to buy on days when the stock has consecutive days

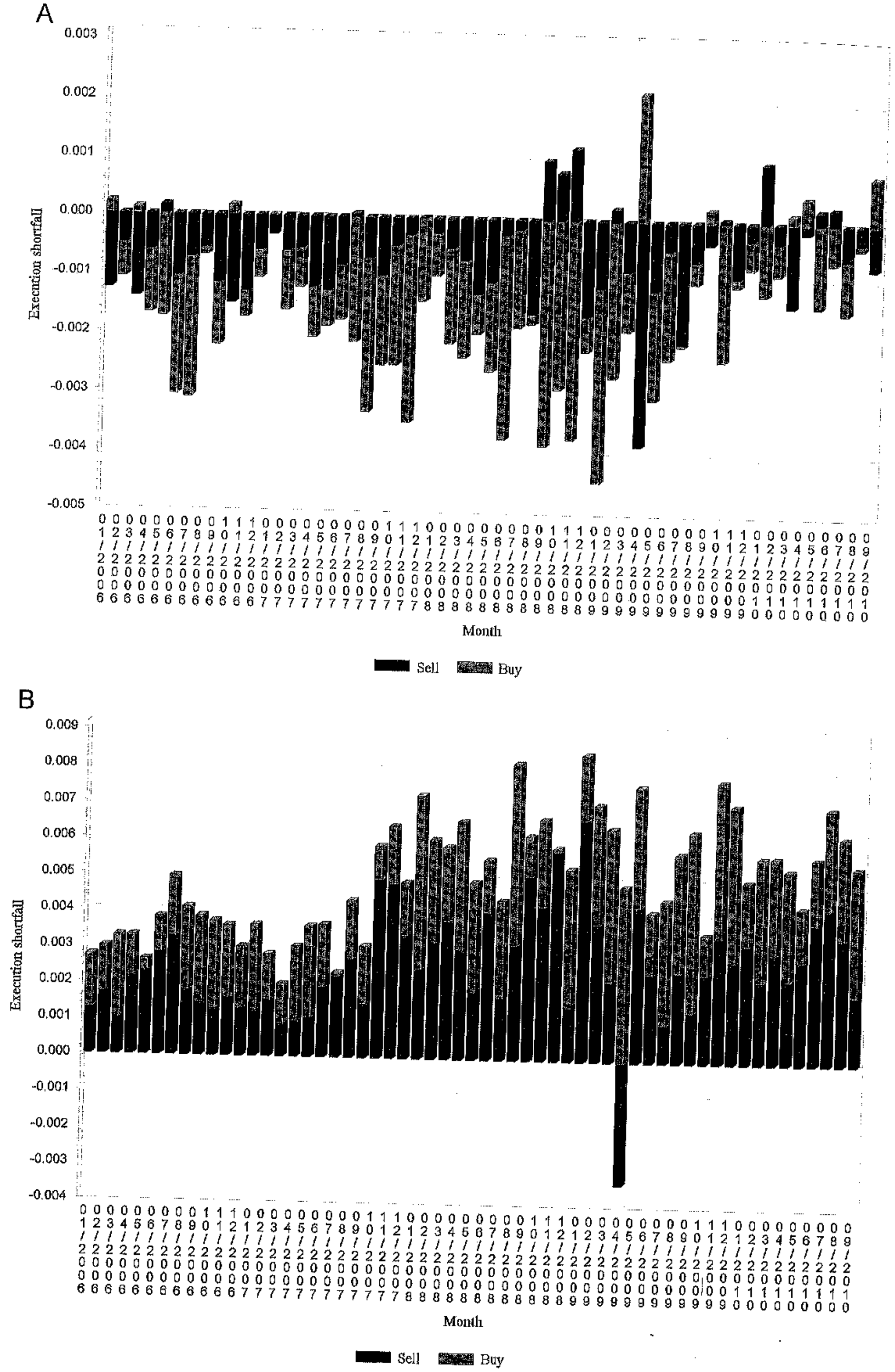

Fig. 3. Execution shortfall for buys and sells during the financial crisis. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell orders, we multiply by −1). We calculate the volume-weighted average execution shortfall across all orders for each institution quintile (based on trading style) each month separately for buy and sell trades. The figure plots the execution shortfall for liquidity supplying (Quintile 1, see Panel A) and liquidity demanding (Quintile 5, see Panel B) institutions in the month following

of positive returns. Thus, LD institutions pay a premium to consume liquidity even on their buy orders during the crisis.

In Fig. 4, we examine whether trading costs differ across LS and LD institutions for certain types of stocks. We decompose the total execution costs of LS and LD institutions into the costs associated with each market-value quintile, following a methodology similar to the buy-sell decomposition. Consistent with Fig. 3, the patterns reveal that LS institutions tend to get paid for executions while LD institutions tend to pay for execution across all firm-size groups.

Trading costs for LD institutions and LS institutions are not expected to be mirror images of each other. This is because it is highly unlikely that LD buy-side institutions trade directly with LS buy-side institutions. It is more likely that LD institutions trade for the most part with short-horizon liquidity providers, such as NYSE Specialists, broker-dealers, and high-frequency firms, and short-horizon liquidity providers offset their inventory position with long-horizon liquidity providers, such as LS institutions. Thus, the difference between the LS and LD execution shortfall is a measure of the compensation for short-horizon liquidity providers.

4.4. Trading style and liquidity factor exposures

The results thus far indicate that not all institutions pay higher trading costs during the crisis. The evidence in Figs. 1 and 2 suggests that trading cost patterns of LD institutions are similar to those observed for the overall market (i.e., effective spreads). But what determines the trading costs of LS institutions? Theoretical papers recognize that shocks to intermediary funding can impair the provision of liquidity (see Brunnermeier and Pedersen, 2009; Acharya and Viswanathan, 2011). In the recent crisis, traders experienced a significant increase in margin requirements on loans, a sharp increase in borrowing costs, and a severe decline in lending activity among intermediaries. Specifically, the TED spread, which is the difference between the London Interbank Offered Rate (LIBOR) and the U.S. Treasury bill rate, increased from about 0.5% in July 2007 to a record 4.5% during the crisis-peak. Krishnamurthy (2010) observes that monthly dealer repo activity dropped from about \$4 trillion in July 2007 to \$2.5 trillion in January 2009.[11] The *Noise* measure proposed by Hu, Pan, and Wang (2012), which proxies for the (inverse of) amount of arbitrage capital in the market, increased from 4 bps before the crisis to 15 bps in the crisis. If LS institutions are long-horizon liquidity suppliers, are they sensitive to funding liquidity shocks, similar to other liquidity suppliers? When intermediary capital is scarce and/or funding cost is high, do LD institutions pay more to complete executions while LS institutions get paid more for liquidity provision? In this section, we examine the association between TS, liquidity measures, and proxies for funding liquidity.

In Table 4, the dependent variable is the monthly execution shortfall for LD and LS institutions, respectively, over the 1999–2009 period. The explanatory variables include proxies for funding liquidity including Chicago Mercantile Exchange (CME) margin (on S&P 500 futures contract), TED spread, Dealer repos, and the Noise measure. Dealer repos are the cumulative difference in short-term lending by U.S. primary dealers reported by the New York Federal Reserve. Repos are included to capture the credit conditions similar to the TED spread, but repos are a more specific measure of capital available to market intermediaries.

We find strong empirical support for the three-group framework of market intermediation. Specifically, in the regression with Dealer repo as the explanatory variable, the coefficient for LD institutions is negative and the coefficient for LS institutions is positive (both highly statistically significant). Thus, an increase in short-term dealer lending activity reduces trading costs for LD institutions but increases trading costs for LS institutions. Stated differently, since LS institutions have negative execution shortfall (see Table 2), the interpretation is that LS institutions get paid less for liquidity provision when dealer capital is plentiful (see Fig. 5). Similarly, for the Noise measure, the positive coefficient for LD institutions suggests that LD institutions pay more to complete executions when arbitrage capital is constrained while the negative coefficient for LS institutions suggests that they get paid more for liquidity provision when capital is constrained. For CME margin, the coefficients for both LD and LS institutions are statistically insignificant while for TED spread, only the coefficient for LS institutions is statistically significant with a negative sign. Since the proxies for funding liquidity are highly correlated, we run a principal component analysis and report results with two principal components as explanatory variables. The first and the second principal component explain 53% and 33%, respectively, of the total variance and are significant in both regressions. Overall, the results support the three-model framework presented in the study that dealer funding has the opposite effects on the LD and LS institutional groups. That is, LD institutions pay more to complete executions, while LS institutions get paid more for liquidity provision when funding liquidity is scarce.

Table 4 also examines the association between execution shortfall and traditional liquidity measures such as market-wide effective spreads, ILLIQ, and the Pastor and Stambaugh (2003) liquidity level measure.[12] Effective spreads and ILLIQ are monthly averages across stocks. For LD institutions, the coefficients on effective spreads and ILLIQ are positive and statistically significant, and the model Adjusted-R^2 exceeds 68%. The strong association with effective spreads (see Fig. 5), which measures the cost of immediacy for small market orders, supports the idea that LD trading style corresponds with liquidity

[11] See Table 4 in Krishnamurthy (2010) for evidence that it became more costly to obtain financing for riskier securities. Specifically, for asset-backed securities, the repo haircuts increased from 10% in spring 2007–40% during the fall of 2008. During the same period, the repo rates remained stable at 2% for short-term U.S. Treasuries.

[12] We thank Lubos Pastor for providing monthly market liquidity statistics on his Web site.

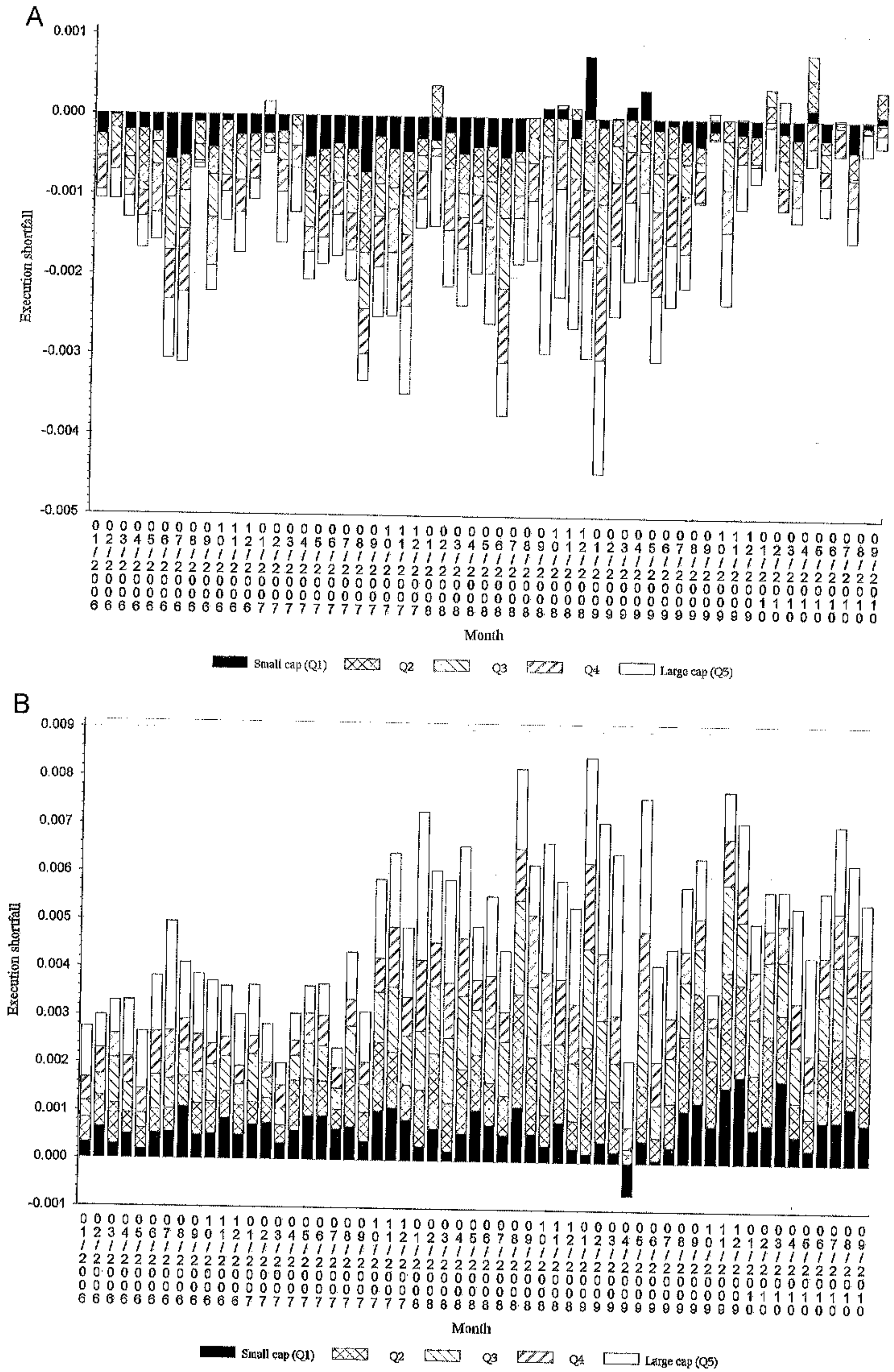

Fig. 4. Execution shortfall for market value quintiles during the financial crisis. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell orders, we multiply by −1). We calculate the volume-weighted average execution shortfall across all orders for each institution quintile (based on trading style) each month separately for trades in each NYSE market-value quintile. The figure plots the execution shortfall for liquidity supplying (Quintile 1, see Panel A) and liquidity demanding (Quintile 5, see Panel B) institutions in the month following the trading style ranking.

Table 4
Trading style and liquidity exposure.
This table presents regression coefficients of the execution shortfall of liquidity supplying (LS) and liquidity demanding (LD) institutions on proxies for funding liquidity and traditional liquidity measures over the sample period 1999–2010. We sort institutions into quintile portfolios based on Trading style (TS). We classify Q5 institutions as LD and Q1 institutions as LS. We calculate the volume-weighted execution shortfall (in percentage) across the orders for each Style quintile in the month following the TS ranking. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell orders, we multiply by −1). Ted spread is the difference between LIBOR less T-bill 3-month interest rates (in percent). CME margin is the margin on S&P500 futures contract traded in the Chicago Mercantile Exchange for the month. Noise is the Treasury market noise measure from Hu, Pan, and Wang (2012). Dealer repos are the primary dealer net overnight funding positions from the New York Fed ($B). Principal components 1 and 2 are the first and second principal components of the funding liquidity measures. TAQ trades are signed based on the modified Lee and Ready (1991) algorithm. ILLIQ is measured as the absolute value of daily return for the stock divided by the dollar trading volume for the day in the stock. Liquidity level is the Pastor and Stambaugh (2003) illiquidity measure. Newey-West adjusted p-values are reported below the coefficient estimates.

	Liquidity Demanding institutions							Liquidity Supplying institutions						
Funding liquidity:														
CME margin	0.007							−0.005						
	(0.10)							(0.10)						
TED spread		0.001							−0.001					
		(0.06)							(0.00)					
Dealer repo			−0.018							0.063				
			(0.00)							(0.00)				
Noise				0.001							−0.001			
				(0.00)							(0.02)			
Principal component 1					0.003		0.001					−0.002		−0.001
					(0.01)		(0.98)					(0.02)		(0.88)
Principal component 2					−0.005		−0.001					−0.002		−0.001
					(0.00)		(0.38)					(0.01)		(0.04)
Traditional liquidity measures:														
Effective spread (%)						1.867	1.831						−0.999	−1.037
						(0.00)	(0.00)						(0.00)	(0.00)
Amihud ILLIQ						58.374	52.830						−23.01	−33.020
						(0.00)	(0.00)						(0.21)	(0.20)
Liquidity level						−0.001	−0.001						0.0012	0.009
						(0.06)	(0.05)						(0.04)	(0.18)
Intercept	0.002	0.002	0.003	0.002	0.002	0.0002	0.003	−0.001	−0.001	−0.002	−0.001	−0.001	−0.0003	−0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.02)	(1.74)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)	(0.32)
Adj.-R^2 (%)	0.6	1.7	35.2	11.1	26.1	68.1	66.7	0.2	2.9	7.6	4.9	6.9	33.5	32.3

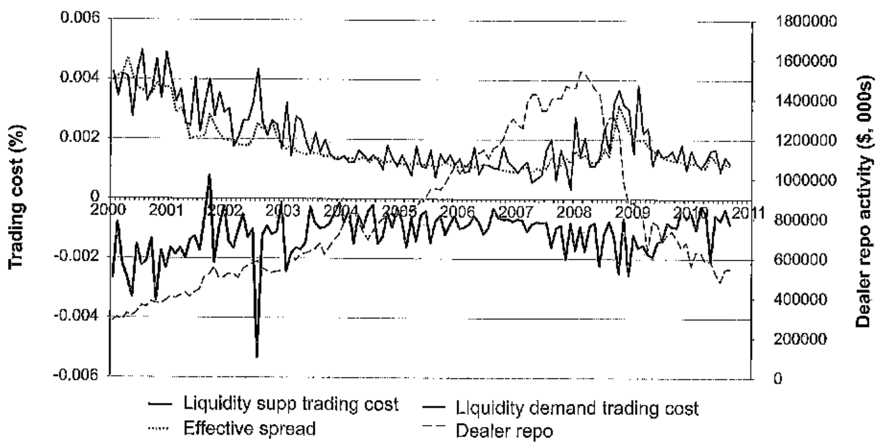

Fig. 5. Execution shortfall, effective spreads, and dealer repurchase activity. The figure plots the patterns in execution shortfall for liquidity demanding (LD) and liquidity supplying (LS) institutions, effective spreads, and Dealer repurchase activity from 2000 to 2010. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell orders, we multiply by −1). Execution shortfall is a measure of institutional trading costs. We sort institutions into quintile portfolios based on TS and classify Q5 institutions as LD and Q1 institutions as LS. We sign TAQ trades used in the effective spread calculation based on the modified Lee and Ready (1991) algorithm. Dealer repos are the primary dealer net overnight funding positions from the New York Fed ($000s).

consumption. For LS institutions, the effective spread coefficient has a negative sign and the model Adjusted-R^2 exceeds 33%. The lower (or more negative) execution shortfall for LS institutions when effective spreads are higher suggests that LS institutions are paid more for supplying liquidity when liquidity is scarce. As can be

seen from Fig. 5, LS institutions are relatively better off during the peak of the financial crisis. This heterogeneity in liquidity exposure across institutions based on their trading style is a novel finding of our study. We note that trading style has important implications for the liquidity risk management of institutions. In the rest of the paper, we examine the implications of trader heterogeneity for long-horizon recovery patterns after the crisis.

5. The trading activity of liquidity supplying (LS) institutions in the crisis

5.1. Do LS institutions change trading behavior during the crisis?

How do institutions respond to a liquidity shock? One possibility is that institutions whose trading style corresponds with liquidity provision in normal times switch roles and consume liquidity in light of investor redemptions or other funding shocks during the crisis. Although the results in Table 3, Panel A suggest that TS for LS institutions is persistent, it is possible that average effects in Table 3 are dominated by the trading behavior of institutions in non-crisis months. In Fig. 6, we provide an explicit analysis of the time series of TS scores during the 2007–2009 financial crisis. Specifically, we sort institutions into quintiles based on their TS in January to April 2007 and then report TS for quintiles formed in this period for each month between May 2007 and December 2009. We find that Trading style for LS institutions remains negative and Trading style for LD institutions remains positive in the crisis. We find no evidence suggesting that LS institutions switched roles from liquidity provision to liquidity consumption.

Another possibility is that although LS institutions continue to supply liquidity, they curtail trading activity in light of higher funding risk during the crisis. We calculate the relative dollar trading volume share of LS institutions as a proportion of all Abel Noser Solutions volume in the month. Since LS institutions are identified using prior month ranking, we use the trading volume of Abel Noser Solutions institutions ranked in the prior month to calculate total Abel Noser Solutions volume. In results not reported in the paper, we plot the relative volume for each month in the crisis benchmarked against the pre-crisis months. We find that LS institutions' participation increases sharply in August to October 2008, when the crisis became severe, but that LS institutions do not sustain this higher level of participation in November 2008. Overall LS institution participation exceeds those observed before the crisis in 16 of the 18 months between May 2008 and December 2009. Thus, we find no evidence that LS institutions curtail trading activity relative to the other institutions in the Abel Noser Solutions data set.

We analyze other dimensions of an institution's decision to supply liquidity including the speed of execution and the size of the order. In light of higher uncertainty, it is possible that LS institutions reduce order size and/or increase order execution speed during the crisis. A buy-side trading desk typically breaks up a large order and works the order over time. The analysis thus far aggregates all executions by the same institution on the same side (buy or sell) in the same stock on each day. The choice of daily aggregation is based on discussions with Abel Noser Solutions officials and institutional traders regarding a reasonable horizon to aggregate orders for an institutional decision. However, the daily aggregation does not capture some large orders with multiday executions. Further, because the intraday time stamps in the Abel Noser Solutions database are incomplete, the daily aggregation does not permit an analysis of execution speed within the day. We therefore implement an algorithm to "stitch" seemingly related orders in the database into a single multiday execution. Specifically, we group all orders from the same institution with the same side of the trade in a given stock over adjacent days into a multiday order.[13] We use the opening price on the first day of the multiday order as the pre-trade benchmark price for all executions that comprise a multiday order. We delete observations where the execution shortfall exceeds an absolute value of 10%.

Fig. 7 presents an analysis of LS institutions' multiday order size and execution speed. The relative order size is the ratio of average multiday order size (in dollars) in a crisis month relative to average multiday order size in the benchmark period. Consistent with funding shocks affecting liquidity provision, we find that LS institutions reduce order size during the crisis (see Fig. 7, Panel A). Specifically, order size for large and small stocks declines by 50% and 70%, respectively, but reverts towards pre-crisis levels by the fourth quarter of 2009. While order size declines for both large and small stocks, LS institutions' response on execution speed differs markedly between large and small stocks (see Fig. 7, Panel B). Execution speed is defined as the average proportion of a multiday order executed on each day. As an example, execution speed for an order that is executed in a single day is 1.0. The statistic is lower if institutions spread the trade over an increasing number of days and higher if institutions concentrate execution over fewer days. Our results indicate that execution speed declines for large stocks but increases for small stocks during the crisis.

5.2. Do liquidity supplying institutions withdraw from certain stocks?

The evidence thus far suggests that LS institutions continue to supply liquidity in the crisis. We present preliminary evidence that these institutions speed up executions in small stocks while trading larger stocks more patiently. Variations in institutional response based on stock characteristics are predicted by several theoretical models. The key idea is summarized by Gromb and Vayanos (2012) who note that liquidity providers should

[13] Given that our "order-stitching" algorithm is an imperfect approximation for observed executions that constitute an order, we truncate our sample to include orders that span five or fewer trading days, based on the approach in Anand, Irvine, Puckett, and Venkataraman (2012). We selected five days after speaking with several professional traders on a reasonable choice for this purpose. In our sample, five days lies on the 95[th] percentile of the distribution of the duration for stitched orders.

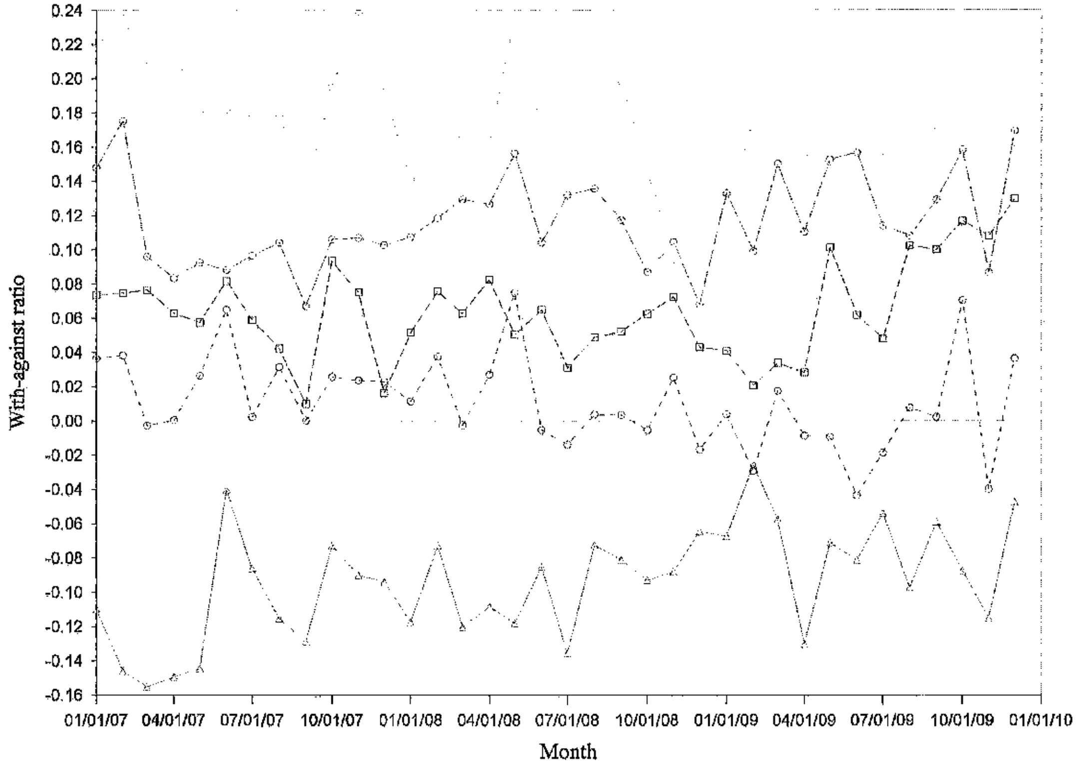

Fig. 6. Trading style persistence during the crisis. This figure presents our measure of trading style (TS) for institutions ranked into TS quintiles during a benchmark period (January–April 2007). Institutions are classified based on trading patterns observed for the institution during the benchmark period. Specifically, we classify a buy (sell) order as being $Volume_{With}$ if the stock return for the day is positive (negative) and $Volume_{Against}$ if the stock return for the day is negative (positive). For each institution, we calculate a TS based on the aggregate dollar trading volume with and against the stock return in the benchmark period as follows: Trading style$=[\Sigma Volume_{With}-\Sigma volume_{Against}]/[\Sigma Volume_{With}+\Sigma volume_{Against}]$. We sort institutions into quintile portfolios based on the TS during the benchmark period and classify Q5 institutions as Liquidity demanding (LD) TS and Q1 institutions as Liquidity supplying (LS) TS. We present the average TS of the institutions in a quintile in subsequent months, where TS for a quintile is measured as an equal-weighted average across institutions in the quintile.

withdraw from opportunities that tie up more capital. Huang and Wang (2009) predict less liquidity provision for small stocks and Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009) predict less liquidity provision for volatile stocks. In this section, we investigate whether LS institutions withdraw from riskier stocks in a crisis.

In Table 5 we report trading activity of LS institutions in stock characteristic quintiles formed on NYSE market cap in Panel A, return volatility in Panel B, and *Noise* beta in Panel C. Similar to Fig. 7, the benchmark statistic is based on the LS institutions' trading activity in the stock characteristic quintile from January 2008 to April 2008.[14] In Panel A of Table 5 we report that LS institutions are more active during the benchmark period in large stocks (49% of trading activity) than small stocks (4.2% of trading activity). We calculate a *relative proportion* measure over the September 2008 to November 2009 period, defined as the ratio of LS institutions' proportion of their total trading in a stock characteristic quintile over a crisis-month relative to the same measure over the benchmark period. The relative proportion accounts for time-series variation in overall trading activity in the crisis. A relative proportion of 1.0 indicates that LS trading activity in a crisis-month is no different from the benchmark period. We report the relative proportion and p-value of the test that the relative proportion for a month equals one. The test statistic for each stock characteristic quintile is constructed using the standard deviation of daily relative proportions in the event period. The statistic comparing differences in relative proportions across quintiles tests for differences in the daily time series of relative proportions across the two groups.

The results on LS activity patterns in Panel A strongly support theoretical predictions. For small firms, the relative proportion declines to 0.35 in November 2008 suggesting that LS participation in small stocks in November 2008 is only 35% of LS participation observed for small stocks before the crisis (see Fig. 8). For large stocks, the patterns are distinctly different as relative proportion increases to 1.22 in November 2008. These patterns indicate that LS institutions tilt their trading activity away from small stocks during the crisis.

[14] We recognize that the benchmark period includes the collapse of Bear Stearns in March 2008. We replicate the analysis using January 2007–April 2007 as the benchmark period and find similar results.

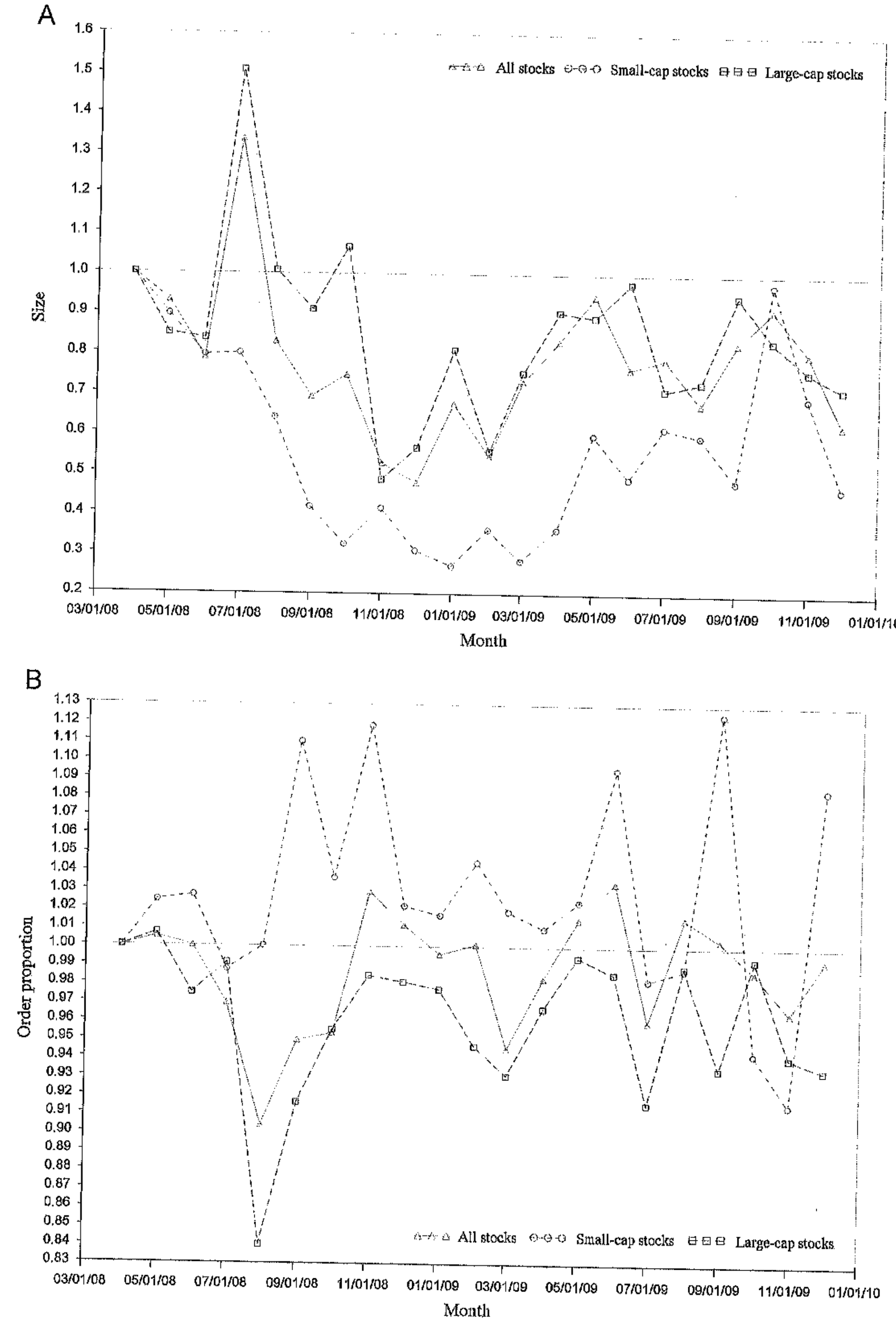

Fig. 7. Stitched order size and trading strategies of LS institutions during the crisis. This figure shows relative order size and execution speed for liquidity supplying (LS) institutions from May 2008 to December 2009. We group all orders from the same institution with the same side of the trade in a given stock over adjacent days into a multiday order. Panel A presents the relative order size (in dollars), which is the ratio of the average multiday order size in a crisis-month relative to the average multiday order size in the benchmark period. Panel B presents the average multiday order proportion executed in a day relative to a benchmark period. Our sample includes institutions with one hundred or more orders in a month. The observation for April 2008 represents the average of the first four months of 2008 (i.e., benchmark period) and equals one by construction.

Table 5

Do LS institutions avoid riskier stocks during the financial crisis?

The table reports on the trading behavior of liquidity supplying (LS) institutions during the financial crisis. Each month, we assign institutions into quintile portfolios based on Trading style (TS) for the prior month. The lowest quintile institutions are classified as LS institutions. We calculate the daily relative proportion of dollar volume traded in a particular stock characteristic quintile by LS institutions (as a group). The proportions are calculated relative to the daily average in the benchmark period (January to April 2008). The equal-weighted daily averages within a month are reported below. Our sample includes institutions with one hundred or more orders in a month. Panel A presents the relative proportion of trading activity across NYSE market value quintiles. Panel B presents the relative proportion of trading activity across volatility quintiles. Panel C presents the relative proportion of trading activity across noise beta quintiles. p-values are reported for tests that the relative values equal one.

	Quintile	Benchmark period 01–04/2008	Relative to benchmark period								
			9/ 2008	10/ 2008	11/ 2008	1/ 2009	3/ 2009	5/ 2009	7/ 2009	9/ 2009	11/ 2009
Panel A: Proportion of trading volume in market-value quintile											
Proportion of volume in quintile	Small cap	4.20%	0.44	0.41	0.35	0.43	0.28	0.48	0.64	0.67	0.83
p-value (test relative proportion=1)			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Proportion of volume in quintile	Large cap	49.72%	1.28	1.28	1.22	1.19	1.20	1.10	0.95	1.05	1.09
p-value (test relative proportion=1)			0.00	0.00	0.00	0.00	0.00	0.00	0.09	0.07	0.00
p-value small=large			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Panel B: Proportion of trading volume in volatility quintile											
Proportion of volume in quintile	Low volatility	37.10%	1.19	1.29	1.23	1.31	1.21	1.12	0.89	1.06	1.02
p-value (test relative proportion=1)			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.03	0.61
Proportion of volume in quintile	High volatility	9.21%	1.04	0.82	0.82	0.73	0.83	0.88	1.08	0.89	1.05
p-value (test relative proportion=1)			0.32	0.00	0.00	0.00	0.00	0.03	0.15	0.01	0.59
p-Value low=high			0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.73
Panel C: Proportion of trading volume in noise beta quintile											
Proportion of volume in quintile	Low beta	9.96%	0.77	0.85	1.00	1.09	0.93	0.95	1.03	1.00	0.94
p-value (test relative proportion=1)			0.00	0.00	0.95	0.06	0.14	0.38	0.62	0.95	0.07
Proportion of volume in quintile	High beta	11.84%	0.82	0.69	0.61	0.58	0.76	0.89	0.99	0.95	0.96
p-value (test relative proportion=1)			0.00	0.00	0.00	0.00	0.00	0.01	0.84	0.24	0.34
p-value low=high			0.34	0.00	0.00	0.00	0.01	0.33	0.59	0.47	0.67

The patterns for volatility quintiles in Panel B are also supportive of theoretical predictions. We stratify stocks into volatility quintiles based on the standard deviation of daily returns in calendar year 2006. Returns are based on daily bid-ask closing quote midpoints obtained from CRSP. Only stocks with at least 50 observations are included in the analysis. In the benchmark period, LS institutions are more active in low-volatility stocks than high-volatility stocks. This is consistent with Panel A results since smaller stocks tend to be more volatile. As predicted by theory, the relative proportion of LS institutions in November 2008 declines for high-volatility stocks to 82% of the benchmark and increases for low-volatility stocks to 123% of the benchmark.

In Panel C, we report LS institutions' activity in *Noise* beta quintiles. A stock's Noise beta measures the sensitivity of the stock's liquidity to the availability of capital to arbitrageurs (or liquidity providers) in financial markets. We estimate Noise beta as the stock-specific coefficient from a regression of each stock's execution cost on the Noise measure from Hu, Pan, and Wang (2012). Trading activity in low and high Noise beta stocks is similar in the benchmark period, but exhibits distinctly different patterns in the crisis. To be specific, while trading activity of LS institutions in low Noise beta stocks in November 2008 is no different from the benchmark period, their activity in high Noise beta stocks declines to 61% of the benchmark activity. The results provide direct evidence that LS institutions withdraw from stocks with greater dependence on arbitrage capital when capital is scarce.

If funding constraints drive institutional participation, we expect trading patterns to revert to normal levels once funding constraints are not binding. Indeed, we find that the reduction in LS trading activity in risky stocks is temporary. In Panel A, the relative proportion for small stocks, which declines to 0.28 by March 2009, slowly reverts to 0.83 by November 2009. Similarly, the relative proportion for high-volatility stocks and the high Noise beta stocks is insignificantly different from 1.0 to July 2009.

To summarize, the 2007–09 financial crisis provides a convenient laboratory to study how liquidity providers behave in a crisis. As far as we are aware, there is little direct empirical evidence on institutional behavior mainly because crisis events of the magnitude observed in 2007–09 are rare but also because publicly available data sets do not provide details on institutional trades. An important finding of the study is that long-horizon liquidity

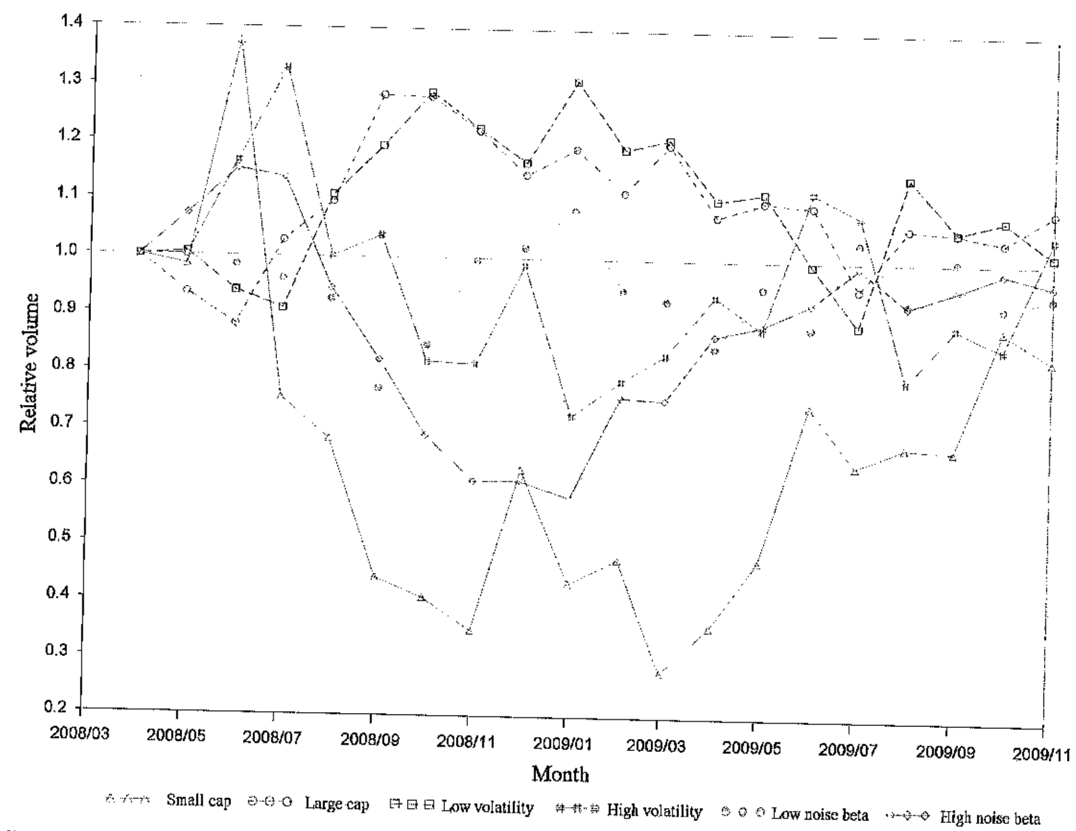

Fig. 8. Trading preferences of LS institutions during the crisis. This figure shows relative trading activity of liquidity supplying (LS) institutions for stocks in extreme quintiles formed on market cap, volatility, and noise beta during the time period from May 2008 to December 2009. Each month, we assign institutions into quintile portfolios based on Trading style (TS) for the prior month and classify the lowest quintile as LS institutions. We calculate the daily relative proportion of dollar volume traded in a particular stock characteristic quintile by LS institutions (as a group). The proportions are calculated relative to the daily average in the benchmark period (January–April 2008). The equal-weighted daily averages within a month for the time period from April 2008 to December 2009 are plotted. Our sample includes institutions with one hundred or more orders in a month. The observation for April 2008 represents the average of the first four months and equals one by construction.

suppliers withdraw from risky stocks in a crisis. The decline in liquidity provision is temporary but participation does not fully recover for an extended period of time. These results suggest that long-horizon recovery patterns after a crisis can be explained at least in part by trading preferences of long-horizon liquidity providers.

5.3. *The cross-section of trading costs in the financial crisis*

Are post-crisis recovery patterns different for riskier stocks or stocks experiencing decline in LS participation? Theory predicts that stock characteristics such as market cap and volatility are important determinants of liquidity suppliers' preferences. However, it is difficult to identify all of the stock characteristics that affect trader participation. We therefore account for the aggregate influence of omitted factors that influence LS participation decisions by forming quintiles based on the change in LS participation during the financial crisis.

Similar to Table 2, we report trading costs observed before the crisis, during crisis-peak months, and several months after the crisis. In Table 6, Panel A presents the patterns in trading costs for large and small stocks. In both pre-crisis benchmark periods, we show that large stocks have lower trading costs than small stocks. Trading costs increase for both sets of stocks during crisis-peak months. To be precise, trading costs for large stocks increase from 8 bps before the crisis to 26 bps in November 2008 while trading costs for small cap stocks increase from 18 bps before the crisis to 73 bps in November 2008. Consistent with theory, the (one-way) difference in trading costs between small-and large-cap stocks increases from 10 bps before the crisis to 46 bps in November 2008 (p-values of difference-of-differences tests relative to both benchmark periods equal 0.014).[15] The trading cost differential declines from the crisis-peak during the last two quarters of 2009 but still remains twice as large as those observed before the crisis. The results support the idea that small stocks exhibit slower recovery patterns than large stocks.

Results in Table 6, Panel B are supportive of the theoretical predictions from Gromb and Vayanos (2002) and Brunnermeier and Pedersen (2009). Trading costs for high-volatility stocks increase from 19 bps before the

[15] The test statistic in Table 6 uses a methodology identical to that presented in Table 2. Specifically, we use the standard deviation of daily trading costs in both the benchmark and event periods to construct our test statistic.

Table 6
Trading cost resiliency after the crisis.
This table reports the time series of execution shortfalls for stock characteristic quintiles formed on firm size, volatility, and liquidity supplying (LS) institutions' participation. Execution shortfall is measured for buy orders as the execution price minus the market open price on the day of order placement divided by the market open price (for sell orders, we multiply by −1). We calculate the average volume-weighted execution shortfall across all orders for each characteristic quintile each day. We report the average (equal-weighted) execution shortfall across all days (using daily averages) for each NYSE size quintile in each time period in Panel A, for volatility quintiles in Panel B, and for LS institution participation quintiles in Panel C. *p-values*, in parentheses, test for the difference between each time period and the benchmark period. Irresiliency is the average percentage of months in the May 2008–December 2009 period that execution shortfall for stocks in a particular quintile exceed a two-sigma threshold relative to pre-crisis benchmarks. All numbers are in percent.

	Benchmark period #1 01–04/2007	Benchmark period #2 01–04/2008	Relative to benchmark period							Irresiliency
			9/2008	10/2008	11/2008	Q1 2009	Q2 2009	Q3 2009	Q4 2009	%
Panel A: Size										
Quintile 1 (large)										
Execution shortfall	0.075	0.126	0.122	0.231	0.263	0.226	0.210	0.135	0.102	40
p-value (vs. Bench #1)			(0.112)	(0.004)	(0.001)	(<0.001)	(<0.001)	(<0.001)	(0.010)	
p-value (vs. Bench #2)			(0.884)	(0.045)	(0.009)	(<0.001)	(<0.001)	(0.564)	(0.071)	
Quintile 5 (small)										
Execution shortfall	0.179	0.227	0.347	0.513	0.725	0.492	0.458	0.347	0.313	75
p-value (vs. Bench #1)			(0.001)	(0.001)	(0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)	
p-value (vs. Bench #2)			(0.063)	(0.004)	(0.002)	(0.001)	(0.001)	(0.010)	(0.057)	
Difference (Q5−Q1)										
Execution shortfall	0.105	0.101	0.225	0.282	0.462	0.265	0.248	0.212	0.211	
p-value of diff vs. Bench #1 diff			(0.049)	(0.079)	(0.014)	(0.041)	(0.032)	(0.018)	(0.010)	
p-value of diff vs. Bench #2 diff			(0.068)	(0.020)	(0.014)	(0.046)	(0.039)	(0.029)	(0.021)	
Panel B: Volatility										
Quintile 1 (low)										
Execution shortfall	0.065	0.111	0.061	0.178	0.245	0.225	0.188	0.122	0.089	35
p-value (vs. Bench #1)			(0.908)	(0.018)	(0.003)	(<0.001)	(<0.001)	(0.001)	(0.047)	
p-value (vs. Bench #2)			(0.238)	(0.153)	(0.022)	(<0.001)	(0.002)	(0.584)	(0.173)	
Quintile 5 (high)										
Execution shortfall	0.187	0.293	0.341	0.427	0.476	0.395	0.437	0.316	0.259	45
p-value (vs. Bench #1)			(0.017)	(0.001)	(0.006)	(<0.001)	(<0.001)	(<0.001)	0.009	
p-value (vs. Bench #2)			(0.357)	(0.052)	(0.065)	(0.025)	(<0.001)	(0.460)	(0.267)	
Difference (Q5–Q1)										
Execution shortfall	0.122	0.182	0.280	0.249	0.231	0.170	0.249	0.194	0.170	
p-value of diff vs. bench #1 diff			(0.034)	(0.079)	(0.037)	(0.270)	(0.001)	(0.008)	(0.062)	
p-value of diff vs. bench #2 diff			(0.118)	(0.273)	(0.471)	(0.802)	(0.101)	(0.723)	(0.748)	
Panel C: Change in LS institution participation										
Quintile 1 (high)										
Execution shortfall	0.143	0.219	0.174	0.241	0.265	0.260	0.263	0.170	0.180	45
p-value (vs. Bench #1)			(0.503)	(0.075)	(0.094)	(<0.001)	(<0.001)	(0.250)	(0.059)	
p-value (vs. Bench #2)			(0.335)	(0.687)	(0.521)	(0.234)	(0.217)	(0.057)	(0.089)	
Quintile 5 (low)										
Execution shortfall	0.086	0.152	0.223	0.370	0.379	0.332	0.315	0.209	0.187	60
p-value (vs. Bench #1)			(0.007)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(<0.001)	(0.001)	
p-value (vs. Bench #2)			(0.142)	(<0.001)	(0.005)	(<0.001)	(<0.001)	(0.010)	(0.080)	
Difference (Q5–Q1)										
Execution shortfall	−0.057	−0.068	0.049	0.129	0.114	0.073	0.051	0.039	0.006	
p-value of diff vs. bench #1 diff			(0.053)	(0.003)	(0.014)	(<0.001)	(<0.001)	(<0.001)	(0.006)	
p-value of diff vs. bench #2 diff			(0.020)	(0.002)	(0.011)	(<0.001)	(<0.001)	(0.001)	(0.012)	

crisis to 48 bps in November 2008. [16] Trading costs for low-volatility stocks also increase from 7 bps to 25 bps but the difference-in-differences tests generally indicate that high-volatility stocks experience larger liquidity deterioration in the crisis. These findings are consistent with Hameed, Kang, and Viswanathan (2010), who show that bid-ask spreads increase more for high-volatility stocks following negative market returns. Although trading costs decline for both groups of stocks by the end of 2009, the trading cost differential remains higher than

[16] The trading cost differential between high- and low-volatility stocks increased from 12 basis points in Benchmark #1 (January–April 2007) to 18 basis points in Benchmark #2 (January–April 2008), which is consistent with higher uncertainty in financial markets surrounding the sale of Bear Stearns to JP Morgan in March 2008.

those observed in the January–April 2007 benchmark period. Results are supportive of slower recovery patterns for high-volatility stocks relative to low-volatility stocks after the crisis.

In Table 6, Panel C reports the results for stock quintiles formed on change in LS participation (as a proportion of total Abel Noser Solutions volume), defined as the difference between the stock's average LS participation during the crisis-peak months (September 2008–March 2009) and the stock's average LS participation in Benchmark period #2 (January 2008–April 2008). Quintile assignments based on change in LS participation are made within each market-value quintile to adjust for differences in magnitudes across large and small stocks. In the benchmark period, the trading costs for the stock quintile with the largest increase in LS participation is 14 bps and trading costs for the stock quintile with the largest decrease in LS participation is 8 bps. The trading cost differential, which is −7 bps in the benchmark period, increases to 11 bps in November 2008. The trading cost differential becomes zero by the fourth quarter of 2009, but the differential remains higher than in the benchmark period. The results support the prediction that stocks experiencing a decline in LS participation exhibit (relatively) larger increases in trading costs in the crisis and slower recovery patterns after the crisis.

6. Modeling the determinants of stock resiliency

In the previous sections, we show that LS institutions continue to trade against the market during the crisis but withdraw participation from risky securities during the crisis-peak and slowly increase participation in risky securities in the several months after the crisis. While the institutions in our sample represent a small subset of financial intermediaries involved in liquidity provision, the behavior of LS institutions supports theoretical predictions on the optimal investment strategy for an arbitrageur with financial constraints (Gromb and Vayanos, 2012). We also show that markets remain illiquid after the crisis and the speed of post-crisis recovery varies across stocks. So what determines resiliency? In this section, we examine the determinants of resiliency for the cross-section of stocks.

We introduce a new *Irresiliency* measure to the literature that is motivated by the variations in recovery patterns reported in Table 6. In an attempt to summarize the overall patterns in liquidity deterioration and post-crisis recovery, we estimate a model-free Irresiliency measure, which captures the percentage of crisis months when a stock's trading costs are above a two-sigma threshold relative to their trading costs in a pre-crisis benchmark period. We choose the model-free approach and the two-sigma benchmark after examining the time-series properties of trading costs. An important observation is that the recovery pattern is nonlinear for many individual stocks; a simple model of increasing costs to a peak and then a gradual recovery did not generally fit the data. In particular, our irresiliency measure allows for temporary drops in post-crisis costs, which are sustained for some stocks but transient for others.[17]

As preliminary evidence, we estimate Irresiliency for each of the stock characteristic quintile portfolios in Table 6. The irresiliency measure is the percentage of months when execution costs exceed its two-sigma threshold during the May 2008 to December 2009 period. Thus, higher values of Irresiliency are associated with slower recovery patterns during and after the crisis. The results are reported in the last column of Table 6. In Panel A, Irresiliency for large stocks is 40%, while for small stocks, it is 75%; in Panel B, Irresiliency for the low-volatility and high-volatility quintiles are 35% and 45%, respectively; in Panel C, Irresiliency for stocks with increasing and decreasing LS participation is 45% and 60%, respectively. The results indicate that smaller stocks, more volatile stocks, and stocks with a large decline in LS participation are less resilient, which is consistent with post-crisis recovery patterns observed in Table 6. This result is noteworthy since Irresiliency is a simple summary statistic designed to capture a complex nonlinear pattern of liquidity deterioration and recovery. For the 2,223 stocks in our sample with adequate data to construct this measure, the median value for Irresiliency is 50%, with a minimum value of 5% and a maximum of 95%.

In Table 7, we present two specifications for modeling the determinants of post-crisis recovery. In Panel A we present a cross-sectional model that predicts the percentage of months a stock's execution costs exceed its two-sigma threshold during the May 2008–December 2009 period. Although the distribution of Irresiliency is approximately normal, since the dependent variable is discrete (there are 20 months in the estimation period), we estimate the cross-sectional regression with an ordered logit specification. The explanatory variables include stock characteristics predicted by theory, sensitivity to funding liquidity, and institutional participation. The funding variables, TED spread, Noise, Dealer repos, and Liquidity level are stock-specific coefficients from a regression of a stock's execution cost on a particular funding variable. Liquidity supply (benchmark) and Liquidity demand (benchmark) are ex ante variables,

[17] In estimating the benchmark execution shortfall cost and standard deviation (used to construct the two-sigma threshold) for each stock, we face a tradeoff between the timeliness of the information used in our estimates and the length of the estimation period. The Irresiliency measure estimates these benchmark statistics over the period from January to April 2008. Since stock-specific estimates of the standard deviation in trading costs are quite noisy over short horizons, we calculate a market-wide average standard deviation to construct our two-sigma threshold. Relative to the stock-specific benchmark, the two-sigma threshold represents approximately a 32% increase in stock-specific trading costs, on average. In robustness tests, we expand the benchmark period to include less-timely data, calculate stock-specific estimates of the mean and standard deviation of execution shortfall over this expanded period, and find that results are robust to this alternate benchmarking estimation. In addition, we employ a shrinkage estimator for stock-specific variance as suggested by Geske, Roll, and Zhang (2008) over the January to April 2008 benchmark period and find results that are qualitatively similar to those reported (although the frequency of two-sigma violations is reduced, on average). Finally, we calculate the average root mean squared error from a regression of stock-specific execution costs on a time trend to construct our two-sigma threshold and find that our results are robust to this alternative estimation.

Table 7
Determinants of post-crisis resiliency in trading costs.
This table presents regressions investigating the determinants of stock resiliency during and after the financial crisis (May 2008–December 2009). In Panel A we present an ordered logit cross-sectional estimation, where the dependent variable is the percentage of months a stock's trading costs exceed a two-sigma threshold in the crisis period relative to their trading costs in January–April 2008. In Panel B we present a probit panel estimation, where the dependent variable is a binary variable indicating whether the monthly trading costs for a stock exceed a two-sigma threshold in a particular month. Size is the market value of equity ($B) as of the end of the prior year. Volatility is the stock's contemporaneous (average in Panel A) monthly volatility. Ted spread is the difference between LIBOR less T-bill 3-month interest rates (in percent). Liquidity supply is the percentage of all a stock's trades executed by liquidity supplying institutions in a particular month. Liquidity demand is analogous for liquidity demanding institutions. Noise is the Treasury market noise measure from Hu, Pan, and Wang (2012). Dealer repos are the net primary dealer net overnight funding positions from the New York Fed ($B). Liquidity level is the Pastor and Stambaugh (2003) illiquidity measure. In Panel A, the Ted spread, Noise, Dealer repos, and Liquidity level variables are stock-specific beta coefficients from a regression of execution shortfall against each variable. *p-values* are presented in parentheses below the coefficient estimates.

	(1)	(2)	(3)	(4)
Panel A: Cross-sectional estimation.				
Size	−0.007	−0.007	−0.007	−0.007
	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	12.06	11.39	12.08	11.82
	(0.010)	(0.015)	(0.010)	(0.012)
Ted spread	0.178	−0.159	0.493	0.243
	(0.295)	(0.487)	(0.007)	(0.217)
Liquidity supply (benchmark)	−0.936	−0.913	−0.972	−0.947
	(0.129)	(0.138)	(0.115)	(0.124)
Liquidity demand (benchmark)	1.74	1.79	1.94	1.75
	(0.179)	(0.167)	(0.134)	(0.178)
Liquidity supply change	−3.04	−3.02	−2.97	−3.04
	(0.001)	(0.001)	(0.001)	(0.001)
Liquidity demand change	5.02	5.04	5.14	5.05
	(0.001)	(0.001)	(0.001)	(0.001)
Noise		224		
		(0.029)		
Dealer repos			−25.761	
			(0.001)	
Liquidity level				1.32
				(0.511)
N	2,223	2,223	2,223	2,223
Pseudo R-squared %	0.83	0.87	0.99	0.84
Panel B: Panel estimation				
Intercept	−0.319	−0.152	0.007	−0.125
	(0.001)	(0.001)	(0.806)	(0.001)
Lag dep var	0.100	0.098	0.098	0.100
	(0.001)	(0.001)	(0.001)	(0.001)
Size	−0.003	−0.003	−0.003	−0.003
	(0.001)	(0.001)	(0.001)	(0.001)
Volatility	1.86	1.13	1.43	1.86
	(0.001)	(0.001)	(0.001)	(0.006)
Ted spread	4.56	1.89	6.59	4.25
	(0.001)	(0.020)	(0.001)	(0.001)
Liquidity supply	−0.739	−0.725	−0.731	−0.741
	(0.001)	(0.001)	(0.001)	(0.001)
Liquidity demand	0.369	0.366	0.363	0.369
	(0.001)	(0.001)	(0.001)	(0.002)
Noise		0.010		
		(0.001)		
Dealer repos			−0.0002	
			(0.001)	
Liquidity level				−0.065
				(0.370)
N	42,236	42,236	42,236	42,236
Pseudo R-squared %	2.88	2.92	2.93	2.88

measured once for each stock. Liquidity supply change and Liquidity demand change represent the average stock-specific change in the participation of LS and LD institutions during the crisis period (May 2008–December 2009) relative to a stock's Liquidity supply and Liquidity demand (benchmark) values.

Consistent with theoretical predictions and the empirical evidence in Table 6, we find that the coefficient on firm size is negative and the coefficient on stock volatility is positive, and both coefficients are statistically significant. These findings suggest that smaller and more volatile firms are less resilient in that trading costs are

abnormally high for an extended period after the crisis. The coefficients on two aggregate funding liquidity proxies, Noise and Dealer repo, are significant and consistent with the conclusion that aggregate funding liquidity measures also affect resiliency in equity markets. When liquidity capital is scarce, stocks that exhibit greater dependence on arbitrage capital (Noise) are less resilient. Similarly, when primary dealer funding is low, stocks more dependent on primary dealer funding are less resilient. These findings support theoretical predictions that financially constrained liquidity providers are less willing to make markets in some securities and their lack of participation affects liquidity recovery in the equity market. However, the stock's sensitivity to the Pastor-Stambaugh (2003) liquidity level measure is not a significant predictor of individual stock resiliency.

Panel B presents a cross-sectional time-series probit estimation of the likelihood that a stock exceeds its two-sigma threshold in a particular month. Specifically, the dependent variable is a binary variable that equals one if the execution shortfall for a particular stock is above the two-sigma threshold in a particular month during the May 2008–December 2009 period, and equals zero if it is below the threshold. Panel estimation offers two advantages relative to the cross-section: first, we can use the levels of each of the funding variables rather than stock-specific beta coefficients, allowing us to ascertain whether the funding levels affect overall resiliency and not just resiliency for highly sensitive securities. Second, the panel allows us to use information in monthly levels of institutional participation rather than the average across all crisis months as used in Panel A. The model is estimated for a sample of 2,223 stocks with a minimum of ten trading days of Abel Noser Solutions data available in each month of the sample period.

The panel-data estimation presented in Panel B allows us to confirm and elaborate on the conclusions of the cross-sectional estimation.[18] The *Lag dependent variable* effectively removes autocorrelation from the errors in the regression and also demonstrates that a significant degree of irresiliency is persistent. Firm size and volatility have significant effects on stock resiliency, consistent with results in Panel A. Funding liquidity levels are also consistent determinants of stock-specific resiliency. The regression coefficient on TED spread is positive and significant in all four specifications indicating that higher funding costs increase the likelihood of higher equity trading costs. Noise has a positive and significant coefficient indicating that the measure, calculated in the Treasury market, has incremental explanatory power in the equity market, even in the presence of TED spread with which it is highly correlated (ρ=0.69).[19] We also show that the decline in primary Dealer repo funding during the crisis period negatively impacts stock resiliency, but the Pastor-Stambaugh (2003) liquidity measure has no significant effects.

In both the cross-sectional and panel specifications, we find that institutional participation significantly influences stock resiliency after accounting for information in stock characteristics and funding liquidity, both of which impact institutional participation. In Panel A, the coefficient on the average Liquidity supply (LS) change is negative and statistically significant while in Panel B, the coefficient on the contemporaneous LS level is negative and statistically significant. These results suggest post-crisis recovery patterns are faster, or stated differently, the likelihood that a stock's trading cost exceeds a two-sigma threshold in the post-crisis period is lower, when the stock's LS institution participation is higher. We conclude that supply-side effects are important determinants of resiliency in equity markets. The results on supply-side effects are observed after controlling for participation by liquidity demanding (LD) institutions. Consistent with contemporary work on fire-sale effects in the crisis (for example, Manconi, Massa, and Yasuda, 2012), we find that the coefficient on LD change in Panel A and the level of LD participation in Panel B are positive and statistically significant. These results suggest that trading costs for stocks that are subject to more interest from LD institutions are likely to stay high after the market crash.

Overall, we conclude that post-crisis trading costs are likely to be higher (lower) when LS (LD) institutions withdraw participation in a stock and likely to be lower (higher) when LS (LD) institutions increase participation in a stock. These results support the hypothesis that long-horizon stock resiliency is affected by the trading preferences of buy-side institutional investors.

7. Conclusions

One of the puzzles in the 2007–09 financial crisis is why financial markets remain illiquid for so long, and why long-horizon investors with new capital do not enter the market? We present a framework of market intermediation where buy-side institutions who demand liquidity mainly trade with traditional liquidity providers such as specialists, floor-traders, and broker-dealers. These market intermediaries provide short-term liquidity and then offset their trades with another set of buy-side institutions who are the long-run providers of liquidity. Hence, we posit that the long-horizon resiliency of the market after a stress event is determined by the trading preferences of the long-run liquidity providers. In studying the link between institutional preferences and patterns in trading cost, we provide new evidence on the potential transmission mechanism of illiquidity and the determinants of long-horizon recovery patterns in a crisis.

[18] We perform the regression analysis in Table 7 using both institutional execution shortfall and effective spread as the dependent variable. Results based on execution shortfall are reported in Table 7 but all results and inferences are qualitatively similarly using the effective spread measure.

[19] As discussed in Table 4, the funding variables are generally highly correlated. To account for any potential effects of this correlation on our conclusions, we present four specifications of Panel B. One with TED

(*footnote continued*)
spread alone, and then we sequentially add Noise, Dealer repos, and Liquidity level.

Using the Abel Noser Solutions data set, we identify a set of institutions whose trading style is consistent with liquidity provision. We show that trading costs for these institutions are negatively correlated with traditional liquidity measures such as effective spreads. Consistent with higher risk of liquidity provision during a financial crisis, these institutions earn more when dealer capital is scarce.

Theory predicts that liquidity suppliers who face capital constraints are less willing to make markets in stocks that tie up more capital. We study the trading preferences of liquidity supplying (LS) institutions before the crisis and examine whether preferences are altered during the crisis. We show that LS institutions reduce participation in risky assets in an economically significant way during the crisis-peak. As market conditions improve, LS institutions slowly increase participation in risky stocks over a period of several months after the crisis-peak. These findings support a link between buy-side liquidity provision and the post-crisis recovery patterns in liquidity.

We construct a stock-specific Irresiliency measure and model the determinants of post-crisis recovery patterns. After controlling for the effects of stock characteristics and funding liquidity, our results support the contention that post-crisis recovery patterns are more prolonged when LS institutions withdraw participation and less prolonged when LS institutions increase participation in a stock. Overall, the results support the three-group model of market liquidity presented in the study that liquidity supplying buy-side institutions absorb the long-term order imbalances in the market and are critical to recovery patterns after a liquidity shock. We provide some insight into why some stocks remain illiquid for extended periods after a crisis.

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