Money and Liquidity in Financial Markets [1]

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Abstract

We argue that there is a connection between the interbank market for liquidity and the broader financial markets, which has its basis in demand for liquidity by banks. Tightness in the interbank market for liquidity leads banks to engage in what we term "liquidity pull-back", e.g., selling assets in order to generate liquidity for themselves. By definition, trade in a highly liquid asset involves lower price impact, or transaction costs, on average than an equivalent trade in a less liquid asset. The implication, and our central hypothesis, is thus that increased tightness in the interbank market for liquidity is associated with an increase in the volume of more liquid assets relative to that of less liquid assets. Prices should also fall across the board, but not differentially so across assets with different "liquidity levels." We confirm these hypotheses on the CRSP universe of stocks using the three month Libor-OIS and TED spreads as measures of tightness in the interbank market.

– All the rivers run into the sea; yet the sea is not full: unto the place from whence the rivers come, thither they return again.
Ecclesiastes 1:7

1 Introduction

We study the connection between the interbank market for liquidity and the broader financial markets. That such a connection exists is suggested, for example, by the experience of the recent financial crisis, where we saw both a breakdown in the interbank market and a collapse in the prices of financial assets. There is also evidence in the extant literature that financial markets are affected by monetary phenomena. For example, returns in bond and equity markets appear to be influenced by monetary shocks (Fleming and Remolona 1997, Fair 2002, Piazzesi 2005) and fund flows (Edelen and Warner 2001, Boyer and Zheng 2009, Goetzmann and Massa 2002), as are measures of liquidity in these markets (Chordia, Sarkar, and Subrahmanyam, 2005). However, we are not aware of research that explicitly documents a link between the interbank market and the broader financial markets, as we do in this paper.

Our motivation for this line of inquiry has its basis in a money and banking perspective on financial market activity. Banks need liquidity, or central bank money, to satisfy reserve requirements, allow depositor withdrawals, etc. The central bank determines the quantity of liquidity via its operations and then the interbank market (re)allocates it. However, if the price of liquidity in the interbank market is high, alternative sources of liquidity may be more attractive. Banks that have exhausted credit limits, *must* look for alternative sources. But to paraphrase Friedman (1970), "One bank can increase its money balances only by persuading another one to decrease its balances."[1] And as emphasized by Tobin (1980), "The nominal supply of money is something to which the economy must adapt,

[1]The original Friedman quote is: "One man can reduce his nominal money balances only by persuading someone else to increase his. The community as a whole cannot in general spend more than it receives."

not a variable that adapts itself to the economy – unless the policy authorities want it to." So what alternatives to the interbank market are there?

Banks have, in fact, several alternatives. They can go to the discount window, but this is expensive and a last resort. They can try to induce more deposits, but this is unlikely to be effective within a short time span. Rather, the alternative that we wish to emphasize here, is selling financial assets and/or increasing margins to investors, which in turn may lead to asset sales as investors seek to meet margin requirements.[2] This does not increase the quantity of liquidity in the system, but it can increase the selling bank's liquidity balances, as long as the buying counterparty banks with another bank. One can think of this as a kind of "liquidity pull-back", where a bank dips its ladle into the "ocean" of financial assets and recovers, for itself, liquidity granted to a counterparty some time in the past and stored all the while in the financial asset that now is being sold.

Thus, we argue that there is a connection between the interbank market for liquidity and the broader financial markets arising from (the possibility of) liquidity pull-back. There are two potential facets to this connection. First, a higher price of liquidity, ceteris paribus, should be associated with offsetting drops in asset prices. This is so as to equalize, insofar as possible, the cost of acquiring liquidity directly in the interbank market versus acquiring it indirectly by selling assets in the financial markets. The other facet of the connection relates to the volume of trade, and this will be the main focus of our empirical analysis.

Liquidity pull-back trading is arguably most likely to occur if the interbank market is not allocatively efficient. The crisis is an example of it being so; volume in the interbank market fell (Cassola, Holthausen, and LoDuca, 2008) while central banks around the world injected vast amounts of liquidity to counteract banks' unwillingness to lend to each other. In addition, the findings of Bindseil, Nyborg, and Strebulaev (2009) show that there is a degree of allocational inefficiency in the interbank market even during what we think of as times of normalcy, and Fecht, Nyborg, and Rocholl (2009) find evidence that interbank

[2]Kashyap and Stein (2000) document that many banks hold substantial amounts of securities.

liquidity networks, which are intended to overcome imperfections in the interbank market, are not 100% effective.

Thus, we expect increased tightening in the interbank market to give rise to an increased volume of liquidity pull-back trading. To test this idea, we focus on the cross-sectional implications. In particular, the liquidity pull-back effect on volume should be felt differentially across assets, depending on their degree of liquidity in the financial economics sense of the word. By definition, trade in a highly liquid asset involves lower price impact, or transaction costs, on average than an equivalent trade in a less liquid asset (Black 1971, Kyle 1985). *The implication, and our central hypothesis, is thus that increased tightness in the interbank market for liquidity is associated with an increase in the volume of more liquid assets relative to that of less liquid assets.*

From the perspective advanced in this paper, selling a financial asset is an act of converting low powered money (financial assets) into higher powered money (liquidity). When the price of liquidity goes up, the price of conversion also rises and asset prices therefore fall. However, with respect to this price effect, we expect no differential impact across assets of different liquidity levels, since in equilibrium there should be an equalization across assets of the marginal costs of converting into higher powered money.

We test these hypotheses on the CRSP universe of stocks using the three month Libor-OIS and TED spreads as measures of tightness in the interbank market.[3] The Libor-OIS spread may be a more precise measure of the state of the interbank market, since it is the difference between two interbank rates, rather than an interbank and a treasury rate. However, we have a longer time series of the TED spread. The in-sample correlation between the two spreads is .92.

The empirical design involves forming portfolios of stocks based on the Amihud (2002) price impact measure of liquidity. Our predictions are confirmed in the data: the market share of volume of highly liquid stocks is increasing in either spread, the difference in

[3]Libor is London Interbank Offered Rate, OIS is overnight index swap, TED spread is 3 month Libor less the 3 month treasury bill rate.

portfolio returns between high and low spread days is negative, but the size of the difference does not depend on the degree of liquidity of the portfolio.

While we use it as a general measure of tightness in the interbank market, the Libor-OIS spread can be viewed more specifically as a measure of the price of liquidity. A "Libor transaction" gives the borrower a fixed quantity of liquidity for a fixed period of time. The alternative (in the unsecured end of the market) is borrowing overnight and hedging the interest rate risk using the OIS. But this entails quantity risk; a bank cannot be sure that it will get the desired quantity of liquidity every day over the next three months, say.[4] While the spread thus captures the extra cost of having the liquidity for sure, we believe it also reflects at least an element of the quantity constraints inherent in our concept of interbank market tightness. The drop in interbank activity during the crisis supports this view. In addition, Gorton and Metrick (2009) find that high Libor-OIS spreads coincide with increased haircuts in repos. From a theoretical perspective, standard Akerlof (1970) adverse selection reasoning yields a positive relation between the price of liquidity and unsatiated demand.[5] This may help explain our finding that high spreads are associated not only with falling stock prices but also with an increase in the market share of volume of highly liquid stocks.

The empirical analysis in this paper is motivated by the theoretical framework sketched above. A less bank-centric line of reasoning that is consistent with our findings is as follows: Higher spreads imply higher funding costs for investors, as banks pass on their own borrowing costs. As a result, stock prices fall. In turn, this leads to margin calls and portfolio rebalancing, as already described. This still implies a connection between the interbank market for liquidity and the broader financial markets, but the role of banks is deemphasized. Our perspective differs from that of Grossman and Miller (1988) and

[4]There is also some interest rate risk, since a bank's overnight borrowing costs will not necessarily equal the rate that inputs into the OIS contract.

[5]Well known models of credit rationing in this vein, though not in an interbank setting, include Jaffee and Russell (1976) and Stiglitz and Weiss (1981).

Brunnermeier and Pedersen (2009), where selling pressure originates in the asset market rather than the money market. Brunnermeier and Pedersen in particular emphasize how a liquidity event in the asset market can lead to dramatic falls in prices, as providers of funding liquidity may tighten margins too much if they are uninformed about the cause of the liquidity event. In our framework, a severe decline in stock prices could potentially be triggered by unrest in the interbank market, for example arising from extreme adverse selection in *that* market. Both of these perspectives may well be relevant for understanding the collapse in the stock markets during the crisis.

This paper is related to several other literatures. Liquidity pull-back trading is a potential explanation for the commonality in liquidity found by Chordia, Subrahmanyam, and Roll (2000), Hasbrouck and Seppi (2001), and Huberman and Halka (2001). We also contribute to the literature on trading volume (e.g. Ying 1966, Karpoff 1987, Lo and Wang 2000, Chordia, Huh, and Subrahmanyam 2007) by documenting that the Libor-OIS and TED spreads are associated with cross-sectional variations in volume.

The rest of this paper is organized as follows. Section 2 describes our data sources and section 3 provides descriptive statistics of our sample. In section 4 we examine volume and returns on high and low spread days for different levels of illiquidity. Section 5 contains further regression analysis, Section 6 examines robustness to the set of sample firms, and section 7 concludes.

2 Data

2.1 Spreads (the price of liquidity)

In this paper, the Libor-OIS spread refers to the difference between 3 month USD Libor and the 3 month USD overnight index swap rate.[6] Libor is collected daily over the period 2^{nd} January 1986 to 31^{st} December 2008. This yields a total of 5,817 Libor observations.

[6] Libor is downloaded from http://www.bbalibor.com. The OIS rate is obtained from Reuters.

The OIS data are also daily, but only cover the period from 4^{th} December 2001 to 11^{th} November 2008. Thus, we have 1,716 daily observations of the Libor-OIS spread.

The TED spread is defined as the difference between the 3 month USD Libor rate and the 3 month T-Bill rate.[7] The T-Bill data is available for the entire period for which we have Libor data. But on some days we only have one or the other rate, for example because bank holidays in the U.K. may fall on different days than U.S. holidays. Thus, we have 5,648 daily observations of the TED spread.

2.2 Stock market data (volume and returns)

The stock market data comes from the Center for Research in Security Prices (CRSP). We consider stocks that are listed on the NYSE, NASDAQ and AMEX over the period 1986 to 2008, with CRSP share codes 10 or 11. Thus, we exclude ADRs, closed-end funds, REITs, and shares of firms incorporated outside of the U.S. We also exclude financials by removing firms with Standard Industrial Classification (SIC) codes between 6000 and 6999. Stocks that meet any of the following criteria at any time within a given year are also removed for that year: the stock price exceeds $999 or the firm changes ticker, cusip, or exchange. This leaves us with an average of 4,506 individual stocks per day. The change in exchange removal criterion is used to minimize the impact that any market microstructure changes might have on the stock. In a later section, we also examine the robustness of our findings by removing all NASDAQ stocks.

3 Background, overview, and descriptive statistics

3.1 Spreads (the price of liquidity)

Figure 1 displays the Libor-OIS spread (in basis points, bp) over the period 4 December 2001 to 11 November 2008. The red (shaded dark) section of the graph represent the

[7] The T-Bill data is obtained from http://www.federalreserve.gov/releases/h15/data.htm.

recent financial crisis.[8] Figure 2 superimposes the TED spread on Figure 1. The reactions of both spreads to the subprime crisis are seen to be similar. They fluctuated at low levels until August 2007, when they simultaneously increased sharply. Pre-crisis there is a slight upward trend in the TED spread, while there is a slight downward trend in the Libor-OIS spread. The correlation between the two spreads is 92%.

Figure 3 displays the TED spread (in bp) over the longer period 1986 to 2008. The red (shaded dark) sections of the graph represent crisis periods, while the grey (shaded light) sections represent normal times. As seen, this period covers several crises such as the crash in October 1987 (Black Monday), the invasion of Kuwait (August 1990), the Russian financial crisis and the collapse of Long Term Capital Management (LTCM) at the end of 1998 (see Figure Notes for details). The figure shows that the price of liquidity, as measured by the TED spread, is typically at elevated levels when there is significant financial uncertainty as during a war or a financial crises.

Table 1 provides descriptive statistics on the spreads. The mean TED spread is 55.80 bp, with the mean Libor-OIS spread being somewhat lower at 25.80 bp. The table confirms that the spreads are statistically significantly higher during crises than during normal times. For the TED spread, the non-crisis versus crisis means are, respectively, 48.47 bp and 105.37 bp. For the Libor-OIS spreads, they are 11.34 bp and 67.37. Both spreads reached their peak on the 10^{th} of October 2008, when the TED and Libor-OIS spreads stood at 456.88 bp and 366.33 bp, respectively. The extreme magnitude of these numbers can be seen from the fact that they are equivalent to an increase by a factor of 9 and 8 standard deviations relative to the respective unconditional means, or, in terms of raw numbers, by a factor of 8 and 14 times.

[8] Figure 1 indicates the crisis as starting in February 2007, which is when the first public signs of problems started to emerge. See, for example, BBC News, "Timeline: Sub-prime losses" on http://news.bbc.co.uk/2/hi/business/7096845.stm. Many commentators identify the beginning of the crisis with the second week of August 2007, when the Libor-OIS spread more than doubled. The exact beginning of the crisis is not important for the purpose of this paper.

The recent financial crisis was not only a period of tightness in the market for liquidity, but also a time of declining asset prices. For example, over the period 1 August 2007 to 31 March 2009, the S&P 500 fell by 45.7%. This is by no means unique. In local currency, the DAX, NIKKEI, and the FTSE 100 fell by 46.4%, 52.2%, and 40.8% , respectively. The other major financial crisis in our sample is the stock market crash of October 1987 (Black Monday). Roll (1988) notes that 19 out of 23 markets declined by more than 20 percent over that month. In October 1987 the TED spread had an average value of 195.2 basis points while the average values for September and August of 1987 were 96.8 and 81.8 basis points respectively. This coincidence of extreme tightness in the market for liquidity and extreme falls in stock prices is suggestive of there being a link between the market for liquidity and the stock markets. More scientific evidence that the TED spread affects stock market returns is provided by Ferson and Harvey (1993).

Our focus in this paper, however, is on testing the liquidity pull-back hypothesis by examining the effect of tightness in the interbank market on cross-sectional variations in volume. The figures and summary statistics above illustrate that there is substantial time variation in the price of liquidity, either as measured by the Libor-OIS spread or the TED spread. While much of this variation is due to crisis periods, there is also a fair amount of variation during non-crisis times. The coefficient of variation during non-crisis times is 0.67 and 0.32 for the TED and Libor-OIS spread, respectively. Chordia, Roll and Subrahmanyam (2001) document that there are day of the week and holiday effects in aggregate dollar volume. However, as seen in Table 1, there are no such effects in the Libor-OIS and TED spreads. This is important because it means that our findings below which relate variations in these spreads to the relative volume of stocks with different levels of illiquidity are not driven by systematic day of the week effects.[9]

[9]We use the same Holiday definition as in Chordia, Roll and Subrahmanyam (2001). See Appendix A.

3.2 Illiquidity

To test the idea that the volume of liquid and illiquid stocks responds differently to the price of liquidity we need a measure of the liquidity of stocks. Goyenko, Holden and Trczinka (2009) argue that low-frequency (daily) measures of liquidity perform well and their favored low frequency price-impact measure is the Amihud (2002) ILLIQ (illiquidity) measure. We therefore adopt this measure, which for stock i and month j is defined as:

$$ILLIQ_{ij} = Average\left(\frac{|r_t|}{Volume_t}\right) \tag{1}$$

where, for stock i, $|r_t|$ is the absolute value of the return on day t and $Volume_t$ is the dollar volume on day t. The averaging is across observations for stock i in month j.

Since our goal is to examine whether stocks with different illiquidity react differently to spreads, our sample needs to contain stocks with a large range of illiquidity. We therefore include a large sets of stocks (as described above), but remove some daily observations at the individual stock level in the calculation of ILLIQ in order to ensure that a stock's level of illiquidity is captured properly. First, $ILLIQ$ is not defined when volume is zero and therefore we exclude all zero volume days. Second, in the CRSP database all days without a closing price are given a "closing" price of the bid/ask average and such calculated "closing" prices are flagged by the use of negative numbers. Thus, we exclude observations with a "negative" closing price on either day t or day $t-1$ and a zero return on day t, as this is highly suggestive of stale prices (and spurious reported volume). The logic of the $ILLIQ$ measure suggests that a stock with no price change is quite liquid, but the absence of a closing price suggests the opposite. This restriction results in a loss of less than 2% of our monthly ILLIQ observations.

For each month, stocks are sorted into 10 groups based on their ILLIQ for that month. The 10% most liquid stocks are sorted into Group 1, the 10% most illiquid stocks are in Group 10, etc. Table 2 is a transition matrix that gives the proportion of stocks in group j in month t that move to group i in month $t+1$. The stability of the groups is u-shaped. The more liquid and illiquid groups are more stable than the groups in the middle, which is not surprising. For groups 1 , 5, and 10, the proportion of stocks that remain in the group the next month is 89.88%, 48.46%, and 72.90%, respectively. In the analysis below, when examining volume in month t, we base our analysis on illiquidity groups formed in month $t-1$.

Table 3, Panel A, provides descriptive statistics of illiquidity across all stocks in the sample. The mean value of (monthly) $ILLIQ_{ij}$ in our sample is 17.63 (median 0.134). By way of comparison, Goyenko et al. (2009) report a mean of 6.31 (median 0.104).[10] Thus, the stocks in our sample are more illiquid than those in Goyenko et al.'s sample. There are three potential reasons for this. First, and perhaps most importantly, they require their sample firms to be present in the TAQ master file (because of their objective to compare the performance of high and low frequency measures), which we do not. Second, they consider the time period 1993 to 2005 while we consider 1986 to 2008. Third, they consider a random sample of 400 firms. Both our and the estimates of Goyenko et al. (2009) are high. Using our numbers, a dollar volume of 1 million implies a price increase of 13.4% for the median firm, while using the Goyenko et al. (2009) numbers it would imply a price increase of 10.4%. However, for the most part, we do not make use of stocks' ILLIQ values, except to classify them into groups. Thus, for our purposes, it is the ordinal, not cardinal, accuracy of ILLIQ that matters.[11]

Panel B of Table 3 provides descriptive statistics of the average $ILLIQ_{ij}$ within groups. There is substantial variation across groups. The average $ILLIQ_{ij}$ is 0.001 for Group 1 and 162.601 for Group 10.

[10] These numbers refer to the plain (or raw) ILLIQ multiplied by 1,000,000. That is to say, volume is measured in millions.

[11] In unreported results, we use an Acharya and Pedersen (2005) style truncation of $ILLIQ_{ij}$ in order to reduce the impact of extreme observations. We truncate by setting $ILLIQ_{ij,trunc} = min(0.25 + 0.3 \times ILLIQ_{ij}, 30)$. Since ranking stocks using $ILLIQ_{ij,trunc}$ yields the same ranking as using $ILLIQ_{ij}$, this truncation is only relevant when the actual $ILLIQ$ values are used in a regression. This is only done in Table 8. Footnote 16 discusses the impact on this table of using I$LLIQ_{ij,trunc}$.

3.3 Volume and returns

Our analysis of volume in this paper revolves around three measures of normalized or relative volume. First, for each stock or illiquidity group i and day t, we calculate two normalized volume measures:

$$\text{normalized share volume}_{i,t} = \frac{\text{Volume}_{i,t}}{\text{Average volume for } i \text{ over the previous five days}} \tag{2}$$

where volume is the number of shares traded, and

normalized dollar volume$_{i,t}$ – also defined by RHS(2) but with volume now being the dollar value of trades.

Second, for each pair of illiquidity groups, X and Y, we calculate their relative volume on day t as:

$$\text{Relative Volume of Group } X \text{ to Group } Y_t = \frac{\text{Volume Group } X_t}{\text{Volume Group } Y_t} \tag{3}$$

where volume is measured in dollars.

Third, for each illiquidity group i, we calculate its market share of volume on day t as:

$$\text{Market Share of Volume Group } i_t = \frac{\text{Volume Group } i_t}{\text{Aggregate volume}_t \text{ across all stocks in the sample}} \tag{4}$$

where volume is measured in dollars.

Panel C of Table 3 presents summary statistics of the equally-weighted average of normalized share and dollar volume, which we refer to as market normalized share and dollar volume. The averages of these two measures are 1.007 (share) and 1.009 (dollar). In other words, share volume increases by approximately 0.7% per day, on average, and dollar volume by 0.9%. This increasing trend in volume is also documented by Chordia, Roll, and Subrahmanyam (2008).

The table also reveals that there is significant variation in market volume. On one occasion, the normalized market share volume is 2.318. In other words, the equally-weighted average volume on this day is 231.8% larger than the average volume over the previous five day period. This coincided with a value-weighted return of 3.3% on our sample stocks and it occurred on 17 January 1991, which was close to the liberation of Kuwait. Our measures of volume reach their minimum values (a reduction in volume of roughly 70%) around Christmas (24^{th} and 26^{th} of December), Thanksgiving (end of November), and the 4^{th} of July. That holidays are associated with lower volumes is also documented in Chordia, Roll, and Subrahmanyam (2001).

Panel C of Table 3 also presents descriptive statistics of equal and value-weighted market returns for our sample period. In terms of value weighted returns, the largest drop on a single day is -17.135%, which occurred on "Black Monday" 19 October 1987. The largest daily gain is 11.518% (13 October of 2008).

Finally, Panel C of Table 3 provides summary statistics for the relative volume of Group 10 to Group 1, reported in per mille.[12] The daily mean of this measure is 0.43 per mille. The large fluctuation in the relative volume between these two extreme groups is illustrated by the range of 0.033 to 29.03 per mille.

3.4 Correlations

Table 4 presents correlations among the variables in Panel C of Table 3 as well as the Libor-OIS and TED spreads. There are three noteworthy features of the correlation structure of these variable. First, the correlation between the spreads and market normalized share and dollar volume range from -0.02 to 0.02. Thus, these measures of abnormal market volume do not vary systematically with the price of liquidity. Second, the correlation between the Libor-OIS spread and contemporaneous equally and value weighted market returns are -0.17 and -0.13, respectively. This mirrors the observation we made above that the price of liquidity is often large when markets experience downturns. The correlation between the TED spread and the return on the market is also negative, but less so than for the Libor-OIS spread. Third, the correlation between the Libor-OIS and TED spreads and the

[12] In other words, the "raw" relative volume is multiplied by 10^3 .

relative volume of Group 10 to Group 1 are -0.11 and -0.09, respectively. Thus, changes in the price of liquidity is associated with cross-sectional variations in volume. In particular, a high price of liquidity is associated with an increase in the relative volume of more liquid stocks. It is consistent with the theoretical framework laid out in the introduction and, specifically, with the liquidity pull back hypothesis. In the remainder of the paper, we investigate this more in more detail.

4 Volume and return on high and low spread days

The basic hypothesis put forth in this paper is that liquid and illiquid stocks react differently in terms of volume to changes in the price of liquidity. In this section, we examine this by studying volume and returns across liquidity groups on high versus low spread days. Within each month we select the two days with the highest and the two days with the lowest spreads. We do this separately for the Libor-OIS and TED spreads. For each type of spread, we then generate two time series with monthly observations corresponding to the within-month average values of the variable in question on high and low spread days. Thus, each month in our sample contributes equally to any statistic we calculate. Thus, our procedure controls for changes in the level of the spreads over time (e.g. crisis versus non-crisis periods).[13]

Table 5 contains summary statistics on the monthly times series of the Libor-OIS and TED spreads on their respective high and low days (as described above). Spreads on high

[13]For a given month and spread, if there are more than two highest spread days, then all of those days are weighted equally when calculating the monthly values of the variables we are looking at. If there is a single highest spread day but several second highest spread days, then the latter are weighted equally. For example, if four days have the second highest spread for a particular month then, for that month, each of these four days represent one fourth of a high spread day. For a given variable (e.g. normalized share volume), the monthly observation of the high spread day is then 0.5 times the variable's value on the unique high spread day plus 0.5 times the average value on the second highest spread days. We proceed in the analogous way for low spread days.

and low days are significantly different, both in an economic and statistical sense. For the Libor-OIS spread, the average high and low days are 33.03 bp and 21.69 bp. For the TED spread, they are 70.11 bp and 43.14 bp. Over the period for which we have Libor-OIS spread data, the high and low TED spread series average to 62.31 bp and 38.88 bp.

4.1 Volume and return by illiquidity group

For each illiquidity group, we generate times series on high and low spread days (as described above) for the following variables: normalized share volume, normalized dollar volume, the average of normalized share volume on day t (the high or low spread day) and day $t+1$, the average of normalized dollar volume on day t and day $t+1$, the equally weighted return across stocks in the group, and the equally weighted return across stocks in the group on day t and $t+1$. The volume variables are calculated for the group as a whole (i.e. not averaged across the stocks in the group).

The average values on high and low spread days for these variables are in Table 6. We see that on high spread days, the most liquid stocks (illiquidity group 1) experience an increase in share (dollar) volume of 5.8% (5.4%) relative to the average level over the previous five day period. In contrast, the corresponding number for the most illiquid stocks (group 10) is a drop of 6.7% (7.8%). As reported in the table, a means test shows that the difference is statistically significant, having a t-statistic of 3.76 (2.95). Consistent with the liquidity pull-back hypothesis, this shows that volume is abnormally high (low) for highly liquid (illiquid) stocks on days when the price of liquidity is especially large.

Turning to low spread days, the overall pattern is reversed as compared with high spread days. For the most liquid stocks, neither share nor dollar volume change on low spread days relative to the previous five day period. However, highly illiquid stocks do; they have much higher volume. The increase is 9.0% for share volume and 15.4% in terms of dollar volume. For normalized share volume, the difference between groups 1 and 10 is statistically significant, but for normalized dollar volume it is marginally insignificant (unless we use the day t and day $t+1$ measure, when the difference is significant at the 5% level).

Next, we look at returns. Examining return differences between the least illiquid and the most illiquid group of stocks, we find that illiquid stocks offer higher returns, both on low and high spread days. The difference in returns between groups 1 and 10 is statistically significant in two out of four cases (return variables). With respect to returns, however, the key question for the liquidity pull-back hypothesis is whether liquid and illiquid stocks react differently to increases in the price of liquidity.

Comparing returns in the low spread and high spread sections of the table, we see that returns are larger on low spread days. Moreover, the difference in returns between high and low spread days are very similar across illiquidity groups, consistent with the liquidity pull-back hypothesis.

Panel B of Table 6 goes through a similar exercise for the TED spread. The results parallel those for the Libor-OIS spread.

Table 7 presents the differences across high and low spread days in our volume and return measures for each illiquidity group. This is done on a month by month basis, with the reported differences being averages across all months. A positive number implies that the illiquidity group has higher volume or return when the spread is high as compared to when the spread is low. Presenting the data this way homes in on the prediction of the liquidity pull-back hypothesis that trade in highly liquid stocks increases relative to that of less liquid stocks when the price of liquidity increases. The numbers support our hypothesis. For all four normalized volume measures, the difference in volume between high and low spread days is decreasing in illiquidity, although the difference is only statistically significant for the two extreme groups. In terms of normalized share volume, the difference is 5.9% for Group 1 and -15.7% for Group 1. Moreover, the difference between these number is highly significant (the t-statistic is 4.04).

The liquidity pull back hypothesis also says that while returns should be lower on high spread days, there should be no variation across stocks with different liquidity levels. This is confirmed in the table. For each illiquidity group, returns are lower on high spread days. But in terms of the change in return from low to high spread days, there is no statistically significant difference between groups 1 and 10.

Panel B of Table 7 does the same for the TED spread. Again, the results are more or less the same as for the Libor-OIS spread.

In sum, our findings thus far support the view that high spreads result in an increase in volume for liquid stocks and a decrease in volume for illiquid stocks. This implies that when the market for liquidity is tight, investors choose to sell assets for which the price impact would be the least. That it is selling pressure that is behind this increased volume is corroborated by the negative returns on high spread days.

4.2 Regression analysis: Normalized share volume

In this section we use regression analysis to further investigate the relation between illiquidity and the difference in normalized share volume between high and low spread days.[14] We use the Fama-MacBeth two step procedure. First, we run the following cross-sectional regression for each month, m, during the sample period

$$HSVOL_{G,m} - LSVOL_{G,m} = \alpha_m + \beta_m \times ILLIQ_{G,m} + \varepsilon_{G,m} \tag{5}$$

where $HSVOL_{G,m} - LSVOL_{G,m}$ is the difference in volume between high and low spread days in month m for illiquidity group G, and $ILLIQ_{G,m}$ is the average ILLIQ across stocks.

In the second step, we average the monthly coefficients. These are reported in Table 8, with Newey-West (3 lags) t-statistics. We run this two step procedure using both the Libor-OIS and TED spreads to determine high and low spread days. We also run it over various time horizons, for example with and without the recent financial crisis.

In specification (1) in Table 8, we use the TED spread as the basis for $HSVOL_{G,m} - LSVOL_{G,m}$. There is a negative and statistically significant (at the 1% level) relation

[14]The choice of the normalized share volume as our variable of interest is arbitrary. The result would not change qualitatively if we used the normalized dollar volume instead.

between the change in normalized volume and illiquidity. In terms of economic impact, going from the 25^{th} to 75^{th} percentile of $ILLIQ_G$ leads to a decrease in the difference in normalized share volume between high and low spread days of 0.78%.[15] This represents a reduction of 48.41% relative to the unconditional mean difference in normalized volume between low and high spread days of 1.62%.

Specification (2) uses the Libor-OIS spread to classify high and low spread days. The relation between illiquidity and the difference in changes in volume between high and low spread days is statistically significant at the 10% level. Going from the 25^{th} to 75^{th} percentile of $ILLIQ_G$ leads to a decrease in the difference in normalized share volume between high and low spread days of 30.53% relative to the unconditional mean.

In specification (3) we classify high and low spread days using the TED spread, but over the Libor-OIS period. The relation between the difference in normalized share volume and $ILLIQ_G$ is negative and statistically significant at the 5% level. Interestingly both statistical and economic impact is stronger for the TED spread over the Libor-OIS period. Going from the 25^{th} to 75^{th} percentile in terms of group illiquidity leads to a reduction in the difference in normalized share volume that represents 59.75% of the unconditional mean.

Specification (4) and (5) consider the TED spread and the Libor-OIS spread prior to the recent turmoil in the interbank market, using only observations prior to July 2007. The slope coefficient in specification (4), that uses the TED spread, is negative and statistically significant at the 5% level. In terms of economic impact, going from the 25^{th} to 75^{th} percentile results in a decrease in the difference of normalized share volume of 66.05% relative to the unconditional mean.

Specification (5), that uses the Libor-OIS spread, also finds that group illiquidity is negatively related to the difference in normalized volume on high and low spread days. The relation is statistically significant at the 1% level. Going from the 25^{th} to 75^{th} percentile

[15]We evaluate the economic impact by going from the 25^{th} to 75^{th} percentile of the distribution to avoid undue impact of extreme illiquidity observations in the upper tail.

now results in a decrease in the difference of normalized share volume of 127.18% relative to the unconditional mean. It is noteworthy that reducing the sample size and removing the recent crisis period, increase both the statistical and economic significance of the results.

These results confirm the results from the previous subsection that the price of liquidity affects volume differently across stocks with different levels of liquidity.[16] In particular, consistent with the theoretical idea put forth in the Introduction, an increase in the price of liquidity leads to an increase in the volume of highly liquid stocks as compared to less liquid stocks. In fact, in one sense, our results are even stronger than they would need to be to support our theory; while the predictions are in terms of the effects on relative volume, our findings in Tables 6 and 7 show that the most liquid (illiquid) stocks have abnormally large (small) volume in an absolute sense on high spread days.

5 Further Regression Analysis

In this section, we run further regressions to investigate the cross-sectional implications on volume of the liquidity pull-back hypothesis. There are two key changes to our analysis as compared to the previous section. First, we now use all days in the sample, rather than only monthly high and low spread days. Second, our regressions now rely only on the ordinal accuracy of ILLIQ, rather than on the cardinal accuracy as in Table 8.

5.1 Market share of volume by illiquidity group

In this subsection, we estimate the sensitivity of the market share of volume to the price of liquidity. The objective is to see whether this sensitivity falls (from positive to negative) as

[16] We have also run the regressions in Table 8 using a truncated illiquidity, so as to reduce undue influence from the extreme upper tail of illiquidity. We truncate in the following manner $ILLIQ_{ij,trunc} = min(0.25 + 0.3 \times ILLIQ_{ij}, 30)$. $ILLIQ_{ij,trunc}$. This is based on the truncation used by Acharya and Pedersen (2005). This improves our results both in terms of statistical and economic significance, but does not qualitatively alter the relation documented in Table 7.

the group number increases, i.e., as the group consists of increasingly illiquid stocks. The liquidity pull-back hypothesis implies that we should see a positive regression coefficient for the group consisting of the most liquid stocks and a negative coefficient for the most illiquid stocks.

In the regressions, we normalize the market share of volume for each group by its time series average. This is so as to facilitate comparisons across illiquidity groups. Thus, for each group X, we run the following time series-regression using daily observations:

$$\frac{Market\ Share\ of\ \ Volume\ \ Group\ X_t}{mean(Market\ Share\ of\ \ Volume\ \ Group\ X\ )} = \alpha + \beta \times spread_t + \varepsilon_t \tag{6}$$

where spread$_t$ is either the Libor-OIS or TED spread on date t. As always, we run separate regressions for each spread. To correct for autocorrelation, the regressions are run using the Cochrane-Orcutt procedure.[17]

Panel A of Table 9 displays the results using the TED spread. The coefficient on the spread is positive for the most liquid group (number 1) and negative for all other groups. All coefficients are statistically significant at the 1% level. In addition, the coefficient on the spread is decreasing (almost monotonically) in the illiquidity ranking of the groups. It is fair to say that these results are consistent with our hypothesis.

In terms of economic impact, a one standard deviation increase in the TED spread leads to an increase in the market share of volume of group 1 of 0.93% relative to the group's unconditional mean. The economic impact is almost monotonically increasing in illiquidity group. For illiquidity group 10, a one standard deviation increase in the TED

[17]We have also run OLS regressions with Newey-West (5 lags) standard errors. In the majority of cases, this yields smaller standard errors and results that are more supportive of our hypothesis than the results using the Cochrane-Orcutt procedure that we report in Table 9. We have also run unit root tests on the Libor-OIS and TED spreads. Using the Augmented Dickey-Fuller test we reject that the Libor-OIS is a unit root at the 5% and that the TED spread is a unit root at the 1% level. We also reject that the Libor-OIS and TED spreads follows a unit root at the 1% level with the Zivot-Andrews test that allows for a structural break. This tests identifies a structural break in August 2007 – which is also when visual inspection reveals a sharp increase in this spread. Results are available from the authors upon request.

spread leads to a fall in the Market share of volume of group 10 of 11.73% relative to this group's unconditional mean.

Panel B of Table 9 uses the Libor-OIS spread. The qualitative results are the same as for the TED spread. Statistical significance is slightly lower, but economic impact is generally larger for the Libor-OIS spread. A one standard deviation increase in the Libor-OIS leads to an increase (decrease) in the market share of volume of group 1 (group 10) of 1.11% (28.35%) relative to the group's unconditional mean.

Panel C of Table 9 uses the TED spread over the shorter period for which we have data on the Libor-OIS spread. The coefficients exhibit the same pattern as in the previous two panels, but statistical significance is spotty. That the TED spread works less well over the shorter Libor-OIS period may reflect that the TED spread is a noisy measure of the price of liquidity. However, the overall conclusion from Table 9 is that the volume of the most liquid stocks relative to the volume of the market as whole is increasing in the price of liquidity. Moreover, the more illiquid a stock is, the lower is its market share of volume as the price of liquidity rises. Our findings here are thus supportive of the liquidity pull-back hypothesis.

5.2 Relative group to group volume

In this subsection, we look at the relative volume of illiquid to liquid stocks more directly by studying the relative volume of group X to group Y variable. Paralleling the market share of volume regressions in the previous section, the relative volume variable is normalized by its time-series mean so as to facilitate comparison across different pairs of groups. For any pair of groups, with $X > Y$ (i.e. group X is the more illiquid), we estimate the following daily time-series regression,

$$\frac{Relative\ Volume\ of\ Group\ X\ to\ Group\ Y_t}{mean\ (Relative\ Volume\ of\ Group\ X\ to\ Group\ Y\ )} = \alpha + \beta \times spread_t + \varepsilon_t \tag{7}$$

This makes a total of 45 regressions for each spread measure. All are run using the Cochrane-Orcutt procedure.[18]

Panel A of Table 10 reports on the 45 TED spread regressions. For each regression, we list the coefficient on the spread and its t-statistics (in brackets). 20 of the 45 coefficients are significantly negative. There is no instance in which a positive coefficient is statistically significant. There is a relatively large degree of insignificance for adjacent groups, especially among less liquid groups. However, in the regressions where group 1 (most liquid stocks) is in the denominator, all regression coefficients are significantly negative. Moreover, the trend is for the coefficient to become increasingly negative as the group in the numerator becomes more illiquid. These results are in line with the liquidity pull-back hypothesis – relatively less liquidity is pulled back from less liquid stocks as the price of liquidity increases.

Economic impact is the largest for the regression involving the most extreme groups, namely numbers 10 and 1. In this case, a one standard deviation increase in the TED spread reduces the relative volume by 13.37% as compared to the unconditional mean. For all other ratios, the impact is below 10% of the unconditional mean. However, when the denominator is either the volume of group 1 or group 2 (row 1 and 2 in the table) the impacts are always above 3% relative to the unconditional mean.

Panel B of Table 10 reports on the same regressions using the Libor-OIS spread variable. We observe the same pattern as for the TED spread, but the results are stronger. The coefficient on the spread is now significantly negative in 39 out of 45 cases. Additionally, the economic impacts are larger. For example, a one standard deviation increase in the Libor-OIS spread reduces the relative volume of group 10 to group 1 by 28.75% relative to the unconditional mean. The minimum "impact number" when group 10 is in numerator

[18]We have also run OLS regressions with Newey-West (5 lags) standard errors. In the majority of cases, this yields smaller standard errors and results that are more supportive of our hypothesis than the results using the Cochrane-Orcutt procedure that we report in Table 10. Results are available from the authors upon request.

is 14.75%.

Panel C of Table 10 uses TED spread over the Libor-OIS period. The results are weaker than for the Libor-OIS spread itself. 20 out of 45 coefficients are significantly negative and economic impact is generally reduced. These weaker results parallel our findings when using the TED spread in the market share of volume regressions over the Libor-OIS period in the previous subsection. Overall, are findings are supportive of the liquidity pull-back hypothesis and that the Libor-OIS spread is a more accurate measure of tightness in the interbank market than the TED spread.

5.3 Panel regressions: Normalized share volume

In this subsection, we panel regressions at the individual stock level and using the normalized share volume as the dependent variable. We run two specifications (for each spread measure). Specification (1) is:

$$\begin{aligned} &\textit{Normalized Share Volume}_{it} = \\ &\alpha + \beta_1 \times \textit{spread}_t \times \textit{Group}_{1,it} + \ldots + \beta_{10} \times \textit{spread}_t \times \textit{Group}_{10,it} + \varepsilon_{it} \end{aligned} \tag{8}$$

where $Group_X$ is a dummy variable that takes the value 1 if the stock belongs to illiquidity group X and 0 otherwise. These are interacted with the spread, which as always is either the Libor-OIS or TED spread, to generate the main explanatory variables. The introduction of group dummies allows us to examine the effect of spreads on stocks with different levels of illiquidity, but without relying on the cardinal accuracy of ILLIQ for the individual stocks. In specification (2), we include the normalized market share volume on day t as a control variable. Standard errors are clustered daily in all regressions. To reduce the effect of outliers we remove observations where the normalized share volume is larger than 5 (daily volume is 5 times the average of the previous five trading days).

If the liquidity pull-back hypothesis holds, we should see a decreasing coefficient on the group dummy × spread interaction variable as the group number increases (stocks become more illiquid).

Panel A of Table 11 reports on the results using the TED spread. The results for specifications (1) and (2) are virtually identical. The spread×group dummy is significantly positive (at the 1% level) for groups 1 through 6 and significantly negative (at the 1% level) for groups 8 through 10. Moreover, within these two subgroups, the coefficient is declining in the group number (as stocks become more illiquid). This is as predicted by our hypothesis. The coefficient on group 7 is not significant, indicating that this is the marginal group.

The economic impacts are large and the difference in impact on illiquid and liquid stocks is apparent. For group 1, a one standard deviation increase in the TED spread (0.4384 percentage points) leads to an increase in normalized share volume 4.18% relative to the unconditional mean. From illiquidity group 2 to group 7 impacts are decreasing and then from group 8 to group 10 absolute impacts are increasing again. For group 10 a one standard deviation increase in the TED spread leads to a decrease in volume of 9.77% which represents a 9.70% decrease relative to the unconditional mean.

Panel B reports on the results using Libor-OIS spread. This time around, these results are weaker than for the TED spread. The pattern of the results is broadly the same, with the more liquid groups (lower numbered groups) having positive spread×group coefficients and the more illiquid groups having negative coefficients. Statistical significance is strong under specification (1), but weak for the intermediate groups under specification (2). This parallels the results in Section 4.1. The contrast to the regression results in Sections 5.1 and 5.2, where the results were much stronger for the intermediate groups, may reflect that the normalized share volume compares volume across days for the same stock or group, whereas our other volume measures focus more on the relative volume of different groups. Thus, the normalized share volume provides a less direct test of what we are after, namely relative changes in volume as the price of liquidity fluctuates. That we nevertheless get results with the normalized share volume is testimony to the fundamental strength of our other results.

With respect to economic significance in Panel B, note that under specification (1) a one standard deviation increase in the Libor-OIS spread leads to an increase in the normalized share volume of stocks in group 1 by 0.99% while for group 10 stocks normalized share volume falls by 5.40% relative to their unconditional means. Under specification (2), the economic impact for group 1 is roughly halved, while the economic impact for group 10 is slightly increased.

Panel C uses the TED spread over the Libor-OIS period. The results are very similar to those using the Libor-OIS spread, though somewhat stronger, especially for specification (2) where statistical and economic significance is now retained. All in all, the findings in this subsection supports the overall message of this paper that the price of liquidity affects volume differentially across stocks. In particular, whether we use the TED or the Libor-OIS spread to measure the price of liquidity, we always get the same result: an increase in the price of liquidity is associated with an increase in volume of liquid stocks, both relative to their own recent volume history and relative to less liquid stocks. The reverse holds for illiquid stocks.

6 Robustness to set of sample firms

We have shown that increases in the Libor-OIS or TED spreads are associated with an increase in the relative volume of liquid stocks. To maximize the variation in liquidity across stocks, we have included stocks listed on all the major exchanges, NYSE, AMEX and NASDAQ. However, it has been noted by, e.g., Atkins and Dyl (1997) and Anderson and Dyl (2007) that the volume of a stock that switches from NASDAQ to NYSE or AMEX often falls. This is due to the dealer structure on NASDAQ which implies a significant amount of transactions between dealers that is recorded as trading volume. The effect is the largest for large volume stocks since for these stocks on NYSE or AMEX, the specialist covers less of the total trade and the market is more of a pure auction market.

One concern could be that this volume effect across exchanges may be affecting our results. For it do so, the distortion in our volume measures for NASDAQ stocks would have to covary with the Libor-OIS and TED spreads. For example, if NASDAQ stocks are less liquid, then on high spread days we would have to see a proportionally lower volume inflation than on low spread days.

To test that our results are not driven by the NASDAQ volume inflation problem, we remove all NASDAQ stocks from the sample and re-run the relative volume regressions (since these are arguably the most direct test of the liquidity pull-back hypothesis that we have in this paper). Removing NASDAQ listed stocks means excluding 63% of our total sample. On this reduced sample, we estimate the same regression as in Table 10 using the Libor-OIS spread as the explanatory variable. For the sake of brevity, we only report the results when we using the most liquid group (group 1) in the denominator of the relative volume measure. The regression coefficients on the spread and the corresponding t-statistics are as follows:

Numerator group:	2	3	4	5	6	7	8	9	10
Spread coefficient:	-0.059	-0.076	-0.070	-0.152	-0.251	-0.247	-0.160	-0.170	-0.176
t-statistic	(-3.16)	(-2.06)	(-1.32)	(-2.17)	(-2.54)	(-2.38)	(-2.17)	(-3.57)	(-2.29)

For all except one regression, we observe a negative and statistically significant relation between the Libor-OIS spread and the relative volume of illiquid to liquid stocks. Moreover, this relation is increasingly negative as the group in the numerator (or the relative volume measure) becomes increasingly illiquid. The results are thus essentially the same as earlier when NASDAQ stocks were included. In terms of economic impact, one standard deviation increase in the Libor-OIS spread now results in a drop in the relative volume of group 10 to 1 of 12.4% relative to the unconditional mean. Thus, the results are strong in terms of economic impact as well. In conclusion, our results are robust to the inclusion of NASDAQ stocks.

7 Conclusion

This paper advances a conceptual framework for thinking about money and liquidity in financial markets. We argue that there is a connection between the interbank market for liquidity and the broader financial markets. This arises because a bank can trade, or take action that leads to trade, in financial markets in order to pull-back liquidity which the bank needs for its ongoing business. Put differently, liquidity pull-back involves the conversion of low powered money (financial assets) into higher powered money. This does not increase the stock of money in aggregate, but can increase the money balances of an individual bank. This line of reasoning has several implications, and the body of the paper is devoted to testing these. All implications are verified in the data.

While testing our conceptual framework and the liquidity pull-back hypothesis has been the motivation behind this study, a more stripped down view of our findings is simply that we document a statistical relation between the state of the interbank market for liquidity, as measured by the Libor-OIS and TED spreads, on the one hand; and volume and return in the stock market, on the other hand.

The main focus of our empirical analysis is on volume. The broad finding is that higher Libor-OIS and TED spreads are associated with an increase in the volume of highly liquid stocks and a decline in that of highly illiquid stocks. This pops out of the data regardless of how we perform our tests. We have tried four different approaches. To reduce noise, all are based on grouping stocks into 10 liquidity ordered portfolios. For the most part, our tests do not depend on the accuracy of the absolute measure of liquidity, but on the relative ranking induced by the measure.

First, we document that the volume of a portfolio, normalized by its own volume over the last 5 trading days, on high spread days relative to low spread days is increasing in the degree of liquidity of the portfolio. An equal number of high and low spread days are chosen across months, to control for time effects. Thus, the crisis does not contribute more high spread days than a non-crisis period of the same duration. The result is also explicitly shown to be robust to excluding the recent crisis.

Second, for each trading day, we calculate the volume of a portfolio as a percentage of total market volume, which we term the portfolio's market share of volume, and regress this on either spread. In the regressions, we normalize each portfolio's market share of volume on a given day by its own sample mean so that we can compare the "volume spread betas" of different portfolios in a meaningful way. The volume spread beta is statistically significantly positive for the most liquid portfolio and negative for all other portfolios. More illiquid portfolios have larger negative volume spread betas, i.e., the market share of volume declines faster for more illiquid portfolios as the spreads rise.

Third, for each trading day, we calculate the volume of a portfolio relative to that of a more liquid portfolio and regress this on either spread. In the regressions, we normalize each portfolio's relative volume on a given day by the respective sample mean. The general finding across these 45 relative volume regressions is that the relative volumes of less liquid portfolios are decreasing in either spread. This corroborates the results from the market share of volume regressions.

Fourth, we calculate the same normalized volume measure as in the first approach, but now on an individual stock level *and* for each trading day, not just high or low spread days. We then regress these normalized volume measures, in a panel, on either spread interacted with portfolio dummies, to control for the liquidity of the stock. Thus, we calculate spread betas for the different portfolios, but now using an individual stock's volume relative to the 5 preceding days as the independent variable. The panel structure allows us to take into account cross-correlation in regression errors on the same day across different stocks. This could occur, for example, if volume is particularly large or small across stocks on a given day for reasons that are exogenous to our model. Once again, we find that spread betas decrease in liquidity.

In addition to our finding on volume, we also document that across liquidity portfolios, returns are decreasing on high spread days. However, the difference in return between high and low spread days does not vary significantly across liquidity groups. This supports the view that the marginal cost of converting financial assets to higher powered money is equalized across assets.

The conceptual framework for thinking about money and liquidity in financial markets that we have outlined in this paper may be useful for understanding a number of liquidity phenomena. As an example, consider the phenomenon of increased correlation during crisis times (King and Wadhwani, 1990) and "flight to quality" (Sundaresan, 2009 p. 343). The recent crisis supports this; nearly all major stock indices such as the S&P 500, the DAX, the FTSE 100, and the NIKKEI fell around 40% to 50% in local currency in the August 2007 to March 2009 period. The liquidity pull-back interpretation of the flight to quality phenomenon is that times when this happens are times when liquidity is extremely dear or difficult to get in the interbank market. Banks therefore engage in liquidity pull-back trading, i.e., converting lower powered money into higher powered money. Put differently, there is a (financial market) credit contraction. The conjecture is that the worse conditions are in the interbank market, the larger are asset cross-correlations and the stronger will flight to quality appear to be. We have presented some cursory evidence on asset returns. Investigating this more thoroughly is an important avenue for future research.

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Figure 1: The LIBOR-OIS spread

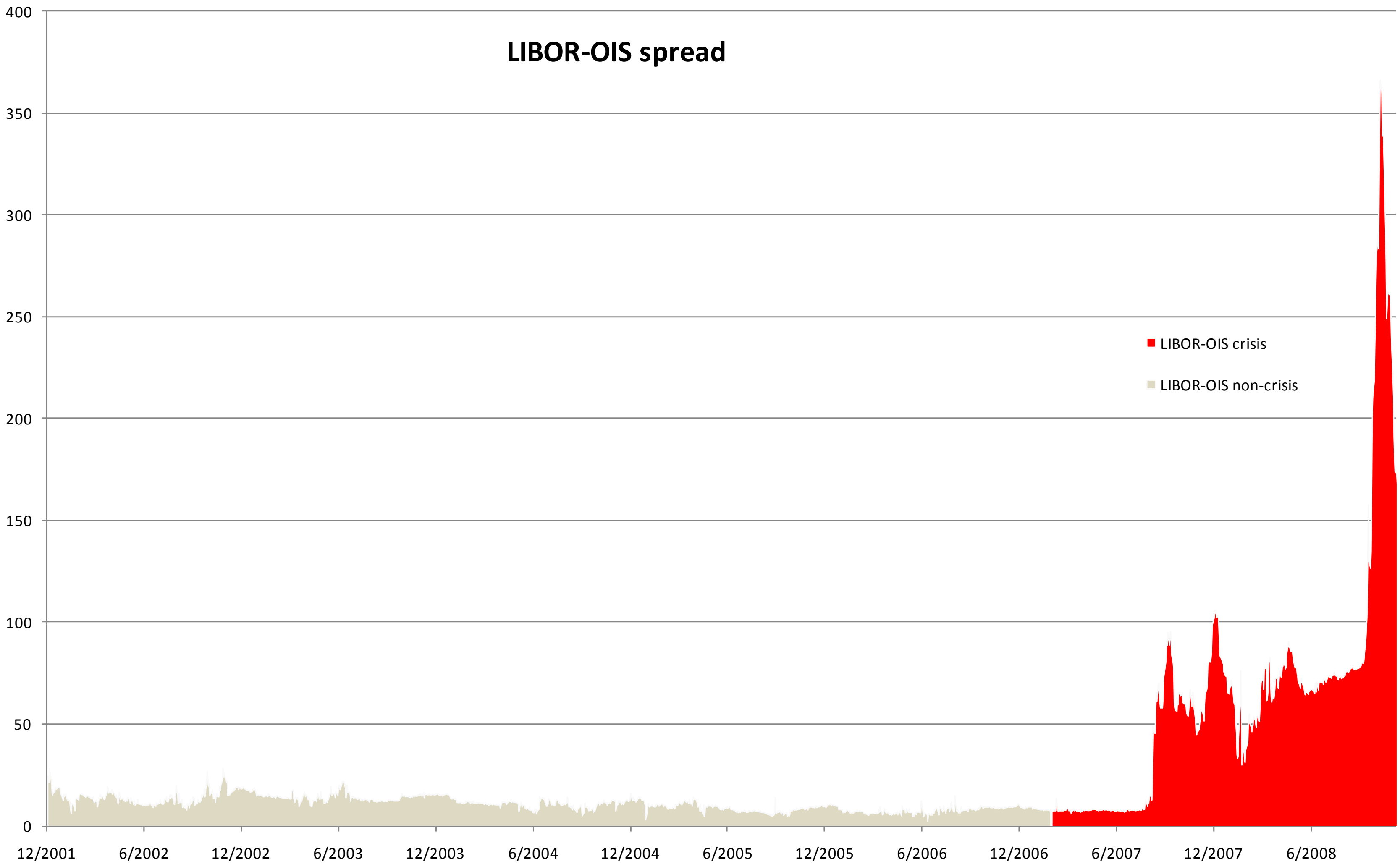

Figure 2: The LIBOR-OIS and the TED spread

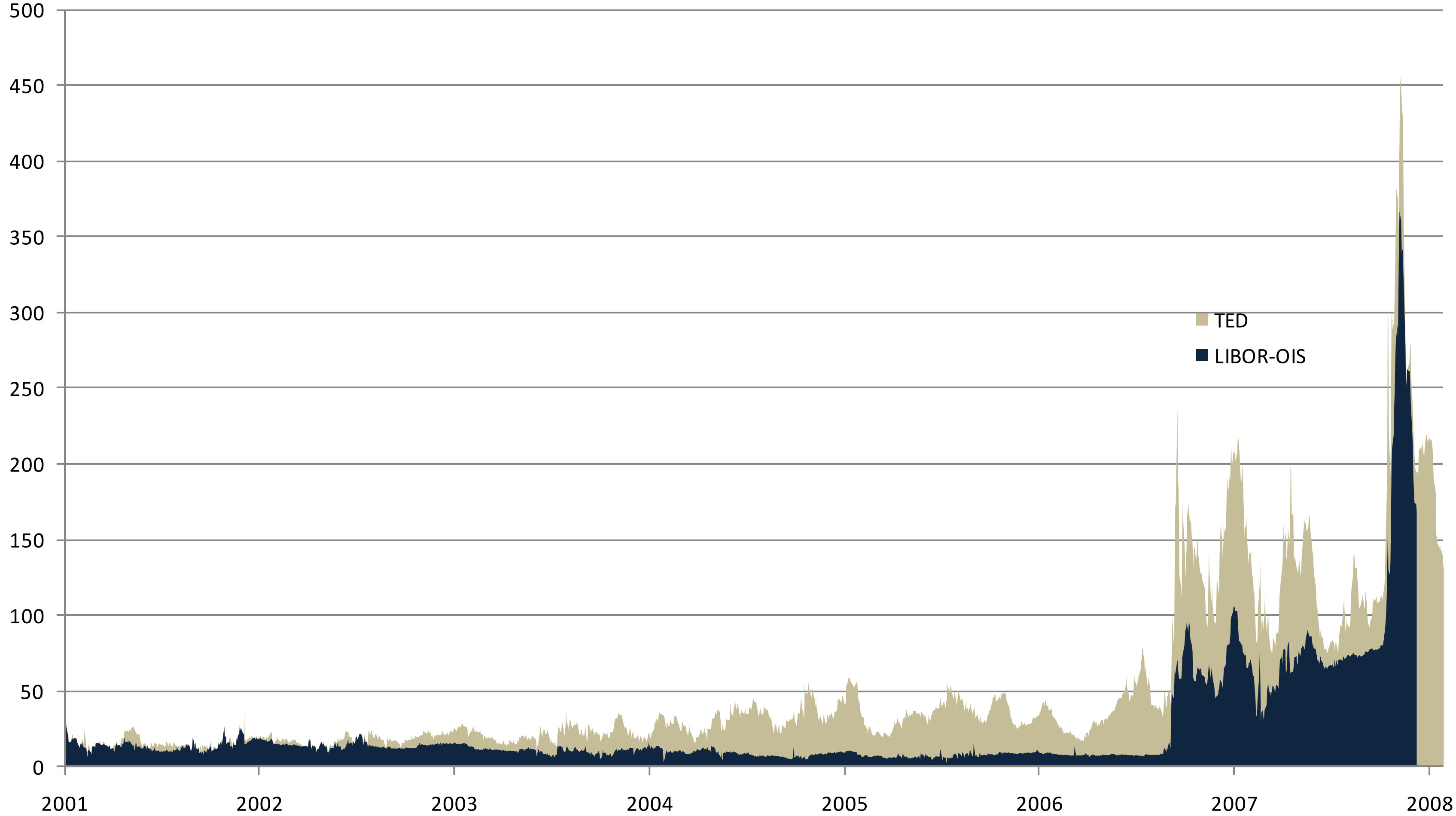

Figure 3: The TED spread

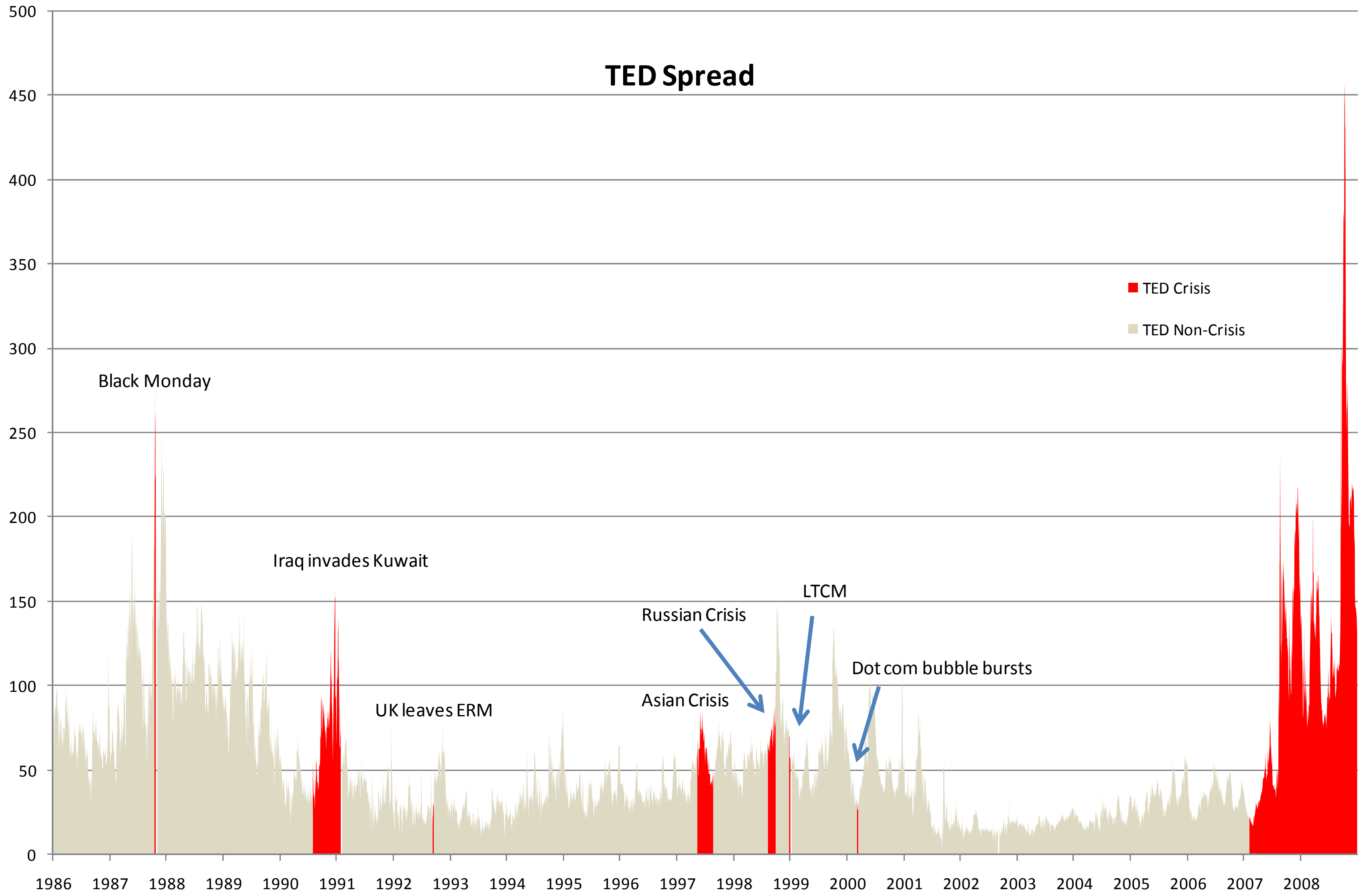

Figure Notes: Crises Dates

Dates	Description of Crisis
15 Oct 1987 - 21 Oct 1987	Black Monday / the 1987 Crash
02 Aug 1990 – 01 Feb 1991	Iraq invasion of Kuwait followed by liberation of Kuwait
15 Sep 1992 – 21 Sep 1992	The U.K. crashes out of the ERM
12 May 1997 – 19 Aug 1997	The Asian financial crisis
13 Aug 1998 – 19 Aug 1998	Russian financial crisis
19 Aug 1998 – 01 Oct 1998	Long Term Capital Management bailout
08 Mar 2000 – 15 Mar 2000	Dot com bubble bursts
01 Feb 2007 – 31 Dec 2008	Subprime mortgage financial crisis

Appendix A: Variable Descriptions

Variable	Description of Variable
TED spread	The three month USD London Interbank Offered Rate (LIBOR) less the three month T-bill rate. Measured in basis points.
LIBOR-OIS spread	The three month USD London Interbank Offered Rate (LIBOR) less the three month USD Overnight Index Swap (OIS) rate. Measured in basis points.
normalized share volume	Share volume in day t divided by the average daily share volume over the previous five day period.
average normalized share volume over day t and t+1	The average of normalized share volume over day t and t+1.
market normalized share volume	The equal-weighted average of normalized share volume over all firms
market average normalized share volume over day t and t+1	The average of market normalized share volume over day t and t+1.
normalized dollar volume	Daily dollar volume in day t divided by the average daily dollar volume over the previous five day period.
average normalized dollar volume over day t and t+1	The average of normalized dollar volume over day t and t+1.
market normalized dollar volume	The equally-weighted average of normalized dollar volume over all firms
market average normalized dollar volume over day t and t+1	The average of market normalized dollar volume over day t and t+1.
market equal weighted return	The daily equally-weighted return of the market. Reported in percent.
market equal weighted return over days t and t+1	The daily two day average equally-weighted return of the market. Reported in percent.
market value weighted return	The daily equal weighted return of the market. Reported in percent.
market value weighted return over days t and t+1	The daily two day average equally-weighted return of the market. Reported in percent.
$ILLIQ_{ij} = Average\left(\frac{\lvert r_t \rvert}{Volume_t}\right)$	r_t is the return on day t and $Volume_t$ is the dollar trading volume on day t. $ILLIQ_{ij}$ is the average of $\lvert r_t \rvert / Volume_t$ over all days in month j. Throughout the paper we report $ILLIQ_{ij} \times 10^6$.
$ILLIQ_G$	The equally-weighted average of $ILLIQ_{ij}$ across all stocks that belong to illiquidity group G.
Market share volume of $\text{Group}_{X,t}$	The dollar volume of all stocks in illiquidity group X (out of ten groups) on day t divided by the dollar volume of all stocks in our sample.
$\frac{\text{Volume of Group}_{X,t}}{\text{Volume of Group}_{Y,t}}$	The dollar volume of all stocks in illiquidity group X (out of ten groups) divided by the dollar volume of all stocks in illiquidity group Y (out of ten groups) on day t.
holiday	A dummy for holidays set such that if a holiday falls on a Friday then the preceding Thursday is set to 1, and if the holiday is on a Monday then the following Tuesday is set to 1, and if the holiday is on any other weekday then the day preceding and following the holiday are set to 1.

Table 1: Descriptive statistics of LIBOR-OIS spread and the TED spread

We present descriptive statistics of the spreads used in our study. The LIBOR-OIS spread data covers the period 04 December 2001 to 11 November 2008. The TED-spread data covers the period 02 January 1986 to 31 December 2008. Spreads are reported in basis points. We report mean, standard error, standard deviation, coefficient of variation, median, minimum and maximum values. We split our sample into weekdays, holidays, crisis and non-crisis days. Our spread variables and the dummy variable Holiday is described in Appendix B. Appendix A lists our crisis periods. The column Diff reports for weekdays the difference between the average spread for that weekday and the average of all other weekdays (e.g., for Mon, the difference between the spread on Mon and the spread on Tue-Fri). For Crisis (Holiday) days the Diff column reports the difference between Crisis and Non-crisis days (Holidays and Non-Holidays). We report the t-statistics for the differences (Diff).

	Variable	N	Mean	Std Error	Std Dev	CoV	Median	Min	Max	Diff	t-stat
All Days	LIBOR-OIS	1716	25.80	1.01	41.74	1.62	11.75	2.51	366.33	---	---
	TED	5648	55.80	0.58	43.85	0.79	41.77	2.63	456.88	---	---
Monday	LIBOR-OIS	304	26.75	2.50	43.65	1.63	12.10	5.50	360.15	1.15	0.44
	TED	983	54.59	1.39	43.43	0.80	40.25	7.00	374.88	-1.46	-0.95
Tuesday	LIBOR-OIS	353	25.50	2.16	40.67	1.59	11.50	4.70	338.95	-0.38	-0.15
	TED	1173	54.83	1.26	43.19	0.79	41.00	2.63	429.50	-1.16	-0.65
Wednesday	LIBOR-OIS	357	25.16	2.14	40.42	1.61	11.80	2.51	342.00	-0.81	-0.33
	TED	1183	56.28	1.29	44.29	0.79	42.50	8.00	433.00	0.62	0.43
Thursday	LIBOR-OIS	352	25.77	2.24	42.05	1.63	11.70	4.61	345.85	-0.04	-0.02
	TED	1158	56.70	1.30	44.33	0.78	43.03	9.00	415.00	1.14	0.79
Friday	LIBOR-OIS	350	25.96	2.26	42.36	1.63	11.71	3.29	366.33	0.20	0.08
	TEDsprd	1151	56.39	1.30	43.94	0.78	42.25	9.25	456.88	0.75	0.51
Holiday	LIBOR-OIS	21	23.52	5.14	23.57	1.00	14.33	5.58	74.00	-2.31	-0.44
	TED	66	59.02	5.31	43.17	0.73	45.50	12.38	201.75	3.26	0.60
Non-Crisis	LIBOR-OIS	1273	11.34	0.10	3.62	0.32	11.00	2.51	28.40	-56.03	-17.79
	TED	4921	48.47	0.46	32.34	0.67	38.50	2.63	258.00	-56.89	-21.28
Crisis	LIBOR-OIS	443	67.37	3.15	66.25	0.98	65.38	6.50	366.33	56.03	17.79
	TED	727	105.37	2.63	71.00	0.67	85.81	14.50	456.88	56.89	21.28

Table 2: Transition probabilities for illiquidity

We present transition probabilities for our illiquidity measure (ILLIQ). During each month of our sample we sort all stocks into illiquidity deciles (1 liquid and 10 illiquid). We then record the illiquidity decile of the stock in the subsequent month. In the table below illiquidity in month t is along the row dimension and illiquidity in month t+1 is in the column dimension. All numbers are percentages.

		Illiquidity Group in month t+1									
		1	2	3	4	5	6	7	8	9	10
	1	89.88	9.76	0.19	0.08	0.04	0.02	0.01	0.01	0.01	0.01
	2	9.84	72.69	16.41	0.85	0.14	0.05	0.02	0.01	0.00	0.00
Illiquidity	3	0.23	15.61	61.07	20.36	2.21	0.39	0.09	0.02	0.01	0.00
Group	4	0.05	1.00	18.35	53.43	22.72	3.53	0.73	0.15	0.03	0.01
in month t	5	0.02	0.20	2.49	19.82	48.46	23.12	4.68	0.98	0.19	0.04
	6	0.01	0.06	0.50	3.61	19.90	45.88	23.52	5.33	1.02	0.18
	7	0.00	0.02	0.14	0.88	4.58	20.14	44.32	23.54	5.59	0.80
	8	0.01	0.00	0.04	0.24	1.18	5.25	20.39	44.20	24.33	4.35
	9	0.01	0.00	0.02	0.06	0.27	1.22	5.33	21.58	48.14	23.36
	10	0.01	0.00	0.00	0.02	0.06	0.26	0.93	4.39	21.43	72.90

Table 3: Descriptive Statistics of Variables

This table provides descriptive statistics of variables used in our study. The data covers the period 2nd January 1986 to 31st December 2008. All of our variables are defined in Appendix B. We have 5,802 daily observations of the changes in volume and returns. Our liquidity measure is the Amihud (2002) illiquidity measure which is defined as $ILLIQ_{ij} = Avg(|r_t| / Volume_t)$ where r_t is the return on day t and $Volume_t$ is the dollar trading volume on day t. This ratio is calculated for all days and all stocks in our sample and averaged over firm i in month j. This implies that we have 1,243,739 firm month ILLIQ observations. In Panel A we provide descriptive statistics $ILLIQ_{ij} \times 10^6$. At the end of each month we split all stocks into ten groups on the basis of $ILLIQ_{ij}$. Stocks in group are the most liquid while stocks in group ten are the most illiquid. Panel B provides descriptive statistics of the ten illiquidity groups over our sample period. Panel C provides descriptive statistics on $(\text{Volume Group}_{10} / \text{Volume Group}_1) \times 10^3$, market returns (in percent) and normalized market volumes.

Panel A: Descriptive Statistics of firm illiquidity

Variable	N	Mean	Std Err	Std Dev	CoV	Median	Min	Max
ILLIQ	1,243,739	17.632	0.566	631.266	35.802	0.134	0.000	291,059

Panel B: Descriptive statistics of group illiquidity

Variable	Group	N	Mean	Median	Std Err	Std Dev	Min	Max
	1	124254	0.001	0.001	0.000	0.00	0.000	0.02
	2	124381	0.008	0.005	0.000	0.01	0.000	0.07
	3	124417	0.026	0.015	0.000	0.03	0.000	0.28
	4	124390	0.077	0.039	0.000	0.10	0.001	0.81
ILLIQ	5	124360	0.201	0.093	0.001	0.26	0.002	2.11
	6	124436	0.493	0.232	0.002	0.62	0.004	4.90
	7	124424	1.190	0.612	0.004	1.42	0.010	11.69
	8	124383	2.987	1.766	0.009	3.32	0.032	26.65
	9	124415	8.858	5.981	0.026	9.21	0.100	77.21
	10	124279	162.601	34.435	5.648	1991.11	0.468	291,059.30

Panel C: Descriptive statistics of market volume and returns

Variable	N	Mean	Std Err	Std Dev	CoV	Median	Min	Max
Market normalized share volume	5,802	1.007	0.002	0.162	0.160	0.998	0.264	2.318
Mrkt ave. norm. share vol. day t and t+1	5,802	1.009	0.002	0.147	0.146	1.000	0.291	2.218
Market normalized dollar volume	5,802	1.009	0.002	0.183	0.181	0.994	0.245	2.689
Mrkt ave. norm. share vol. day t and t+1	5,802	1.010	0.002	0.167	0.166	0.997	0.273	2.370
Market return (EW)	5,802	0.079	0.010	0.828	10.477	0.141	-10.390	10.738
Market ave. return day t and t+1 (EW)	5,802	0.079	0.008	0.642	8.103	0.130	-9.190	5.294
Market return (VW)	5,802	0.042	0.013	1.058	25.038	0.073	-17.135	11.518
Market ave. return day t and t+1 (VW)	5,802	0.042	0.009	0.759	17.915	0.072	-10.927	6.412
$\text{Volume Group}_{10} / \text{Volume Group}_1$	5,802	0.430	0.011	0.847	1.972	0.325	0.033	29.308

Table 4: Correlation Table

This table reports correlations between our variables of interest. All of our variables are defined in Appendix B. For all correlation except those with the LIBOR-OIS spread there are 5,648 daily observations from 2nd January 1986 to 31st December 2008. The correlations with the LIBOR-OIS spread are based on 1,703 daily observations from 4th December 2001 to 11th November 2008.

	Market normalized share volume	Mrkt ave. norm. share vol. day t and t+1	Market normalized dollar volume	Mrkt ave. norm. dollar vol. day t and t+1	Market return (EW)	Market ave. return day t and t+1 (EW)	Market return (VW)	Market ave. return day t and t+1 (VW)	TED spread	LIBOR-OIS spread	Volume $ILLIQ_{10}$ / Volume $ILLIQ_1$
Market normalized share volume	1	0.85	0.95	0.80	-0.01	0.02	0.02	0.02	0.02	0.01	-0.05
Mrkt ave. norm. share vol. day t and t+1	0.85	1	0.81	0.95	-0.06	-0.03	-0.01	0.00	0.02	0.01	-0.03
Market normalized dollar volume	0.95	0.81	1	0.85	0.05	0.06	0.08	0.06	0.01	-0.02	-0.06
Mrkt ave. norm. dollar vol. day t and t+1	0.80	0.95	0.85	1	0.01	0.03	0.05	0.06	0.00	-0.02	-0.04
Market return (EW)	-0.01	-0.06	0.05	0.01	1	0.77	0.87	0.60	-0.10	-0.17	0.02
Market ave. return day t and t+1 (EW)	0.02	-0.03	0.06	0.03	0.77	1	0.68	0.87	-0.09	-0.18	0.02
Market return (VW)	0.02	-0.01	0.08	0.05	0.87	0.68	1	0.71	-0.05	-0.13	0.01
Market ave. return day t and t+1 (VW)	0.02	0.00	0.06	0.06	0.60	0.87	0.71	1	-0.03	-0.14	0.01
TED spread	0.02	0.02	0.01	0.00	-0.10	-0.09	-0.05	-0.03	1	0.92	-0.09
LIBOR-OIS spread	0.01	0.01	-0.02	-0.02	-0.17	-0.18	-0.13	-0.14	0.92	1	-0.11
Volume $ILLIQ_{10}$ / Volume $ILLIQ_1$	-0.05	-0.03	-0.06	-0.04	0.02	0.02	0.01	0.01	-0.09	-0.11	1

Table 5: Descriptive statistics of High and Low spread days

We consider spreads on low and high days. For each month we select the two highest spread days as high days and the two days with the lowest spread as low days. If more than one day has the highest spread within a month then all of those days are considered high. When there is only one day with the highest spread and if more than one day has the second highest spread then those days are weighted according to their frequency. E.g., if four days have the second highest spread for a particular month then each of the four days represent one fourth of a high spread day. Likewise, multiple lowest days implies that they are all considered low and multiple second lowest days implies that they are weighted according to their frequency. We average spreads over high (low) days within each month using the described weightings and provide descriptive statistics of monthly high and low spread days.

Spread	Day	N	Mean	Std Error	Std Dev	CoV	Median	Min	Max
TED spread	Low	276	43.14	2.01	33.33	0.77	32.72	6.31	252.31
	High	276	70.11	3.22	53.55	0.76	54.39	15.28	444.94
LIBOR-OIS spread	Low	84	21.69	3.85	35.31	1.63	10.05	3.56	243.69
	High	84	33.03	5.87	53.81	1.63	13.80	7.75	363.24
TED (LIBOR-OIS period)	Low	84	38.88	4.74	43.42	1.12	21.05	8.16	252.31
	High	84	62.31	8.02	73.48	1.18	34.06	15.28	444.94

Table 6: High and Low Spread Days: Volume and Returns by Illiquidity Group

This table presents sorts capturing the effect of spreads on stocks of various levels of illiquidity. All of our variables are defined in Appendix B. In the month prior to the observation month, all of our stocks are sorted into ten groups based on $ILLIQ_{ij}$. The stocks that are in group one are the most liquid while those that are in group ten are the least liquid. We identify high and low spread days as in Table 4. For each low (high) spread day we calculate all volume measures for each illiquidity group. For example, for illiquidity group 1 the normalized share volume is the total share volume of all stocks in group 1 on day t divided by the average share volume of all stocks in group 1 over the previous five day period. We then average normalized share volume over high days within each month. Finally, we report the average normalized share volume over all months in our sample. We follow this procedure for all four volume measures. We also report the equally-weighted returns of each illiquidity group. Returns are first averaged over low (high) days within the month and then over all months in sample. In Panel A high and low spread days are classified according to the LIBOR-OIS. In Panel B we follow the exactly same procedure, but use the TED spread to classify high and low days.

Panel A: The LIBOR-OIS spread

LIBOR-OIS		**ILLIQUIDITY**											
		1	2	3	4	5	6	7	8	9	10	Diff 1-10	t-stat
Low	Normalized share volume	0.999	1.010	1.012	1.028	1.030	1.053	1.035	1.037	1.060	1.090	-0.091	-2.34
	Norm. share vol. day t and t+1	1.004	1.015	1.014	1.022	1.041	1.043	1.040	1.040	1.054	1.121	-0.117	-2.67
	Normalized dollar volume	1.006	1.010	1.010	1.024	1.028	1.019	1.020	1.012	1.039	1.154	-0.148	-1.64
	Norm. dollar vol. day t and t+1	1.011	1.016	1.013	1.024	1.038	1.023	1.031	1.017	1.048	1.144	-0.134	-1.99
	Return (EW)	0.176	0.204	0.237	0.240	0.242	0.267	0.244	0.203	0.234	0.328	-0.152	-1.26
	Return day t and t+1 (EW)	0.045	0.052	0.093	0.106	0.114	0.140	0.166	0.142	0.182	0.310	-0.265	-2.69
High	Normalized share volume	1.058[b]	1.052	1.056[c]	1.044	1.058	1.093	1.128	1.037	1.031	0.933[a]	0.125	3.76
	Norm. share vol. day t and t+1	1.047[c]	1.042	1.051	1.045	1.052	1.075	1.094	1.031	1.021	0.975[a]	0.072	1.96
	Normalized dollar volume	1.054[b]	1.049	1.045	1.034	1.041	1.071	1.091	1.046	1.087	0.922[b]	0.132	2.95
	Norm. dollar vol. day t and t+1	1.044	1.041	1.040	1.032	1.031	1.048	1.065	1.035	1.076	0.954[b]	0.089	2.01
	Return (EW)	-0.048	-0.041	-0.073[c]	-0.047[c]	-0.081[c]	-0.036[c]	0.016	-0.016[c]	0.019[c]	0.176[c]	-0.225	-1.83
	Return day t and t+1 (EW)	0.081	0.080	0.042	0.043	0.026	0.057	0.060	0.037	0.058	0.169	-0.089	-0.86

a, b and c denotes statistical significance between in the difference in the variable between high and low spread days at the 1%, 5% and 10% level respectively.

Panel B: The TED spread

TED		ILLIQUIDITY 1	2	3	4	5	6	7	8	9	10	Diff 1-10	t-stat
Low	Normalized share volume	1.004	1.012	1.009	1.014	1.016	1.024	1.013	1.021	1.024	1.033	-0.030	-1.72
	Norm. share vol. day t and t+1	1.016	1.025	1.022	1.020	1.022	1.033	1.016	1.022	1.028	1.039	-0.022	-1.33
	Normalized dollar volume	1.005	1.013	1.010	1.014	1.018	1.019	1.008	1.010	1.022	1.021	-0.016	-0.77
	Norm. dollar vol. day t and t+1	1.017	1.024	1.023	1.020	1.026	1.027	1.013	1.017	1.031	1.035	-0.018	-0.85
	return (EW)	0.107	0.126	0.132	0.135	0.133	0.138	0.109	0.120	0.163	0.369	-0.262	-4.14
	Return day t and t+1 (EW)	0.038	0.043	0.061	0.062	0.061	0.073	0.079	0.096	0.152	0.385	-0.348	-6.37
High	Normalized share volume	1.052[a]	1.041[b]	1.034[c]	1.032	1.038	1.034	1.040	1.028	1.036	0.997[c]	0.056	3.22
	Norm. share vol. day t and t+1	1.035	1.029	1.023	1.031	1.034	1.038	1.032	1.024	1.032	1.003	0.032	1.75
	Normalized dollar volume	1.050[a]	1.040[b]	1.029	1.031	1.035	1.035	1.044	1.052[c]	1.036	1.004	0.046	2.29
	Norm. dollar vol. day t and t+1	1.035	1.028	1.021	1.027	1.036	1.034	1.031	1.048	1.022	1.042	-0.007	-0.18
	Return (EW)	0.004	0.002	-0.006	0.001	-0.013	-0.014	0.016	0.049	0.089	0.359	-0.355	-4.42
	Return day t and t+1 (EW)	0.119	0.124	0.109	0.108	0.086[c]	0.078[c]	0.090[c]	0.087	0.118	0.391	-0.272	-4.71

a, b and c denotes statistical significance between in the difference in the variable between high and low spread days at the 1%, 5% and 10% level respectively.

Table 7: Differences in Volume and Returns between High and Low Spread Days

We present results of the difference in changes in volume between high and low spread days over illiquidity groups. All of our variables are defined in Appendix B. In the month prior to the observation month, all of our stocks are sorted into ten groups based on $ILLIQ_{ij}$. We identify high and low spread days as in Table 4. We calculate our volume and return measures for high and low spread days separately as described in Table 5. For each month we average our measures over all low (high) days. We then subtract the average value of the measure on low days from the average value of the measure on high days over all sample months. Finally, we report the monthly average difference between high and low spread days for our measure. In Panel A high and low spread days are classified according to the LIBOR-OIS. In Panel B we follow the exactly same procedure, but use the TED spread to classify high and low days.

Panel A: LIBOR-OIS spread

	ILLIQUIDITY											
High spread – Low spread	1	2	3	4	5	6	7	8	9	10	Diff 1 -10	t-stat
Normalized Share Volume	0.059	0.042	0.044	0.016	0.027	0.039	0.093	-0.001	-0.029	-0.157	0.216	4.04
Norm. Share Volume (t, t+1)	0.043	0.027	0.037	0.023	0.011	0.032	0.054	-0.008	-0.033	-0.146	0.189	3.26
Normalized Dollar Volume	0.048	0.039	0.035	0.010	0.012	0.052	0.071	0.034	0.047	-0.232	0.280	2.81
Norm. Dollar Volume (t, t+1)	0.033	0.024	0.027	0.008	-0.008	0.025	0.035	0.017	0.027	-0.190	0.223	2.69
Return EW	-0.224	-0.245	-0.310	-0.287	-0.323	-0.304	-0.228	-0.219	-0.215	-0.152	-0.072	-0.39
Return EW (t,t+1)	0.036	0.028	-0.051	-0.063	-0.088	-0.083	-0.106	-0.104	-0.125	-0.141	0.177	1.17

Panel B: TED spread

	ILLIQUIDITY											
High spread – Low spread	1	2	3	4	5	6	7	8	9	10	Diff 1 -10	t-stat
Normalized Share Volume	0.049	0.029	0.024	0.017	0.022	0.011	0.027	0.007	0.012	-0.037	0.086	3.28
Norm. Share Volume (t, t+1)	0.019	0.004	0.001	0.010	0.012	0.005	0.016	0.003	0.004	-0.036	0.055	2.04
Normalized Dollar Volume	0.046	0.027	0.019	0.018	0.017	0.016	0.036	0.042	0.014	-0.017	0.062	2.03
Norm. Dollar Volume (t, t+1)	0.018	0.004	-0.002	0.007	0.010	0.007	0.018	0.031	-0.009	0.007	0.011	0.23
Return EW	-0.103	-0.124	-0.138	-0.133	-0.146	-0.152	-0.093	-0.071	-0.074	-0.010	-0.093	-0.97
Return EW (t,t+1)	0.081	0.080	0.048	0.046	0.025	0.005	0.012	-0.009	-0.034	0.006	0.076	1.06

Table 8: Regression analysis: Differences in Changes in Volume and Illiquidity

This table documents the relation between the differences in normalized share volume between low and high spread days and illiquidity. All of our variables are defined in Appendix B. High and low spread days are classified as in Table 4. We split our sample into ten groups based on $ILLIQ_{ij}$ in the previous month. Our dependent variable is the monthly difference in normalized share volume between low and high spread days for each illiquidity group. We calculate the monthly mean normalized share volume for high and low days as in Table 5. For each month and illiquidity group, we then subtract the mean normalized share volume on low days from the mean normalized share volume on high days to get our dependent variable ($HSVOL_{G,M}$-$LSVOL_{G,M}$). Subscripts G and m refer to illiquidity group and month respectively. Our independent variable is $ILLIQ_{G,m}$, the mean ILLIQ for illiquidity group G in month m. For each month m in our sample we estimate the following cross-sectional regression:

$$HSVOL_{G,m} - LSVOL_{G,m} = \alpha_m + \beta_m \times ILLIQ_{G,m} + \varepsilon_{G,m}$$

We report the average of all the cross-sectional coefficient estimates (α_m, β_m) with corresponding t-statistics. Standard errors are estimated using the Newey-West procedure with three lags. In specification (1) we use the TED spread as the basis for high and low spread. Specification (2) is identical to specification (1) except that we use the LIBOR-OIS spread to identify high and low spread days. Specification (3) uses the TED spread, but considers the time period for which the LIBOR-OIS is available. Specifications (4) and (5) use the TED and LIBOR-OIS spread respectively, but consider the period prior to the financial crisis (07/2007).

Illiquidity and the difference in normalized volume on high and low spread days

Spread / Period	Intercept	t-stat	$ILLIQ_G$	t-stat	Adj. R^2	N
(1) TED	0.023	(1.91)	-0.0042	(-2.28)	14.28%	275
(2) LIBOR-OIS	0.034	(1.14)	-0.0150	(-1.80)	18.07%	83
(3) TED (OIS-period)	0.019	(0.76)	-0.0125	(-2.21)	20.30%	83
(4) TED (pre 07/2007)	0.019	(1.71)	-0.0040	(-2.05)	13.70%	257
(5) LIBOR-OIS (pre 07/2007)	0.026	(0.80)	-0.0168	(-2.79)	16.49%	66

Table 9: Market share of volume and spreads

We investigate the relation between the market share of volume of one illiquidity group to total market volume (Market share volume $Group_x$ defined in Appendix B) and spreads. We divide the market share volume by its time-series average to facilitate comparison between groups. Specifications (1) to (10) estimate the following daily time-series regression:

$$\frac{Market\ Share\ Volume\ Group_{x,t}}{mean\ (Market\ Share\ Volume\ Group_{x})} = \alpha + \beta \times SPREAD_t + \varepsilon_t$$

where x refers to ILLIQ group. Estimation is performed using the Cochrane-Orcutt procedure. In Panel A we use the TED spread as our independent variable. Panel B is identical to Panel A except that we consider the LIBOR-OIS spread as independent variable. In Panel C we use the TED spread, but consider the period for which the LIBOR-OIS spread is available.

Panel A: Market share of volume and the TED spread

Dependent Variable Market share of:	Intercept	t-stat	Spread	t-stat	Adj. R^2	N
Group 1	1.002	(233.61)	0.0214	(5.47)	0.51%	5647
Group 2	1.001	(96.36)	-0.062	(-5.11)	0.44%	5647
Group 3	1.002	(60.07)	-0.085	(-4.96)	0.42%	5647
Group 4	0.987	(42.71)	-0.090	(-4.23)	0.30%	5647
Group 5	0.977	(41.53)	-0.1143	(-4.38)	0.32%	5647
Group 6	0.965	(41.38)	-0.1347	(-4.67)	0.37%	5647
Group 7	0.966	(38.02)	-0.1605	(-5.07)	0.44%	5647
Group 8	0.940	(31.76)	-0.1449	(-3.93)	0.25%	5647
Group 9	0.939	(23.17)	-0.1378	(-2.60)	0.10%	5647
Group 10	0.982	(15.36)	-0.2288	(-2.64)	0.11%	5647

Panel B: Market share of volume and the LIBOR-OIS spread

Dependent Variable Market share of:	Intercept	t-stat	Spread	t-stat	Adj. R^2	N
Group 1	0.961	(144.92)	0.0263	(2.51)	0.31%	1702
Group 2	1.092	(91.64)	-0.0250	(-1.11)	0.01%	1702
Group 3	1.200	(55.26)	-0.1079	(-2.74)	0.38%	1702
Group 4	1.262	(33.95)	-0.1932	(-3.10)	0.50%	1702
Group 5	1.177	(25.30)	-0.1642	(-2.11)	0.20%	1702
Group 6	1.096	(27.15)	-0.2487	(-3.28)	0.57%	1702
Group7	0.946	(25.55)	-0.2826	(-3.95)	0.85%	1702
Group 8	0.774	(22.81)	-0.2865	(-4.39)	1.06%	1702
Group 9	0.778	(12.31)	-0.3113	(-2.47)	0.30%	1702
Group 10	1.064	(6.70)	-0.6250	(-1.96)	0.17%	1702

Panel C: Market share of volume and the TED spread over the LIBOR-OIS period

Dependent Variable Market share of:	Intercept	t-stat	Spread	t-stat	Adj. R^2	N
Group 1	0.965	(138.98)	0.0057	(0.93)	-0.01%	1702
Group 2	1.082	(86.01)	0.0078	(0.53)	-0.04%	1702
Group 3	1.180	(50.19)	-0.0168	(-0.67)	-0.03%	1702
Group 4	1.236	(30.95)	-0.0484	(-1.29)	0.04%	1702
Group 5	1.157	(23.34)	-0.0473	(-1.01)	0.00%	1702
Group 6	1.060	(23.53)	-0.0565	(-1.11)	0.01%	1702
Group 7	0.922	(21.93)	-0.1000	(-2.00)	0.18%	1702
Group 8	0.761	(20.03)	-0.1250	(-2.79)	0.40%	1702
Group 9	0.765	(10.98)	-0.1394	(-1.58)	0.09%	1702
Group 10	1.076	(6.17)	-0.3550	(-1.59)	0.09%	1702

Table 10: Relative volume of illiquidity groups and spreads

We investigate the relation between the relative volume (*Volume of Group$_X$ / Volume of Group$_Y$* defined in Appendix B) and spreads. We divide relative volume by its time-series average to facilitate comparison between specifications. We estimate the following daily time-series regression:

$$\frac{Volume\ of\ Group_{x,t} \,/\, Volume\ of\ Group_{y,t}}{mean\,(Volume\ of\ Group_{x} \,/\, Volume\ of\ Group_{y})} = \alpha + \beta \times SPREAD_t + \varepsilon_t$$

where x and y refer to illiquidity groups. Since we have ten illiquidity groups and x is always larger than y there are 45 different specifications. We use the Cochrane-Orcutt estimation procedure. In Panel A we report the estimates of β when using the TED spread as our independent variable with corresponding t-statistics in brackets below. Each cell reports β for the relative volume of different ILLIQ groups. Columns refer to the group of the numerator and rows refer to the group of the denominator (e.g., the upper leftmost cell reports results for when Volume of Group$_2$ / Volume of Group$_1$ is the dependent variable). Panel B is identical to Panel A except that we consider the LIBOR-OIS spread as independent variable. Panel C considers the TED spread over the same period that the LIBOR-OIS spread is available.

Panel A: The impact of the TED spread on relative volume

		Group of numerator								
		2	3	4	5	6	7	8	9	10
Group of denominator	1	-0.084	-0.103	-0.109	-0.138	-0. 177	-0.205	-0.192	-0.188	-0.297
		(-5.18)	(-4.75)	(-4.11)	(-4.28)	(-4.91)	(-5.28)	(-4.32)	(-3.00)	(-2.80)
	2		-0.073	-0.080	-0.106	-0.111	-0.125	-0.098	-0.078	-0.171
			(-7.50)	(-4.69)	(-4.77)	(-4.17)	(-3.78)	(-2.37)	(-1.32)	(-1.97)
	3			-0.041	-0.044	-0.047	-0.059	-0.034	-0.007	-0.063
				(-4.23)	(-2.70)	(-2.15)	(-1.99)	(-0.85)	(-0.12)	(-0.83)
	4				0.005	-0.007	-0.016	0.011	0.032	-0.000
					(0.42)	(-0.38)	(-0.57)	(0.29)	(0.59)	(-0.00)
	5					-0.005	-0.003	0.031	0.056	0.015
						(-0.39)	(-0.15)	(0.99)	(1.17)	(0.22)
	6						-0.001	0.031	0.044	-0.011
							(-0.09)	(1.14)	(0.99)	(-0.18)
	7							0.018	0.021	-0.064
								(0.89)	(0.57)	(-0.99)
	8								0.011	-0.087
									(0.36)	(-1.27)
	9									-0.116
										(-1.35)

Panel B: The impact of the LIBOR-OIS spread on the relative volume

		Group of numerator								
		2	3	4	5	6	7	8	9	10
Group of denominator	1	-0.063	-0.154	-0.255	-0.239	-0.326	-0.362	-0.362	-0.382	-0.746
		(-1.84)	(-2.92)	(-3.28)	(-2.53)	(-3.61)	(-4.23)	(-4.52)	(-2.52)	(-1.95)
	2		-0.081	-0.157	-0.140	-0.224	-0.268	-0.283	-0.304	-0.609
			(-4.66)	(-3.74)	(-2.19)	(-3.38)	(-4.14)	(-4.49)	(-2.35)	(-1.99)
	3			-0.073	-0.073	-0.143	-0.195	-0.217	-0.234	-0.511
				(-3.21)	(-1.62)	(-2.85)	(-3.78)	(-4.35)	(-2.25)	(-1.97)
	4				-0.028	-0.085	-0.148	-0.174	-0.190	-0.437
					(-1.34)	(-2.75)	(-4.17)	(-4.68)	(-2.23)	(-1.87)
	5					-0.067	-0.144	-0.176	-0.190	-0.438
						(-3.98)	(-5.29)	(-5.28)	(-2.49)	(-1.97)
	6						-0.111	-0.157	-0.174	-0.437
							(-4.70)	(-4.81)	(-2.15)	(-2.06)
	7							-0.101	-0.130	-0.450
								(-2.68)	(-1.58)	(-1.97)
	8								-0.049	-0.427
									(-0.73)	(-1.69)
	9									-0.411
										(-1.29)

Panel C: The impact of the TED on the relative volume during the LIBOR-OIS period

Group of denominator	Group of numerator: 2	3	4	5	6	7	8	9	10
1	-0.002	-0.028	-0.065	-0.064	-0.076	-0.130	-0.157	-0.174	-0.431
	(-0.08)	(-0.80)	(-1.33)	(-1.06)	(-1.19)	(-2.09)	(-2.79)	(-1.61)	(-1.58)
2		-0.027	-0.043	-0.039	-0.056	-0.103	-0.133	-0.144	-0.360
		(-2.05)	(-1.51)	(-0.98)	(-1.24)	(-2.23)	(-3.01)	(-1.56)	(-1.64)
3			-0.021	-0.022	-0.035	-0.081	-0.114	-0.115	-0.314
			(-1.30)	(-0.77)	(-1.03)	(-2.22)	(-3.26)	(-1.55)	(-1.68)
4				0.006	-0.011	-0.065	-0.103	-0.100	-0.267
				(0.44)	(-0.53)	(-2.51)	(-3.86)	(-1.64)	(-1.60)
5					-0.019	-0.082	-0.121	-0.113	-0.279
					(-1.52)	(-4.03)	(-5.12)	(-2.07)	(-1.75)
6						-0.081	-0.130	-0.115	-0.302
						(-4.71)	(-5.67)	(-2.00)	(-1.99)
7							-0.096	-0.092	-0.320
							(-3.61)	(-1.57)	(-1.94)
8								-0.018	-0.276
								(-0.37)	(-1.53)
9									-0.263
									(-1.16)

Table 11: Regression analysis: Spreads, Illiquidity and Individual Stock Volume

We examine the relation between spreads, illiquidity and individual stock volume. All of our variables are defined in Appendix B. Our dependent variable is NORMALIZED SHARE VOLUME at the stock level. We remove observations with NORMALIZED SHARE VOLUME greater than five. $Group_1$ is a dummy variable that takes the value 1 if a stock belongs to illiquidity group 1 (i.e., the bottom ten percent in terms of illiquidity), 0 otherwise. $Group_2$ to $Group_{10}$ are dummy variables that take the value 1 if a stock belongs to that liquidity group. Our main independent variables are the LIBOR-OIS and the TED spread interacted with the illiquidity dummy variables $Group_1$ to $Group_{10}$ ($SPRD\times Group_1$ - $SPRD\times Group_{10}$). We estimate the following pooled panel regression;

$$\text{NORMALIZED SHARE VOLUME}_{it}=\alpha+\beta_1\times SPRD_t\times Group_{1,it}+\ldots+\beta_{10}\times SPRD_t\times Group_{10,it}+\varepsilon_{it}$$

where i refers to firm and t refers to day. In some specifications we use as a control variable the market normalized share volume. Standard errors are clustered around time. In Panel A we use the TED spread as spread variable, in Panel B we consider the LIBOR-OIS and in Panel C we consider the TED spread over the LIBOR-OIS period.

Panel A: The TED spread

	(1)		(2)	
	estimate	t-stat	estimate	t-stat
intercept	0.967	(304.37)	0.9677	(289.77)
MRKT NORM. SHARE VOL.	--	--	-0.0004	(-0.70)
$SPRD\times Group_1$	0.0959	(15.31)	0.0960	(15.29)
$SPRD\times Group_2$	0.0977	(16.38)	0.0979	(16.35)
$SPRD\times Group_3$	0.0856	(14.14)	0.0858	(14.12)
$SPRD\times Group_4$	0.0726	(12.00)	0.0728	(11.98)
$SPRD\times Group_5$	0.0543	(9.06)	0.0544	(9.05)
$SPRD\times Group_6$	0.0319	(5.32)	0.0321	(5.32)
$SPRD\times Group_7$	0.0027	(0.47)	0.0029	(0.49)
$SPRD\times Group_8$	-0.0422	(-7.46)	-0.0421	(-7.42)
$SPRD\times Group_9$	-0.1065	(-17.53)	-0.1064	(-17.50)
$SPRD\times Group_{10}$	-0.2229	(-29.61)	-0.2228	(-29.61)
Clustering	Time		Time	
Adj R^2	0.55%		0.55%	
N	24,429,664		24,429,664	

Panel B: The LIBOR-OIS spread

	(1)		(2)	
	estimate	t-stat	estimate	t-stat
intercept	1.0121	(257.52)	0.8675	(22.50)
MRKT NORM. SHARE VOL.	--	--	0.1055	(3.71)
SPRD×Group$_1$	0.0240	(1.94)	0.0130	(1.16)
SPRD×Group$_2$	0.0269	(2.21)	0.0159	(1.46)
SPRD×Group$_3$	0.0271	(2.09)	0.0163	(1.41)
SPRD×Group$_4$	0.0291	(2.21)	0.0183	(1.56)
SPRD×Group$_5$	0.0297	(2.21)	0.0189	(1.59)
SPRD×Group$_6$	0.0239	(1.71)	0.0133	(1.06)
SPRD×Group$_7$	0.0148	(1.10)	0.0043	(0.36)
SPRD×Group$_8$	-0.0082	(-0.70)	-0.0188	(-1.75)
SPRD×Group$_9$	-0.0421	(-3.62)	-0.0526	(-4.59)
SPRD×Group$_{10}$	-0.1303	(-8.61)	-0.1406	(-8.85)
Clustering	Time		Time	
Adj R^2	0.087%		0.54%	
N	6,333,758		6,333,758	

Panel C: The TED spread over the LIBOR-OIS period

	(1)		(2)	
	estimate	t-stat	estimate	t-stat
intercept	1.0105	(218.47)	0.8682	(22.55)
MRKT NORM. SHARE VOL.	--	--	0.1040	(3.69)
SPRD×Group$_1$	0.0242	(2.73)	0.0177	(2.21)
SPRD×Group$_2$	0.0257	(2.92)	0.0191	(2.43)
SPRD×Group$_3$	0.0260	(2.73)	0.0195	(2.30)
SPRD×Group$_4$	0.0277	(2.78)	0.0212	(2.38)
SPRD×Group$_5$	0.0271	(2.64)	0.0208	(2.26)
SPRD×Group$_6$	0.0240	(2.25)	0.0177	(1.85)
SPRD×Group$_7$	0.0170	(1.72)	0.0109	(1.22)
SPRD×Group$_8$	0.0021	(0.25)	-0.0042	(-0.56)
SPRD×Group$_9$	-0.0265	(-3.29)	-0.0327	(-4.35)
SPRD×Group$_{10}$	-0.0931	(-10.14)	-0.0992	(-11.07)
Clustering	Time		Time	
Adj R^2	0.12%		0.56%	
N	6,286,269		6,286,269	