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Market liquidity and institutional trading during the 2007 - 8 financial crisis

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Market Liquidity and Institutional Trading During the 2007-8 Financial Crisis

Ser-Huang Poon, Michael Rockinger, Konstantinos Stathopoulos

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Market Liquidity and Institutional Trading

During the 2007-8 Financial Crisis

Ser-Huang Poon, Michael Rockinger, Konstantinos Stathopoulos*

October 2011

Abstract

During the financial crisis in 2007-8, the quoted spread for the average S&P 1500 firm increased by 50%, while the systematic liquidity risk increased by 34%. We find that the trading of a firm's equity by institutional investors increased the firms' quoted spreads, and led to a higher liquidity commonality during the crisis. Institutional sell-side herding contributed strongly to both effects. Our results are robust to different specifications and consistent with theoretical and anecdotal evidence regarding the role of herding during a crisis.

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Market Liquidity and Institutional Trading

During the 2007-8 Financial Crisis

1. Introduction

During 2007-8 the average quoted spread for the S&P 1500 firms was 50% higher than that in the preceding three years while the amount of market driven cross-sectional variations in the quoted spreads increased from 7% to 42%. Our paper makes two important contributions to the literature on the impact of institutional investor (II) trading on market liquidity. First, we show that it is important to recognize the difference between the number of institutional shareholders (II count) and the amount of shares they hold (II holdings). There has been a substantial literature on the proportion of institution shareholdings but little research focus on the number of IIs holding the shares. This number is important as it is a (noisy but readily available) proxy for the level of II trading and the potential institutions' sell-side herding during market downturn. Second, and more importantly, we illustrate the significant effect of II sell-side herding and correlated trades on both trading costs and liquidity risk during the 2007-8 financial crisis. When further dissecting the IIs into five investor types, according to the SEC 13f classification, and three investment styles, according to Bushee (2001), we find that our results fit the characteristics of these investor types and styles well. While the results on spreads apply to both the pre-crisis and the crisis periods, the impact of II count and herding on spread commonality is significant only during the crisis period. Our results confirm the recent theoretical predictions (e.g., Huang and Wang, 2009; Kyle and Xiong, 2001) regarding the impact of II trading behavior on market illiquidity during market crises, and highlight the importance of supply side sources of illiquidity.

Demsetz (1968) and Benston and Hagerman (1974) argue that the number of investors holding a firm's equity is a proxy for the number of transactions, since it is positively related to the number of potential buyers and sellers of the stock. Several empirical papers illustrate that the breadth of share ownership is associated with higher market liquidity (Amihud et al., 1999; Grullon et al., 2004; Lipson and Mortal, 2007). This could either be because higher trading activity reduces trading costs and therefore increases market liquidity, or because highly liquid shares attract more investors to trade the firms' equity in the first place. We find

this result carried through to institutions' holdings; the larger the proportion of shares held by institutions, the smaller is the quoted spread.¹ However, after controlling for institutions' shareholdings, the number of IIs has the opposite effect.² More importantly, we find that the number of IIs proxies for the firm's vulnerability to institutional herding (Nofsinger and Sias, 1999; Sias, 2004; Zhou and Lai, 2009). The contrasting effects between II holdings and number of IIs are prevalent throughout our findings. II herding and correlated trading activity among IIs in general results in order imbalances and increased trading costs. This effect is more pronounced during periods of crisis in the capital markets.

A number of recent theoretical papers highlight the role of II trading in affecting market liquidity during a financial crisis. Brunnermeier and Pedersen (2009) suggest that adverse shocks to the value of collateral induce sell pressure by IIs who reach their risk limits and funding constraints, which in turn leads to market-wide liquidity shortages. Similarly, Garleanu and Pedersen (2007) argue that tighter risk management by IIs during market downturns reduces liquidity provision. Xiong's (2001) theoretical model shows that in the case of extreme return shocks, wealth effects cause convergence traders to liquidate their positions, abandon their usual trading strategies and trade instead in the same direction as noise traders, thereby amplifying the original shock. Kyle and Xiong (2001) show that this effect could cause prices, of fundamentally unrelated assets, to move together and could lead to contagion. Huang and Wang (2009) argue that liquidity demand is endogenous, and liquidity shocks typically occur on the sell side and are of large amount. They anchor their theory on the balance between the need to trade and the cost of trading. Costly trading means non-continuous trade, and increased risk aversion when the need to trade arises, as traders face the uncertainty of the trade not being executed. Risk aversion reduces the desire to hold risky assets, so the impact on order imbalance is asymmetric and is greater on the sell side. Moreover, at low risk levels, the cost of trading outweighs the need to trade, so all traders stay away from the market. Trading takes place only when the idiosyncratic shock and risk aversion are large, and sell side strongly dominates buy side. This big order imbalance drives down market prices even in the absence of changes in the fundamentals or information

¹ In the literature, the larger II holdings are expected to lead to better monitoring and governance and hence reduce the spread in trading costs. There could be a nonlinear pattern when so-called "free rider", or adverse selection, problems emerge as the institutional presence becomes too large.

² The number of IIs is significantly and negatively correlated with the square of II holdings but not correlated with II holdings. So the number of IIs is not a proxy for II holdings; firms with a large number of IIs have smaller squared II holdings and a bigger spread.

asymmetry. Our paper provides empirical evidence that could support these theories. We record a significant correlation between II count and II sell-side herding, which increased from 0.160 pre-crisis to 0.302 during the crisis. We also find overwhelming evidence that II count, II sell-side herding, together with II correlated trades are responsible for the significant increase in bid-ask spread commonality during the financial crisis. In contrast, II holdings have little or no impact on liquidity risk.

To further understand institutional characteristics and their trading patterns, we subdivide IIs according to their ‘type’ and ‘investment style’. Based on the SEC 13f filings, IIs are classified as bank trusts (BNK), insurance companies (INS), independent advisors (IA), public pension funds (PPS) and university and foundation endowments (UFE).³ Furthermore, we use the database constructed by Bushee (2001) to group IIs into quasi-indexers (QIX), transient (TRA), and dedicated (DED) based on their long-horizon trading pattern.⁴ In general, IA dominates our sample firms over the 2004-8 period, and over two-third of the II sector are quasi-indexers. We do not detect any significant correlation between ‘type’ and ‘style’; all three ‘styles’ appear in a similar sector representation within each ‘type’. UFE trades are least correlated with the other IIs and diverge even further in the crisis period. During the crisis, DED trades became less correlated with QIX and TRA. Throughout the full sample period, BNK are net sellers and IA are net buyers.

Our summary statistics bear three important facts for the S&P 1500 sample as a whole: (i) average II holdings and count went up during the crisis; (ii) there was a switch from buy herding during the pre-crisis period to sell herding during the crisis; (iii) the between group herding correlation was stronger pre-crisis when buy side dominated than that during the crisis when sell side dominated. Since the II sector as a whole switched from buy side to sell side during the crisis, but at the same time there was an increase in II holdings and

³ In SEC 13f, the five types of institutional investors are bank trusts (BNK), insurance companies (INS), investment companies (INV), independent investment advisors (IIA), and miscellaneous (MSC). We follow Bushee (2001) and merge INV and IIA into one group, i.e., investment advisors (IA). Bushee has also identified corporate pension funds (CPS), public pension funds (PPS), university and foundation endowments (UFE), which were classified in 13f as MSC. We use in our analysis PPS and UFE, but do not investigate separately (the scarcely represented) CPS and other MSC.

⁴ Bushee (2001) groups IIs into three investment styles, viz. quasi-indexers (QIX), transient (TRA) and dedicated (DED), based on factor and cluster analyses on portfolio characteristics such as portfolio turnover, stability of holdings, block size, percentage ownerships in firms, average investment size. QIX are long-horizon but well-diversified investors. TRA are diversified but high portfolio turnover investors. DED are characterized as making large investments in their portfolio firms and having extremely low turnover. Bushee produced two versions of such classification; one assumes institutions can switch style and the other uses the dominant style for the entire estimation period. We use the version that omits short term switching since the analyses here focus on the difference in trading and holding patterns of particular II groups between pre-crisis and crisis periods.

II count the following observations can be made: (i) IIs, as a sector, were net buyers during the crisis; (ii) institutional sellers reduced their positions but did not divest themselves completely of their shares; (iii) institutional buyers not only covered the positions of the sellers but also bought from some individual investors, leading to an increase in the net II holdings; (iv) there were new IIs entrants or IIs became more diversified during the crisis leading to an overall increase in II count. In the pre-crisis period, trading was strongly dominated by buy side and was highly correlated possibly because a lot of the buy-sell decisions were information driven. During the crisis, accurate information was scarce; the reduced trading correlation indicates that IIs' choices on which stocks to buy or sell diverged in this period. Nevertheless, the correlation of trading pattern at sell side turns out to be an important indication whether the II count and herding is to result in liquidity risk; for example, UFE and DED were the two groups with low correlated trades to the other II groups and exerted no impact on liquidity risk.

Shares in companies with more institutional shareholders are more likely to suffer from II herding when they exit at the same time, creating excess order imbalances and wider spreads.⁵ We do not equate herding to irrational behavior and do not make any attempt to discern which of the possible herding reasons drives our results. All or some of the herding explanations could contribute to the herding results presented here. Companies with smaller numbers of IIs but large II holdings do not suffer as much, possibly because these IIs have better information about the firms, and are more likely to offload their shares in a more orderly manner to minimize the price impact. Koch et al. (2010) find strong commonality among the Amihud price impact measure of stocks owned by mutual funds which have high turnover and are experiencing liquidity shocks from their investors' withdrawals. Similarly, our results for the effects of II count, holdings and herding on quoted spreads and commonality are strongest among the Independent Advisor (IA) group, which includes

⁵ Institutions are more likely to herd than individuals as they can respond faster, they are subject to similar informational and regulatory environments, and their managers face heightened moral hazard problems, which makes them more reactive to bad news. Sias (2004) lists five explanations for institutions' herding: informational cascade, investigative herding, reputational herding, fads and characteristic herding. Informational cascades happen when IIs infer information from each other's trades when information is noisy. Investigative herding occurs because IIs follow the same signals. Reputational herding refers to the situation where IIs choose to share the blame rather than taking independent decisions. Fads, or following the trend, refers to IIs following the same investment strategies because they are considered novel. Characteristic herding refers to IIs being attracted to securities with the same set of characteristics. Recent theoretical models suggest other reasons for IIs' herding behavior; for example, IIs are subject to the same funding constraints (Brunnermeier and Pedersen, 2009) and risk regulations (Garleanu and Pedersen, 2007). It is beyond the scope of this paper to investigate the sources of II herding. Instead, we document its existence and demonstrate its impact on market liquidity.

mutual funds. Among the five II types, IA are the most likely to be subject to institutional constraints and the least able to stick to their trading strategies during a financial crisis.

We recognize that there might be spurious relations and omitted variables that might explain our results. Therefore, we run a battery of tests to try to alleviate such concerns. We include in our model specifications several market and accounting-based control variables, which the literature has identified as important determinants of trading cost and liquidity risk. In addition, we use industry and firm fixed effect specifications to account for omitted variables. In all our models, we cluster the standard errors at the firm level to control for time-series dependence, and add year dummies to capture the effect of cross-sectional dependence. We also run regressions based on the changes in the variables, instead of their levels, and our main findings remain the same.

An alternative explanation for our results could be related to the composition of ownership and, in particular, the lack of individual (retail) investors in firms with a high number of IIs. Amihud et al. (1999) argue that the higher the number of individual investors holding a firm's equity, the higher the noise trading, and hence the higher the market liquidity. In addition, they find that a reduction in the proportion of shares held by individual investors is associated with an increase in adverse selection costs, since the market makers have to deal with the remaining better informed investors. However, in our sampled firms, the number of IIs is positively, significantly, correlated with both the number of individual investors and their proportional representation. Our results do not appear to be driven by the lack of individual investors in high II count firms. Our findings are consistent with the recent evidence of Corwin and Lipson (2011) that it is the correlated trades of professional and not retail traders that drive commonality in the prices and liquidity of NYSE listed stocks. We also confirm that our findings are not driven by blockholders. We find firms with blockholdings have fewer IIs and lean towards buy side herding during the crisis. But for firms with above median blockholdings, the impact of II count and herding on market liquidity is stronger possibly due to the impact of reduced free float on order imbalances.

The remainder of the paper is organized as follows. In Section 2, we describe our data sources, variable definitions and provide some descriptive statistics. In Section 3, we report our results. Section 4 provides some discussion and concluding remarks.

2. Data

2.1 Sample Firms

We identify all the constituents of the S&P 1500 index, that is, the union of S&P Mid-Cap 400, S&P 500 and S&P Small-Cap 600, for the years 2004 to 2008. This index covers about 90% of the U.S. market capitalization. We choose 2004 as the beginning of our sample period since it is the first full year after the implementation of the Sarbanes-Oxley Act (SOX) in 2003. The recent literature suggests that the enactment of SOX in 2002 has affected firms in various ways, for example by increasing disclosure levels but at the same time increasing the costs of compliance and reporting (e.g., Ahmed et al., 2010). Therefore, we expect institutional investment preferences to change after the enactment of SOX, and so concentrate on the post-SOX era to avoid biasing our results with the effect of an exogenous event. The choice of 2004 also helps us to create comparable pre-crisis and crisis periods (2004-6 vs. 2007-8).⁶

We use CUSIP as a unique firm identifier that allows us to merge the information from different databases.⁷ We delete from our sample firms that have multiple CUSIPs or have changed their CUSIPs during the sample period. Also, so as to avoid data matching problems across the different databases, our final sample includes only December fiscal year end firms, which account for 65% of the S&P 1500 firms. We cannot foresee any reasons why this restriction would bias our results in favor of our predictions. To identify the firms' fiscal year ends, we use Compustat's "datadate" variable. Missing values in this variable and the exclusion of non-December year end firms leaves us with 1,276 unique firms and an unbalanced panel of 5,591 firm-years.

We access the following databases to retrieve our data: CRSP for daily firm market information, including stock prices, closing bid and ask prices, number of shares outstanding,

⁶ We avoid providing a definition of what is a crisis and when did the crisis start. We simply follow Fahlenbrach and Stultz (2011) and classify 2007-8 as the crisis period. One could argue that the early part of 2007 is not a crisis period. The fact that we conduct our analyses at an annual frequency does not allow us to split 2007 in different sub-periods. But the classification of the earlier part of 2007 as a crisis period should work against us finding significant relationships.

⁷ The CUSIP (Committee on Uniform Security Identification Procedures) identifier is a unique code for companies and issues and is used extensively across different financial databases. CUSIP has three types: 6-digit, 8-digit and 9-digit. CUSIP 6 is a company identifier. CUSIP 8 is a stock/security identifier. CUSIP 9 has an extra check digit, which allows checking for consistency across the CUSIP formats. Normally, the first 6 and 8 digits of CUSIP 9 are CUSIP 6 and CUSIP 8 respectively, except for those companies dropped from our database, as explained in the main text.

share volume and stock returns; Compustat North America for annual accounting information, such as book value of assets and debt, as well as number of shareholders, as reported by the firm; Thompson Reuters 13f for institutional ownership characteristics; I/B/E/S consensus files, accessed through Datastream, provide information on analyst coverage.

2.2 Variable Definitions

In this Section we describe the key institutional variables used in this study, our proxies for stock market liquidity and liquidity commonality, as well as control variables identified in previous studies as important determinants of liquidity and commonality.

Institutional Investors (IIs) and stock liquidity

The extensive literature on institutional investment highlights the importance of the effect of institutional ownership on a firm's market liquidity (e.g., Dennis and Weston, 2001; Sarin et al., 2000; Agarwal, 2007). We follow the extant literature and define institutional ownership (*II holdings*) as the ratio of the number of shares held by IIs to the total number of shares outstanding. The Thomson Reuters 13f database reports institutional holdings on a quarterly basis. Since all our sample firms have December fiscal year-end, we use the II information for the last quarter. Demsetz (1968) and Benston and Hagerman (1974) long argued that the breadth of shareholder base proxy for the share trading activity. Thus, following Agarwal (2007), we use as a proxy for institutional trading the number of IIs holding a firm's equity (*II count*).⁸

Different types of institutions such as bank trusts, insurance firms, independent advisors, pension funds and endowment funds, have distinct investment preferences because of differences in their fiduciary responsibilities (Chung et al., 2010). More importantly, the extant literature also classifies IIs according to their investment styles (see Bushee 1998; 2001). In order to further understand institutional characteristics and their trading patterns, we use the indicator variables developed by Brian Bushee.⁹ In terms of investment types, Bushee

⁸ Indeed, II count is positively and significantly correlated with share dollar volume, both in the crisis and the pre-crisis period. In contrast, the correlation between II holdings and dollar volume is negative and insignificant for all periods.

⁹ <http://acct3.wharton.upenn.edu/faculty/bushee/>, accessed in May 2010.

(2001) uses the 13f classifications and categorizes IIs into BNK, INS, IA, PPS and UFE (see footnote 3 for further details). Bushee also groups IIs into quasi-indexers (QIX), transient (TRA) and dedicated (DED) (see footnote 4 for further details). We merge this information with the 13f data to create separate holding and count measures for each institution type and each investment style.

Institutional herding is defined here as the ratio of the number of buyers to overall number of institutional buyers and sellers. Using the SEC 13f data for each quarter, we count the number of institutions that increased (decreased) their holdings in a given firm and classify them as buyers (sellers) for calculating the herding ratio. Our herding measure is the average ratio across the four quarters in every fiscal year. Note that this herding measure is principally a ‘head-count’ measure and takes no consideration of the size of the trades. Since IIs need not liquidate all their holdings to be included in this head-count measure, it is possible for II count and II holdings to both increase whilst there is sell-side herding. Furthermore, Lakonishok et al. (1992), Sias (2004), and Chung and Zhang (2011) subtract from the herding measure the cross-sectional mean, that is, the expected proportion of buyers in the market. We do not follow this practice, given our empirical setting and in particular our interest in comparing the crisis with the pre-crisis period. Herding measures that are adjusted for the cross-sectional average could result in drawing the wrong conclusion, i.e., that there is no difference between the herding measure in the pre-crisis and crisis periods. In Section 3, we also describe two variations to the herding measure that we calculate to test the robustness of our results.

As a proxy for a stock’s market liquidity, we use the observed quoted spread. Goyenko et al. (2009) find that this daily liquidity measure is among the best when compared with its high frequency benchmarks.¹⁰ The annualized spread is calculated as

$$\begin{aligned}
 Spread_y &= \frac{1}{D_y} \sum_{t=1}^{D_y} \frac{\max(Ask_t - Bid_t, 0)}{Mid_t} \\
 Mid_t &= \frac{Ask_t + Bid_t}{2}
 \end{aligned}
 \tag{1}$$

where Ask_t and Bid_t are, respectively, the closing ask and bid prices on day t in year y , and D_y is the total number of trading days in year y . This is what is known as round trip spread. We

¹⁰ Goyenko et al. (2009) use effective spread, realized spread and price impact, calculated from intraday Trade and Quote (TAQ) and Rule 605 data as benchmarks when comparing low frequency estimates.

did also calculate annualized sell-side and buy-side spreads but the correlations between the three measures are very high. Hence, we kept only the round trip spread.

In order to calculate liquidity commonality, we follow Chordia et al. (2000) and Brockman et al. (2009) and run the following time-series regressions using monthly observations for each firm in our sample:

$$\begin{aligned} \Delta \text{Spread}_{f,m} = & \alpha + \beta_1 \Delta \text{Spread}_{M,m} + \beta_2 \Delta \text{Spread}_{M,m+1} + \beta_3 \Delta \text{Spread}_{M,m-1} + \delta_1 \text{Return}_{M,m} \\ & + \delta_2 \text{Return}_{M,m+1} + \delta_3 \text{Return}_{M,m-1} + \delta_4 \Delta \text{Volatility}_{f,m} + \varepsilon_{f,m} \end{aligned} \quad (2)$$

where Δ denotes the proportional change in the variable between successive months. The information on the market (M) is calculated using the equal-weighted average (for Spread or Return) for all firms in our sample except firm f . Firm return volatility is calculated for the month m using daily information. We run these time-series regressions separately for the years 2004-6 (pre-crisis) and 2007-8 (crisis). We define *Liquidity Beta* as the contemporaneous coefficient of the changes in the market portfolio spread (i.e., β_1). *Liquidity Beta* captures the systematic liquidity risk of a firm. We also use *Liquidity Adj. R²* as an alternative measure of liquidity commonality. This measure takes the values of the adjusted R²s from the firm-level time-series regressions in equation (2) and accounts for both the systematic and idiosyncratic variations (Brockman et al., 2009).

Control Variables

We use several control variables identified in the literature as determinants of stock market liquidity. It has been widely documented that the level of the stock price is related to a firm's market liquidity, since it controls for price discreteness and also acts as a proxy for firm risk, that is, low prices are associated with higher risk (Stoll, 2000). We estimate the annual stock price using the average of the daily closing prices. We also control for the volatility of daily returns, using an annualized figure of the standard deviation of the daily returns over a year. High volatility translates to high firm risk and high inventory costs for traders. At the same time, it is associated with a high level of information asymmetry between company insiders and outsiders, as well as between investors with different information sets (i.e., the adverse selection argument). For all these reasons, we expect to observe a negative relationship between return volatility and liquidity. High trading volume is associated with decreases in inventory risk (Stoll, 1978a,b; Hameed et al., 2010) and should

therefore lead to higher liquidity, that is, lower spreads. Firm market performance, i.e., stock returns, can affect the firm's return volatility and therefore liquidity (Hameed et al., 2010), thus it is important to control for it. The daily return is averaged over the year and annualized.

In addition to these market-based control variables that are frequently used in the literature, we also examine the impact of several accounting-related firm characteristics. Firm size is expected to be positively correlated with market liquidity. Larger firms are more visible and more carefully scrutinized by both investors and analysts. An increase in information disclosure will render prices more efficient and this benefit is greater for large firms if they can attract IIs (Diamond and Verrecchia, 1991). Hence, the shares of larger firms are expected to be more liquid. We control for firm size by including in our models the value of total assets, retrieved from Compustat.¹¹

Stock liquidity also interacts with capital raising behavior. Companies with liquid stocks prefer raising equity to debt (Lipson and Mortal, 2009). Lesmond et al. (2008) find that leverage-increasing activity increases bid-ask spreads and vice versa. Amihud and Mendelson (2008) explain that, the higher the company's leverage, the more sensitive is its value of equity to information asymmetry and adverse selection. This explains why leverage reduces stock liquidity leading to wider bid-ask spreads and higher price impact costs. We measure financial leverage as the ratio of long-term debt to total assets, as reported in Compustat. Stock liquidity depends, among other things, on the shareholder base; the larger the base, the more liquid is the stock (see Amihud et al., 1999; Grullon et al., 2004; Lipson and Mortal, 2007). We capture the breadth of ownership by measuring the number of shareholders, as reported in the firms' annual reports in Compustat.

Another important parameter, which affects decision making within a firm and has a direct impact on firm performance, is shareholder rights. Managers who are protected from shareholders' action against them are expected to be less efficient and less transparent. Bebchuk et al. (2009) construct an E-index (Entrenchment Index), which is based on six shareholder rights provisions. The higher the level of the E-index, the higher is the level of managerial entrenchment. Bebchuk et al. find that the E-index is better related to firm valuation than the G-index (which is an index based on 24 provisions, developed by Gompers et al., 2003). Managerial entrenchment is expected to have a negative relationship to market

¹¹ We use the book value of assets, and not the market value of equity, as a proxy for firm size, to reduce the cross-correlation in our multivariate models. Using market capitalization does not alter our results.

liquidity, since entrenchment leads to higher trading costs for shares if investors are deterred by the entrenchment provisions.¹² Finally, a key factor in the theory of liquidity through inventory control is the information asymmetry between the market maker and the investors, and the resulting adverse selection problems that face the market maker when he trades with an informed investor. One external influence that reduces information asymmetry is the role played by the security analysts. The larger is the number of analysts following the company, that is, the greater the analyst coverage, the more liquid is the company's stock (see Brennan and Subrahmanyam, 1995; Irvine, 2003). We measure analyst coverage using the number of next-year forecasts (FY1) issued by analysts. The number of year-one earnings forecasts (F1NE) is obtained from the I/B/E/S history file through Datastream.

2.3 Summary Statistics

Table 1 presents the summary statistics for our sample. Panels A, B and C provide, respectively, details about the distributions of the stocks' market liquidity, institutional investors and other firm characteristics for the pre-crisis period (2004-6), the crisis period (2007-8) and their differences. A Wilcoxon rank-sum test reveals that, for most of our variables, we can reject the hypothesis that the pre-crisis and crisis periods are drawn from the same distribution.

Consistent with expectations, Panel A shows that the average quoted spread increases from 0.157% to 0.235% during the 2007-8 financial crisis accompanied by an increase in the standard deviation. A similar pattern applies to the liquidity commonality, as measured by R^2 , with the mean value increasing from 6.9% to 41.5%. The Liquidity Beta has a different pattern, with a drastic decrease in cross-sectional standard deviation but a significantly higher average level in the crisis period.¹³

Panel B shows, on average, institutions hold 76% of our sampled firms' equity. The largest holders by far are independent advisors (IA) holding about half of all shares held by the II sector; IA are also large in number. The next in line are BNK, INS, PPS and UFE in that order (see footnote 3 for explanations of abbreviations). As they are also smaller in number, their average holdings are much larger than that of IA with the exception of UFE.

¹² We retrieve the information on the Entrenchment Index (E-Index) from Lucian Bebchuk's website: <http://www.law.harvard.edu/faculty/bebchuk/data.shtml>, accessed in May, 2010.

¹³ The reduction in the variations of beta is a well known phenomenon as correlation with the market goes to 1. Nevertheless, subsequent scatter plots reveal sufficient variations in liquidity beta for it to produce a significant relationship with institutional variables, even when extreme values are removed.

UFE are universally small in number and small in proportional holdings. In terms of investment style, QIX have the largest holdings and head count, followed by TRA and DED in that order. Between the pre-crisis and crisis periods, IIs increased their holdings in the average S&P 1500 firm from 74.5% to 78.7%. Similar increases can be found for most II types and styles. Interestingly, the average number of IIs increases from 232 before the crisis, to 261 during the crisis. Thus, our subsequent findings on the effect of II count on market liquidity are not driven by a reduction in the number of unique institutions we include in our analysis during the crisis.¹⁴

Panel C shows that the average firm in our sample is large, which is the result of our decision to study S&P 1500 firms. The average stock price is \$35 and the average book value of assets is just above \$20 billion. Over the entire sample period, the average stock return and return volatility are 2.9% and 39% respectively with a strong boom and bust pattern between the pre-crisis and crisis periods. Finally, the average firm has 20% leverage, just over 31,000 shareholders, approximately ten analyst forecast reports published about its one-year-ahead earnings and a 2.76 E-index, which reveals a tendency for more entrenched managers.

Table 2, Panel A, compares the medians¹⁵ and standard deviations of our main herding measure for the pre-crisis and crisis periods. A value above (below) 0.5 indicates buy- (sell-) side herding. The sell-side herding of IIs increases during the crisis period across all types and styles.¹⁶ A K-sample test finds the differences to be statistically significant for all types and styles, except for DED. Interestingly, the cross sectional standard deviation of the herding measure dropped substantially during the crisis compared to the pre-crisis period for all groups with the exception of UFE. This indicates a substantial convergence of within group trading behavior during the crisis. Panel B presents the correlation coefficients across types/styles for the herding measure. The correlations are all higher in the pre-crisis period than in the crisis period. This indicates some asymmetry between buy-side and sell-side herding behavior, that is, the different groups of IIs buy together in good times but sell

¹⁴ Our sample covers 3,349 (3,097) unique institutions during crisis (pre-crisis). Thus, the reported results in this paper are not driven by a wave of defaults, M&As or a divestment by institutions of their shares in the U.S. equity markets.

¹⁵ The mean values indicate a similar trend in most cases but in the pre-crisis period the means are driven by some clustering at the left tail of the distribution making some means smaller than medians and smaller than their counterparts in the crisis period.

¹⁶ In this paper, we use the quarterly 13f filings of S&P 1500 firms to determine changes in II ownership. This results in us not capturing all the net trades during the quarter, as well as short positions. These weaknesses in our data collection should bias our tests against finding significant results. Despite this, our herding measure clearly captures sell-side herding behavior among IIs during the crisis.

differently during crises. The IA group has the most highly correlated trading pattern, both within the group and with other groups. UFE trading pattern has the least in common within the group, as well as with the other groups.

Using quarterly data from 1983-1997, Sias (2004) documents that BNK exhibit the strongest evidence of herding. Our results for 2007-8 indicate that all institutions increased sell-side activities, with UFE experiencing the largest swing from buy to sell. INS, IA and PPS all have much larger swings than BNK. In Sias's sample, BNK are the largest II shareholders, compared to the other IIs, with an average head count of 189 (20% of total number of IIs). In our more recent sample period, the influence of BNK is much reduced and taken over by IA. During 2004-8, the number of average BNK per firm is 4 (which is less than 2% of total IIs per firm). BNK average holding is 14% which is about one-fifth of total II holdings. This might explain the different BNK behavior reported by Sias and this study.

3. Results

3.1 Effect of II count and holdings on market liquidity

Table 3 presents our OLS regression results regarding the relationship between market liquidity and institution ownership. To alleviate concerns about endogeneity and spurious inferences, we include in all pooled-sample regressions the control variables¹⁷ that the literature identifies as important determinants of market liquidity. All model specifications include industry fixed effects to control for time-invariant omitted industry-level factors that affect liquidity.¹⁸ We also include year effects to control for cross-sectional dependence, that is, market-wide factors that affect a stock's market liquidity. Our reported p-values are based on heteroskedasticity-robust standard errors, clustered at the firm level. Clustering the errors at the firm level allows us to control for time-series dependence. We present separately the results for the crisis and pre-crisis periods as well as those with and without the accounting-based control variables.

¹⁷ In order to reduce the impact of outliers we take the natural logarithm of the following variables that have skewed distributions: stock dollar volume, stock price, assets and number of shareholders. We also take the cumulative distribution function (cdf) of return volatility, instead of its level, to avoid multicollinearity issues. Indeed, a variance inflation factor (VIF) analysis for all of our model specifications reveals no significant problems, after these transformations.

¹⁸ Falkenstein (1996) states that IIs seek liquidity. The significance of II holdings on the right hand side of a regression explaining liquidity could therefore be due to an endogeneity bias. Agarwal (2007) performs a test of causality to investigate whether II ownership causes liquidity or if, instead, the relation is due to IIs seeking to invest in liquid stocks. He argues that the former holds.

In Table 3, II count is positive and significant in all specifications; it increases the quoted spread in both pre-crisis and crisis periods. This is consistent with our conjecture that the nature of II trading behavior increases trading costs. Later on in our analysis, in Table 6, we provide direct evidence of this by illustrating that it is sell-side herding that has the main effect on trading costs. Consistent with Agarwal (2007), we also find that II holdings decrease quoted spreads.¹⁹

All the market-based control variables are highly significant and have the predicted signs, that is, stock returns and volatility are positively associated with spread, whereas stock dollar volume and stock price are negatively associated with it. In contrast, none of the accounting-based control variables appear to be significantly related to spread. Still, we keep them in the subsequent analyses since, in several specifications, some of these control variables appear to be marginally significant and increase the overall R^2 . Finally, we note the differences in the levels of the coefficients between specifications covering the same sub-period. Unreported analysis, using step-wise regressions, reveals that the introduction of the E-index variable reduces the sample size by 232 observations and accounts for most of the drop in the sizes of the II count and holdings coefficients. Further investigation shows that 79% of the missing observations in the E-index come from non-S&P 500 firms. Thus, we conclude that the changes in the coefficients are a manifestation of a firm size effect.

We then investigate whether the positive relationship between II count and spread is sensitive to the II type and investment style. Table 3, Panel B, reports only the II count and holdings coefficients, as well as the regression R^2 , from the regressions we run for each II type and style. The regression model used is similar to that of Panel A, using the full set of control variables. The positive effect of II count and the negative effect of II holdings remain

¹⁹ The literature reports ambiguous results on the effect of II holdings on spread. For instance, Dennis and Weston (2001) document a negative relation between the percentage of shares held by IIs and the log of the spread; their study is constructed in the same manner as ours. Sarin et al. (2000), on the other hand, find a non-significant relation between holdings and spread. Agarwal (2007) argues that the relation between spread and institutional holdings should be U-shaped. This relation arises from a tradeoff between IIs increasing the spread due to adverse selection and decreasing it due to the information efficiency brought about by informed trading. Differences in the estimation methods, sample periods, and data sources used in these studies may explain some of the differences between the various empirical findings, e.g., Agarwal reports average II holdings of 36%, which is less than half of that of our sample (i.e., 76%). Also, in our study the correlation between II count and II holdings is low, 2.2%. It shows that the result on the effect of II trading on spread is not driven by multicollinearity. We also perform our analysis excluding II holdings and the positive, significant relation remains (untabulated result). Moreover, II count cannot be a proxy for the squared II holdings; the pairwise correlation between these two variables is negative and only 4% in our sample. Still, we re-run our analyses including the squared II holdings and II count to capture non-linearity and our results remain unchanged (untabulated result).

for almost all II types and styles. The only exception is PPS during the pre-crisis period, but their effects become highly statistically significant during the crisis.

Next, we run a series of alternative model specifications to further examine the robustness of the results reported in Table 3. Table 4 reports two of them. Instead of examining the levels, we look at the annual changes in all of the variables. Regressions based on variable changes are typically less likely to capture spurious relationships. In columns 2 and 4, we also add the lagged change in the spread. This allows us to reduce autocorrelation in the residuals, caused by any non-stationarity in the time-series of spreads. Our results remain unchanged. Finally, we also run panel data regressions using firm fixed effects (untabulated results). The coefficient of II count remains positive and highly significant (at the 1% level) in all specifications. II holdings remain negatively related to spread, but they are highly significant (at the 1% level) only for the pre-crisis period (significance is at the 10% level during the crisis). We note that running firm fixed effects models when the time-series of the panel is short could introduce more bias into the coefficients compared to the OLS models. We therefore re-run our panel data regressions for the full sample period, using an indicator (crisis dummy) variable for the crisis period. The results remain unchanged. Finally, we interact all the independent variables with the crisis dummy to capture marginal effects. Consistent with the above results, the marginal and base effects of II count on spread are positive and highly significant.

We now turn our attention to the relation between liquidity commonality and institutional ownership. To date, the literature on commonality in liquidity has identified firm size, industry effects and market conditions (see Chordia et al., 2000; Brockman et al., 2009; as well as Karolyi et al., 2011) as the main determinants of commonality. Watanabe and Watanabe (2008) also show that commonality in liquidity is related to periods of increased information asymmetry. Consistent with the prior analysis, we run OLS regressions and include industry and year fixed effects. We also control for firm size using the book value of the firm's total assets. We cluster the heteroskedasticity-robust standard errors at the firm level. We run our analyses both for the systematic (beta) and overall (R^2) liquidity risk.²⁰

Table 5 reports the results for the crisis period. We do not present the results for the pre-crisis period, essentially because the parameter estimates are largely insignificant. In

²⁰ Using scatter plots we identify liquidity risk and II count values that could be considered as outliers. We run several sensitivity tests using different cut-off points for excluding observations. Our results are not driven by extreme values.

panel A, we present the result for the overall II count and holdings. Panel B reports only the coefficients for count and holdings from separate regressions per II type and style. In line with our prediction, II count is positively and significantly associated with both the liquidity beta and R^2 . II count for DED did not drive liquidity R^2 and has only weak impact on liquidity beta. We demonstrate in the next Section that II count proxies for II sell-side herding, and provide evidence that DED was the least likely to herd in the crisis of 2007-8. Finally, there is no significant association between liquidity commonality and the level of institutional shareholdings (only for TRA is II holdings negative significant in both models).

3.2 Impact of institutional herding on market liquidity

In this Section we illustrate that II herding is the reason behind the positive effect of institutional trading on trading costs and liquidity commonality during crises. Table 6 presents the results on the effect of II herding on quoted spread and liquidity risk. The model specifications used are identical to these in Tables 3 and 5, but instead of capturing II count and holdings, we now use the II herding measure to capture the impact of the II trading behavior on market liquidity.

The coefficient of II herding is negative and highly significant in most specifications. So, with the clear exceptions of UFE and DED, sell-side herding during the crisis increased quoted spread, liquidity R^2 and liquidity beta for most groups. It appears that the larger the sell-side herding by IIs of a firm's stock (the smaller the value of the II herding measure) the larger is the quoted spread, as well as liquidity R^2 and beta of the firm during the crisis. In the pre-crisis period, trading was dominated by buy side. All the liquidity R^2 and liquidity beta results for the pre-crisis period are statistically insignificant (untabulated result).²¹ It appears that only strong sell-side herding affects liquidity risk. This could also explain the finding of Watanabe and Watanabe (2008) that high liquidity risk states of the economy are short-lived and characterized by heavy trading. During the crisis period, the herding measures for UFE and DED have the largest within group standard deviation and the smallest correlation with other groups. This explains the lack of results for these two groups. DED investors are, by definition, buy-and-hold investors, who engage with a firm for the long-term; they are not expected to have similar herding behavior to other institutions during a crisis. Indeed, the

²¹ The negative relation between II herding and spread exists even in the pre-crisis period, though the impact of sell-side herding on trading costs is smaller (untabulated). This is reasonable given the prevalence of buy-side herding in 2004-2006.

change in DED herding measure in Table 2 is not significant during the crisis. The herding behavior of IIs is much more pronounced for QIX and TRA investors.

Recently, Koch et al. (2010) document that correlated trading can also induce liquidity commonality. Our findings corroborate the findings of Koch et al. (2010) on the impact of mutual fund trading (in our classification included in the IA group) on liquidity commonality. However, our findings also highlight the significant impact of the trading activities of other IIs, such as BNK and INS, during a crisis, as well as that only correlated sell-side herding and not the correlated buy-side herding can have such an impact.²² In order to test the robustness of our results, in Table 7, we follow Sias (2004) and run standardized regressions where all variables are transformed to have zero mean and unit variance.²³ This standardization allows us to compare the sizes of the coefficients. We observe that the herding by QIX investors has a more pronounced (similar) effect on liquidity beta (overall liquidity R^2) than (to) that of TRA investors. The coefficients of DED herding are very close to zero and several times smaller than those of QIX and TRA investors. In untabulated results, we repeat this analysis using a dollar-weighted herding measure,²⁴ proposed by Bohl and Voronkova (2003). The coefficients for overall herding remain negative and significant but are weaker, further indicating that the head count measure has a stronger impact than the dollar volume weighted holdings in driving liquidity risk.

3.3 Further robustness checks

We run four additional (untabulated) analyses, in order to further strengthen our inferences. First, as we mention in the introduction the results are not driven by the lack of individual (retail) investors in firms with high institutional presence. The number of IIs is positively, significantly, correlated with both the number of individual investors and their proportional representation. Our results do not appear to be driven by the lack of individual investors in high II count firms.

Second, if our conjectures regarding the role of II count are correct, one would expect a greater impact of sell-side herding on liquidity in firms with a greater number of IIs. In

²² This also corroborates the results of Brennan et al. (2011) who show that sell-side illiquidity is priced far more strongly than buy-side illiquidity.

²³ For each variable, both dependent and independent, we subtract the cross-sectional average and then divide by the cross-sectional standard deviation.

²⁴ Dollar herding is the ratio of the dollar value of shares bought to the dollar value of all shares transacted (bought and sold) over the period.

order to test this, we create a dummy variable which takes the value one (zero) for any firms with above (below) median number of IIs during the crisis. We re-run the analyses of Table 6 but now also include an interaction term of the II count dummy and II herding, as well as the uninteracted variables. This interaction term, which captures the marginal effect of II herding on liquidity in firms with high II count, is negative and highly significant in all regressions. Thus, we confirm that the impact of sell-side herding on increasing illiquidity, i.e., higher spread and liquidity risk, is more pronounced in high II count firms.

Third, firms with blockholders have lower free float and less liquid stocks (Rubin, 2007). Sell-side herding in these firms should result in greater order imbalances, hence we expect greater impact of sell-side herding on liquidity in the presence of blockholders. We classify firms into two groups, that is, with or without a blockholder(s). We use, in separate analyses, indicator variables based on the holdings of the largest shareholder and the largest five shareholders. The median holdings of the largest blockholder was around 9% of the equity of the firm during the crisis. The median holdings of the five largest shareholders were 30% during the same period. Therefore, our indicator variables take the value one for values above 9% and 30% respectively, and zero otherwise. Following the analysis above, we interact the indicator variables with II herding to capture marginal effects. As expected, the marginal effect of II herding on spreads and spread commonality is larger in the presence of blockholders (highly economically and statistically significant).

Fourth, Table 6 tests a linear relation between II herding and liquidity. But our predictions are based on sell-side herding only. In order to isolate the effect of sell-side herding we create two new variables: a sell-side herding dummy which takes the value of one when II herding is lower or equal to 0.5, zero otherwise, and a Degree of Imbalance (DOI) variable, which is calculated as the absolute value of the difference of II herding from 0.5. DOI captures the extent of herding imbalance in a firm. We re-run the analyses in Table 6, also including the interaction of DOI with the sell-side herding dummy, as well as the uninteracted terms. The coefficient of the interaction term is positive significant thus confirming that the greater the herding imbalance caused by sell-side herding the higher the spread and liquidity commonality.

4. Discussion and Conclusion

This paper investigates the role of institutional investor trading in escalating market illiquidity during the recent financial crisis. We measure the intensity, scale and flow of institutional trading by the number of IIs holding shares (II count), their proportional ownership (II holdings) and the ratio of institutions' buy trades to all trades (II herding). We study two aspects of market liquidity: trading cost as measured by the quoted proportional spread and commonality in liquidity as measured by R^2 and the beta of the cross-sectional spread variations. Our results suggest that institutions' sell-side herding together with their correlated trades contributed to the increased trading costs and liquidity risk during 2007-8.

Our findings are robust to different model specifications and measures. They provide empirical support for theoretical predictions on the role of trading in exacerbating liquidity shortages during a crisis. In particular, prior theoretical literature predicts the existence of increased selling activity by IIs during a crisis. The rationale is that, during a market downturn, IIs face high selling needs due to increased funding constraints (Brunnermeier and Pedersen, 2009), high risk aversion (Huang and Wang, 2009), tight risk management (Garleanu and Pedersen, 2007), or offloading of assets by convergence traders (Kyle and Xiong, 2001). A common prediction is that these pressures lead to excess order imbalances and inventory costs, hence greater illiquidity. In this paper, we provide evidence that firms with a larger number of institutional investors are more vulnerable to sell-side herding. We report that IIs did indeed increase their selling activity substantially during the financial crisis. More importantly, we show that this sell-side trading activity led to an increase in firms' trading costs and liquidity risk during the crisis. We do not investigate which of the above theoretical predictions drives our results. During a crisis, all of them might play a significant role in raising the selling needs of IIs.

Our results collectively indicate a significant role for II sell-side herding in increasing a firm's trading costs and liquidity risk. They confirm the speculation by Chordia et al. (2000) that liquidity in commonality could be due to institutional herding (p. 14), and provide direct evidence to support the conjecture of Koch et al. (2010) that correlated trading increases commonality in liquidity. Our study extends Koch et al. by showing the impact of II herding on a firm's quoted spread, as well as demonstrating the prevalence of these phenomena across different II types during a crisis. Moreover, our results confirm that a dedicated investment style did help to stabilize and reduce liquidity risk during the 2007-8

financial crisis. Controversial as it may sound, our findings suggest that restricting the number of institutional shareholders holding a firm's equity might help to reduce the firm's liquidity risk during a financial crisis.

Scholes (2000) argues that, during a crisis, market participants first sell the most liquid stocks in their portfolios. Similarly, Anand et al. (2010) report that IIs tilt their selling activity towards less liquidity-sensitive stocks during a crisis. These findings imply that our results for II count and II sell-side herding cannot be driven by reverse causality. Still, we accept that the endogeneity issues cannot be completely resolved. For example, one may argue that II sold stocks in anticipation of a liquidity drain out. Until we can successfully find an instrument to control for such explanation, the endogeneity problem cannot be eliminated.²⁵ But, our results indicate a strong connection between sell-side herding, II count and liquidity risk even if the direction of causality remains as a conjecture. It is the first empirical evidence that is in line with the theoretical predictions of Xiong (2001), Brunnermeier and Pedersen (2009), Garleanu and Pedersen (2007) and Huang and Wang (2009).

In 2007, IIs held 80% of the S&P 1500 equity and accounted for the majority of the trading volume in the markets. Given the size of II participation in the economy, II trading behavior has a large impact on liquidity and trading costs and can easily induce market-wide systemic liquidity risk. So this paper not only provides important policy implications but also some empirical support to theoretical models of extreme liquidity (e.g. Huang and Wang, 2009; Kyle and Xiong, 2001), in particular regarding the role of (IIs') trading activity in exacerbating the liquidity drain-out during the recent financial crisis.

²⁵ Following recent studies, e.g., Faccio et al. (2011) and Laeven and Levine (2009), we calculate the cross-sectional average II count of the *other* firms in the sample in each year, and use it as an instrument in IV regressions. The idea is that the average (market-wide but excluding firm *j*) II count should impact II count in firm *j* but not firm's *j* liquidity. The IV regression results are broadly consistent but the F-statistic of the excluded variable is very sensitive to the model specification used, taking very low values in several cases, which raises concerns about the validity of the instrument in our setting. Hence we do not report these results.

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Table 1
Descriptive Statistics

Panel A: Spread and Commonality

	Pre-Crisis Period (2004-6)			Crisis Period (2007-8)			Diff
	N	Mean	Std. Dev	N	Mean	Std. Dev	
Quoted Spread (%)	3,508	0.157	0.197	2,044	0.235	0.522	0.078***
Liquidity Adj R ²	3,498	0.069	0.217	2,038	0.415	0.348	0.346***
Liquidity Beta	3,498	0.955	3.764	2,038	1.282	1.563	0.327***

Note: Quoted Spread is the annualized proportional spread, based on daily closing bid-ask prices. We follow the specification in Chordia et al. (2000) and run the following time-series regressions, using monthly observations for each firm in our sample to calculate the Liquidity Adj. R² and Liquidity Beta:

$$\Delta \text{Spread}_{f,m} = \alpha + \beta_1 \Delta \text{Spread}_{M,m} + \beta_2 \Delta \text{Spread}_{M,m+1} + \beta_3 \Delta \text{Spread}_{M,m-1} + \delta_1 \text{Return}_{M,m} + \delta_2 \text{Return}_{M,m+1} + \delta_3 \text{Return}_{M,m-1} + \delta_4 \Delta \text{Volatility}_{f,m} + \varepsilon_{f,m}$$

where Δ denotes the proportional change in the variable between successive months. The information on the market (M) is calculated using the equal-weighted average (of Spread or Return) for all firms in our sample except firm f . Firm return volatility is calculated for the month m using daily information. We run these time-series regressions separately for years 2004-2006 (pre-crisis) and 2007-2008 (crisis). We define Liquidity Beta as the contemporaneous coefficient of the changes in the market portfolio spread (i.e., β_1). *** denotes significance of the differences in Means at the 1% level.

Panel B. Institutional holdings and count

	Pre-Crisis	Crisis	Wilcoxon Rank-sum		Pre-Crisis	Crisis	Wilcoxon Rank-sum
<u>II Holdings</u>				<u>II count</u>			
ALL II	0.745	0.787	***	ALL II	0.232	0.261	***
BNK	0.137	0.145	***	BNK	0.004	0.005	***
INS	0.036	0.039	***	INS	0.002	0.002	-
IA	0.440	0.503	***	IA	0.125	0.158	***
PPS	0.028	0.024	***	PPS	0.000	0.001	***
UFE	0.001	0.001	***	UFE	0.001	0.000	***
QIX	0.475	0.490	***	QIX	0.157	0.163	-
TRA	0.164	0.178	***	TRA	0.066	0.075	***
DED	0.105	0.095	***	DED	0.007	0.006	***

Note: II holdings is the ratio of the number of shares held by IIs to the total shares outstanding. II count is the number (in thousands) of IIs holding a firm's shares. We follow Bushee (2001) and classify IIs into the following types and investment styles: bank trusts (BNK), insurance companies (INS), independent advisors (IA), public pension funds (PPS), university and endowment foundations (UFE), quasi-indexers (QIX), transient (TRA), and dedicated (DED). *** denotes the Wilcoxon rank-sum test significance at the 1% level.

Panel C. Firm Characteristics

	Pre-Crisis	Crisis	Wilcoxon Rank-sum
Stock Returns (%)	15.233	-18.313	***
Return Volatility (%)	31.019	53.401	***
Stock Dollar Volume	1.284	2.412	***
Stock Price (\$)	37.530	31.285	***
Assets (\$ mil)	18,252	23,648	***
Leverage	0.192	0.212	***
No of Shareholders (000s)	30.360	32.431	-
E-index	2.295	3.615	***
Analyst Coverage	9.969	9.553	-

Note: Stock Returns is the annualized average of daily returns. Return Volatility is computed as the standard deviation of daily returns over a year. Stock Dollar Volume is the average daily dollar volume over the year. Stock Price is the average of daily closing prices over the year. Assets is the book value of the firm's assets. Leverage is the ratio of long-term debt to total assets. No of Shareholders is the number of shareholders reported in Compustat. E-index is the Bebchuk et al. (2009) entrenchment index, based on six shareholder rights provisions. Higher values of the E-index are associated with higher levels of managerial entrenchment. Analyst Coverage is the number of one-year-ahead earnings forecasts issued by analysts per year. The information is collected through Datastream. *** denotes the Wilcoxon rank-sum test significance at the 1% level.

Table 2

Summary Statistics of Institutional Herding for the Pre-Crisis (2004-6) and Crisis (2007-8) Periods
 Panel A: Median and standard deviations of herding by II types and investment styles

Herding Measures	Median			Standard Deviations		
	Pre-Crisis	Crisis	K-sample test	Pre-Crisis	Crisis	F test
ALL II	0.564	0.486	***	0.215	0.085	***
BNK	0.489	0.460	***	0.211	0.108	***
INS	0.537	0.458	***	0.237	0.122	***
IA	0.572	0.506	***	0.216	0.082	***
PPS	0.500	0.425	***	0.244	0.146	***
UFE	0.583	0.292	***	0.305	0.321	**
QIX	0.536	0.460	***	0.214	0.092	***
TRA	0.599	0.533	***	0.228	0.090	***
DED	0.458	0.449	-	0.235	0.168	***

Panel B: Pair-wise correlations between herding measures by different II types and investment styles

Crisis Pre- Crisis	ALL II	BNK	INS	IA	PPS	UFE	QIX	TRA	DED
ALL II		0.862	0.714	0.956	0.701	0.164	0.953	0.850	0.442
BNK	0.957		0.629	0.739	0.600	0.171	0.879	0.660	0.369
INS	0.937	0.896		0.618	0.584	0.163	0.737	0.601	0.330
IA	0.991	0.934	0.915		0.613	0.116	0.875	0.868	0.443
PPS	0.895	0.855	0.867	0.871		0.156	0.717	0.581	0.322
UFE	0.539	0.519	0.551	0.515	0.560		0.191	0.065	0.048
QIX	0.991	0.963	0.941	0.977	0.900	0.551		0.698	0.407
TRA	0.977	0.919	0.906	0.982	0.862	0.499	0.949		0.339
DED	0.819	0.784	0.766	0.821	0.729	0.431	0.800	0.798	

Note: II herding is defined as the ratio of buyers to active institutions (buyers plus sellers). A value above (below) 0.5 indicates buy- (sell-) side herding. K-sample and F tests are used to identify the statistical significance of the differences between the two periods. ***, ** denote significance at the 1% and 5% levels, respectively. We follow Bushee (2001) and classify IIs into the following types and investment styles: bank trusts (BNK), insurance companies (INS), independent advisors (IA), public pension funds (PPS), university and endowment foundations (UFE), quasi-indexers (QIX), transient (TRA), and dedicated (DED).

Table 3
Spread and Institutional Investors (IIs)

Independent Variables	Spread (%)		Spread (%)	
	Pre-Crisis		Crisis	
II count	0.350***	0.210***	0.637***	0.095***
	[0.000]	[0.000]	[0.000]	[0.000]
II holdings	-0.143***	-0.098***	-0.226***	-0.064***
	[0.000]	[0.000]	[0.000]	[0.001]
Stock returns	0.001***	0.001***	0.001***	0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
Return volatility (cdf)	0.111***	0.097***	0.154***	0.077***
	[0.000]	[0.000]	[0.000]	[0.000]
Stock dollar volume (ln)	-0.084***	-0.063***	-0.143***	-0.044***
	[0.000]	[0.000]	[0.000]	[0.000]
Stock price (ln)	-0.125***	-0.100***	-0.171***	-0.068***
	[0.000]	[0.000]	[0.000]	[0.000]
Assets (ln)		0.006		0.005
		[0.118]		[0.154]
Leverage		0.007		0.017
		[0.679]		[0.253]
No of Shareholders (ln)		-0.001		0.001
		[0.814]		[0.310]
E-Index		0.001		-0.002
		[0.461]		[0.129]
Analyst Coverage		0		0.001
		[0.560]		[0.338]
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3,168	2,608	1,955	1,590
R^2	0.572	0.536	0.392	0.533

Panel B

	Spread (%)					
	Pre-crisis			Crisis		
	II Count	II Holdings	R^2	II Count	II Holdings	R^2
BNK	12.362*** [0.000]	-0.262*** [0.000]	0.558	3.922*** [0.001]	-0.206*** [0.001]	0.521
INS	17.626*** [0.000]	-0.271*** [0.000]	0.554	13.587*** [0.000]	-0.251*** [0.000]	0.539
IA	0.292*** [0.000]	-0.067*** [0.000]	0.558	0.113*** [0.000]	-0.066*** [0.000]	0.527
PPS	-1,734 [0.379]	-0.441 [0.519]	0.533	14.897*** [0.000]	-0.754*** [0.001]	0.523
UFE	11.488* [0.057]	-0.674*** [0.002]	0.528	35.507*** [0.000]	-0.309 [0.335]	0.520
QIX	0.252*** [0.000]	-0.123*** [0.000]	0.532	0.134*** [0.000]	-0.072*** [0.006]	0.531
TRA	1.109*** [0.000]	-0.187*** [0.000]	0.529	0.640*** [0.000]	-0.126*** [0.000]	0.534
DED	5.783*** [0.000]	-0.083** [0.012]	0.505	3.189*** [0.003]	-0.011 [0.625]	0.515

Note: This table reports results from pooled OLS regressions run separately for the pre-crisis (2004-6) and crisis (2007-8) periods. The dependent variable is the firm's quoted spread. All variables are defined as in Table 1. Industry and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. p-values are reported in brackets. ***, ** denote significance at the 1% and 5% levels, respectively. Panel A presents the full regression results for all IIs. Panel B reports only (to conserve space) the coefficients for II count and holdings, as well as the regression R^2 , from regressions run separately for each II type and style.

Table 4
Robustness tests using alternative specifications

Independent Variables	Δ Spread (%)		Δ Spread (%)	
	Pre-Crisis		Crisis	
Δ II count	0.168*** [0.010]	0.161** [0.014]	0.120*** [0.002]	0.089*** [0.000]
Δ II holdings	-0.055** [0.023]	-0.049** [0.044]	-0.052** [0.016]	-0.029** [0.040]
Δ Spread (%) _(t-1)		0.071** [0.011]		0.591*** [0.000]
Δ Stock returns	0.000*** [0.000]	0.000*** [0.000]	0.000*** [0.000]	0.000*** [0.000]
Δ Return volatility (cdf)	0.108*** [0.000]	0.110*** [0.000]	0.013 [0.184]	0.014*** [0.009]
Δ Stock dollar volume (ln)	-0.157*** [0.000]	-0.160*** [0.000]	-0.053*** [0.003]	-0.019** [0.013]
Δ Stock price (ln)	-0.113*** [0.000]	-0.117*** [0.000]	-0.077*** [0.000]	-0.036*** [0.000]
Δ Assets (ln)	0.030** [0.039]	0.029** [0.043]	-0.019** [0.010]	-0.009* [0.070]
Δ Leverage	0.007 [0.838]	0.007 [0.826]	-0.024 [0.283]	-0.018 [0.220]
Δ No of Shareholders (ln)	0 [0.995]	-0.001 [0.880]	0.001 [0.703]	-0.004* [0.088]
Δ E-Index	-0.009 [0.402]	-0.007 [0.509]	-0.001 [0.423]	0 [0.726]
Δ Analyst Coverage	0.002** [0.030]	0.002* [0.062]	0 [0.659]	-0.001** [0.018]
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2,308	2,284	1,527	1,512
R^2	0.515	0.525	0.251	0.727

Note: This table reports results from pooled OLS regressions on the annual changes in a firm's quoted spread. We use annual changes for all independent variables as well. We run separate regressions for the pre-crisis (2004-6) and crisis (2007-8) periods. All variables are defined as in Table 1. In the second and fourth models, we also include the lagged dependent variable. Industry and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. p-values are reported in brackets. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 5
Commonality and Institutional Investors (IIs) during the Crisis
Panel A: IIs and Commonality in Liquidity

Independent Variables	Liquidity R^2	Liquidity Beta
II count	0.230*** [0.003]	1.011*** [0.006]
II holdings	-0.077 [0.180]	-0.058 [0.819]
Assets (ln)	0.004 [0.709]	0.095** [0.050]
Industry FE	Yes	Yes
Year FE	Yes	Yes
Observations	2,038	2,045
R^2	0.08	0.172

Panel B: II Types/Styles and Commonality in Liquidity

	Liquidity R^2			Liquidity Beta		
	II Count	II Holdings	R^2	II Count	II Holdings	R^2
BNK	9.561** [0.023]	-0.132 [0.484]	0.063	50.44** [0.012]	-0.042 [0.951]	0.163
INS	21.46*** [0.001]	-0.367 [0.256]	0.068	116*** [0.000]	0.557 [0.714]	0.170
IA	0.257*** [0.008]	-0.092 [0.113]	0.067	1.207** [0.010]	-0.165 [0.455]	0.164
PPS	8.502 [0.469]	-0.974 [0.270]	0.060	173.2*** [0.000]	-3.011 [0.276]	0.165
UFE	46.90** [0.029]	-1.557 [0.493]	0.061	316.6*** [0.000]	-3.042 [0.824]	0.161
QIX	0.341*** [0.001]	-0.014 [0.863]	0.079	1.460*** [0.002]	0.603* [0.097]	0.174
TRA	0.905*** [0.010]	-0.312*** [0.007]	0.079	4.125** [0.028]	-1.389*** [0.002]	0.174
DED	5.389 [0.147]	-0.144 [0.267]	0.072	31.995* [0.063]	-1.114** [0.037]	0.169

Note: This table reports results from pooled OLS regressions on the effect of IIs on liquidity risk during the crisis (2007-8) period. The dependent variables are the two proxies for liquidity risk used in this study, i.e., Liquidity Adj R^2 and Liquidity Beta. In Panel A (Panel B) we run regressions for all IIs (separately by II type/style). Panel B reports only the coefficients for II count and holdings, as well as the regression R^2 , to conserve space. All variables are defined as in Table 1. Industry and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. p-values are reported in brackets. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 6
 II Herding and Market Liquidity during the Crisis

<i>Herding</i>	Spread (%)		Liquidity R ²		Liquidity Beta	
	<i>coef.</i>	<i>R</i> ²	<i>coef.</i>	<i>R</i> ²	<i>coef.</i>	<i>R</i> ²
ALL II	-0.279*** [0.000]	0.519	-0.403** [0.025]	0.063	-2.594*** [0.001]	0.166
BNK	-0.134*** [0.002]	0.516	-0.207* [0.064]	0.062	-0.780* [0.099]	0.160
INS	0.044 [0.213]	0.510	-0.142* [0.097]	0.058	-0.572* [0.073]	0.160
IA	-0.306*** [0.000]	0.522	-0.296* [0.081]	0.061	-2.460*** [0.001]	0.165
PPS	-0.100*** [0.001]	0.517	-0.174** [0.011]	0.063	-0.597** [0.036]	0.161
UFE	-0.005 [0.348]	0.547	0.024 [0.420]	0.070	-0.022 [0.848]	0.154
QIX	-0.162*** [0.001]	0.514	-0.248* [0.100]	0.061	-1.629*** [0.008]	0.163
TRA	-0.230*** [0.010]	0.518	-0.377** [0.011]	0.063	-1.383*** [0.007]	0.162
DED	-0.011 [0.487]	0.501	0.038 [0.467]	0.054	-0.083 [0.661]	0.160

Note: This table reports results from pooled OLS regressions on the impact of II herding on quoted spreads and liquidity commonality during the crisis (2007-8) period. We use the model specifications presented in Table 3 (Table 5) when the dependent variable is Spread (Liquidity R² or Liquidity Beta), but we replace II count and holdings with II herding. We only report the coefficients for herding and the R² of each regression to conserve space. All variables are defined as in Table 1. Industry and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. p-values are reported in brackets. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.

Table 7: Standardized regressions of Herding on Commonality during the Crisis

Independent Variables	<i>Delta_Liquidity Adj R²</i>				<i>Delta_Liquidity Beta</i>			
	<i>Herding</i>							
<i>Delta_II</i>	-0.269**				-0.367***			
	[0.019]				[0.000]			
<i>Delta_QIX</i>		-0.190*				-0.261***		
		[0.073]				[0.004]		
<i>Delta_TRA</i>			-0.194**				-0.179**	
			[0.036]				[0.016]	
<i>Delta_DED</i>				0.049				-0.004
				[0.373]				[0.919]
<i>Delta_Assets (ln)</i>	0.123***	0.131***	0.136***	0.137***	0.194***	0.204***	0.215***	0.229***
	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,036	2,034	2,036	2,009	2,043	2,041	2,043	2,015
<i>R²</i>	0.063	0.062	0.062	0.054	0.166	0.163	0.161	0.160

Note: We run standardized regressions, as in Sias (2004), where all variables are transformed to have zero mean and unit variance, i.e., we subtract the cross-sectional average and then divide by the cross-sectional standard deviation. The dependent variables are the two proxies for liquidity risk used in this study, i.e., Liquidity Adj R² and Liquidity Beta. All variables are defined as in Table 1. Industry and year fixed effects are included in all specifications. Standard errors are clustered at the firm level. p-values are reported in brackets. ***, **, * denote significance at the 1%, 5% and 10% levels, respectively.