Funding Liquidity, Market Liquidity and TED Spread: A Two-Regime Model

April 18, 2014

Abstract

We study the effect of market liquidity on equity-collateralized funding, accounting for endogeneity. Theory suggests market liquidity can affect funding liquidity in stabilizing and destabilizing manners. Using a new proxy for equity-collateralized funding liquidity, we provide the first evidence of stabilizing financier behavior and confirm the existence of two regimes over the period of July 2006–May 2011. Furthermore, we show that we can separate the two regimes using the yield spread of Eurodollars over T-bills (TED spread) and that a regime switch occurs near a TED spread of 48 basis points.

Keywords: equity-collateralized funding liquidity; market liquidity; two-regime model; financial distress.

1 Introduction

Secondary markets are considered liquid if an investor can quickly execute a significant quantity at a price near fundamental value. Such market liquidity is of great importance: it allows investors to enter and exit trading positions, rebalance portfolios, and smooth consumption. For market makers and other traders to provide liquidity in secondary markets, however, they need to raise capital from financiers in the primary market. This capital is often borrowed against collateral. We refer to the willingness of financiers to provide such loans as funding liquidity. Intuitively, when market makers and traders post more valuable securities collateral, financiers are more willing to lend out funds. Thus the market value of the assets serving as collateral plays a pivotal role in the smooth functioning of capital markets. Moreover, these collateral values might well depend on their market prices, on the uncertainty of those prices (*i.e.* volatilities), and also on their market liquidities. Therefore, asset market liquidity affects funding liquidity and vice versa. This paper empirically studies the effect of asset market liquidity on financier behavior and shows how the level of credit risk in the interbank money market changes this effect.

Despite a longstanding interest in the determinants of market liquidity initiated by Stoll (1978), Amihud and Mendelson (1980), Kyle (1985), Glosten and Milgrom (1985), and others, the role of limited market-maker capital in asset market liquidity has been relatively uninvestigated. Even less is known about how asset market liquidity ultimately feeds back into the supply of funds. Recent theoretical work by Gromb and Vayanos (2002, 2010) and Brunnermeier and Pedersen (2009) suggests limits to arbitrage via linkages between collateral values and funding can lead to vicious cycles of decreasing funding and market liquidity. However, Gromb and Vayanos (2010) and Brunnermeier and Pedersen (2009) also predict virtuous cycles of mutually increasing funding and market liquidity. Unfortunately, data limitations have impeded efforts to confirm and explore these two regimes empirically.

Directly assessing the cost of equity-collateralized funding would require data from the equity repurchase ("repo") market. Unfortunately, such data are not readily available. To measure capital constraints in the secured lending market Mancini-Griffoli and Ranaldo (2011) draw on earlier work by Coffey et al. (2009) and Gorton and Metrick (2010) in using the spread between "Agency Mortgage Backed Securities" and "General Collateral" repo rates. Adrian et al. (2012) describe the institutional features of the secured lending market and the data challenges involved in monitoring lending conditions and systemic risk in repo and securitized lending markets.

In this paper, we introduce and test a new measure of funding liquidity, or rather funding illiquidity, in equity markets. We proxy for the aggregate funding illiquidity of S&P 500 stocks on a given day using a value-weighted average of their stock loan rates. However, not all stock loan rates are informative about the cost of borrowing agains equity collateral, *i.e.* the funding liquidity of equities. In particular, in the stock lending market, only those price movements that can be attributed to changes in the demand for shorting stock are informative about a stocks' collateral value and its funding liquidity. As shown by Cohen et al. (2007), an outward shift in the demand curve for shorting a stock leads to a significant negative abnormal return in the following month. This naturally implies that such an outward shift of the demand curve signals a stock is poorer quality or riskier collateral going forward, *i.e.* its funding liquidity decreased. Consequently, in order to construct the time series of the aggregate funding illiquidity of S&P 500 stocks as a weighted average of stock loan rates, we identify demand shifts in the stock lending market by using data on both prices and volumes of stock on loan using the procedure proposed by Cohen et al. (2007). This identification strategy allows us to cleanly eliminate changes in stock loan rates that are driven by supply shocks to lendable stocks, instead of demand shocks, and that are therefore uninformative about the funding illiquidity of equities. The ability to focus sharply on demand shifts in the stock lending market allows us to make powerful inference about the time series of equity-collateralized funding conditions, inspite the lack of publicly available data on the equity repo market.

In addition, we establish an instrumental variables identification strategy that, for the first time, allows us to capture the endogeneity between market liquidity and funding liquidity. While our objective is to estimate the effect of market liquidity on funding liquidity, a causal relationship operating in the opposite direction is likely also present. We rely on two natural instruments to isolate the exogenous variation in market liquidity: (i) a variable capturing the trend in average time between trades, allowing us to exploit the well-established correlation between trading activity and market liquidity as in George and Longstaff (1993), and (ii) the change in yields for short-term AAA-rated corporate bonds versus change in Treasury bill rates. The latter spread is typically used to capture liquidity-driven action within the bond market independent of credit-risk as in Chen et al. (2005) and Almeida and Philippon (2007). Moreover, as financiers' desire to supply liquidity is typically a function of the collateral asset's fundamental volatility and credit risk, we control for S&P 500 market volatility by adding the VIX as a control variable and for credit risk using the TED spread. To account for the possibility that funding liquidity could feed back into asset market volatility, we add lagged volatility and TED spread to serve as internal instruments as explored in with Bloom et al. (2007). We show these instruments have strong explanatory power for asset market liquidity, volatility and credit risk.

Finally, we put forward a two-regime estimation procedure to distinguish between the *stabilizing* and *destabilizing* financier behavior featured in the aforementioned theoretical literature. On the one hand, when a financier believes a fall in market liquidity is temporary and could recover shortly, he might charge lower rates in response to decreased market liquidity of the stock collateral. This behavior has a stabilizing effect on market liquidity. On the other hand, financiers may destabilize market liquidity by increasing rates in periods of reduced market liquidity, forcing traders to unwind positions at unfavorable prices in order to meet the higher interest payments on their loans. Our analysis is the first to account for these two regimes and the first to offer empirical support for stabilizing financier behavior. We distinguish between these two distinct regimes via Brunnermeier and Pedersen's (2009) proposition that a flight to quality, in the form of aggregate desire to move from investments of lower to higher credit quality, would be part of the spiral effect of a destabilizing reduction in market liquidity.

Episodes of flight to quality are usually detected using credit spreads. As noted by Brunnermeier (2009), many market observers historically focused on the TED spread, defined as the difference in yields between US Eurodollar deposits (effectively three-month USD LIBOR) and US Treasury bills. Thus, by construction, this spread captures the difference in yields between unsecured top-rated interbank and government "riskless" credits.[1] In times of uncertainty, banks increase the interest rates on unsecured loans, driving up LIBOR. A flight to quality would then manifest itself as a widening of the TED spread which, as per Brunnermeier and Pedersen (2009), would suggest a destabilizing spiral between the liquidity of the equity market and the liquidity of the margin loan market. That a flight to quality is part of such a destabilizing spiral is crucial: it allows us to investigate the transition between stabilizing and destabilizing regimes based on the TED spread. We emphasize that our approach of using the TED spread as an explanatory variable for equity-collateralized funding liquidity is not inconsistent with recent articles such as Brunnermeier (2009) using the TED

[1]These banks were once AAA-rated credits; however, that is no longer the case.

spread as a proxy for funding illiquidity. In fact, we predict a strong positive relationship between the TED spread and funding illiquidity through the credit risk and flight-to-quality channels.

For the purpose of exposition, we first explore simpler estimation strategies which fail to account for the endogeneity of market illiquidity and/or fail to distinguish between different regimes. We point out where those specifications disagree with economic intuition or the data. We then explore a two-regime, two-stage least squares estimation where the threshold for the transition between stabilizing and destabilizing states is estimated by the methods of Hansen (2000) and Caner and Hansen (2004), facilitating statistical inference on the estimated threshold. Our results provide direct evidence of the existence of two liquidity regimes.

1.1 Related Literature

This paper belongs to a nascent empirical literature investigating the interplay between limited intermediary capital and asset market liquidity. Until now, this literature has focused on how funding tightness affects asset market liquidity and disregarded the endogeneity between the two. Comerton-Forde et al. (2010) examine time-variation in market liquidity and provide evidence that liquidity-supplier financing constraints matter. In particular, they proxy for funding liquidity in a 1994–2004 sample using a panel of daily revenue and inventory data of NYSE specialists, and find that negative shocks to these variables reduce stock market liquidity. Mancini-Griffoli and Ranaldo (2011) consider the effect of secured versus unsecured borrowing by arbitrageurs during the financial crisis and confirm that funding liquidity affects market liquidity. Hameed et al. (2010) show that changes in the value of equities (collateral) affect market liquidity; they also find effects suggestive of reduced funding liquidity and show that there are economically significant returns for providing stabilizing market liquidity. Most recently, Mancini et al. (2013) study liquidity in foreign exchange markets. They show the existence of important liquidity commonality in these markets and document that, when traders' funding liquidity decreases, market-wide foreign exchange liquidity decreases, suggesting destabilizing liquidity spirals in foreign exchange markets.

Drehmann and Nikolaou (2013) construct a measure of funding liquidity risk, *i.e.* the possibility that over a specific horizon the bank will become unable to settle obligations with immediacy, based on the aggressiveness of banks' bids in the main refinancing auctions conducted at the European Central Bank between June 2005 and October 2008. They show this measure correlates positively with asset market illiquidity during the financial crisis but is otherwise uncorrelated with asset market illiquidity. This observation supports our approach to distinguish between stabilizing and destablizing regimes on the basis of the TED spread. To study these correlations, they present univariate regressions of their funding liquidity measure on a market liquidity index. Since their estimation methods can be biased by the endogeneity between funding and market liquidity, their results are difficult to interpret. Furthermore, endogeneity is central to Gromb and Vayanos's (2002) and Brunnermeier and Pedersen's (2009) theses. Therefore, not accounting for endogeneity ignores a large aspect of the theory being tested.

All of these papers provide evidence for some aspects of the relationship between funding liquidity and market liquidity in various financial markets, but they only cover one direction of causality: how funding liquidity affects market liquidity. We concentrate on equity markets and depart from these existing works by focusing on the reverse causality: how market liquidity affects funding liquidity. We explicitely account for endogeneity using an instrumental variables identification strategy. Furthermore, the preceding papers document that financiers may act in a destabilizing manner. Thanks to a two-regime specification, our paper is the first to also document that financiers may act in a stabilizing manner.

2 Hypothesis development

Four working hypotheses lead to an explanatory regression model for the relationship between (equity-collateralized) funding and market liquidity. We summarize these hypotheses as stating that: (i) funding rates are affected by the expected future value of collateral; (ii) tranquil and stressed regimes for funding liquidity may be discerned by the TED spread; (iii) in the tranquil regime, financiers lower rates in response to market illiquidity; and, (iv) in the stressed regime, financiers raise rates in response to market illiquidity.

Hypothesis 1 *A financier sets the loan rate on a collateralized loan given expectations for the value-evolution of equity collateral. These expectations are influenced by (i) market liquidity, (ii) market volatility (volatility of equity collateral value), and (iii) the level of the TED spread (as an indicator of market stability).*

To test this hypothesis, we regress our measure of funding illiquidity on a market liquidity proxy and control for asset volatility and market-wide credit risk. This is the simplest hypothesis and serves as a sanity check on our data. If these expectations are not met, we should be concerned about the data being representative of a range of market conditions. We account for potential feedback effects of funding liquidity into market liquidity and asset volatility by instrumental variable estimation, and take the lagged TED spread as state variable.

Hypothesis 2 *We distinguish between two regimes: tranquil and stressed markets. These occur on day t when the TED spread on day $t-1$ is below or above some threshold, respectively.*

The models of Gromb and Vayanos (2002, 2010) and Brunnermeier and Pedersen (2009) feature funding rates that can either be stabilizing or destabilizing to market liquidity. Guided by exploratory data analysis and consistent with evidence in Balke (2000) and Drehmann and Nikolaou (2013), we propose a two-regime parametrization. We claim financiers apply different pricing models to periods of low-to-moderate credit risk versus periods of high credit risk and that credit risk is related to market stability. Our use of the TED spread as regime-separator mirrors market watchers' beliefs that the TED spread is a barometer for market sentiment (*e.g.* Krugman (2008)): spreads below some threshold imply relative tranquility in the market and spreads exceeding that threshold imply jitteriness. While Krugman and others have advocated a 100 bp threshold, we take no ex-ante position on the threshold value. Rather, we estimate the critical value of the TED spread using the methods of Hansen (2000) and Caner and Hansen (2004). This methodology allows us to formally test for the presence of a threshold and thus the validity of our two-regime specification. Furthermore, we believe this approach is simpler and easier to interpret than other methods like regime switching as in Acharya et al. (2013) and logistic smooth transition models as in Christiansen et al. (2011).

Hypothesis 3 *In tranquil markets, a financier decreases rates charged to brokers in response to increased market illiquidity. This response is stabilizing for market liquidity.*

When a financier observes an increase in market illiquidity, he may see that increase as a temporary deviation from equilibrium levels of liquidity. In that case, an increase in market illiquidity will lead financiers to lower rates to entice market participants to the market and preserve the business of lending to intermediaries. We believe a financier sees rises in market illiquidity as temporary when the TED spread remains below some threshold. Therefore, a financier will charge stabilizing rates: an increase in market illiquidity will lead to a decrease in financing rates. Testing this hypothesis tests Brunnermeier and Pedersen's (2009) Proposition 2 "(stabilizing margins and the cushioning effect)" and the case in Gromb and Vayanos's (2010) Proposition 2 where $u > (W_0 + 2x_0\varphi_0)/2\bar{\varepsilon}$ and $W_0 + 2x_0\varphi_0 \geq 2\bar{\varepsilon}x_0$.

Hypothesis 4 *In stressed markets, a financier raises rates charged to brokers in response to increased market illiquidity. This response is destabilizing for market liquidity.*

When a financier observes an increase in market illiquidity, he may see that increase as a permanent shift from equilibrium levels of liquidity. In that case, an increase in market illiquidity will lead financiers to increase rates since market participants cannot be enticed to the market and they seek a safety buffer against declines in the collateral value for broker loans. We believe a financier sees rises in market illiquidity as permanent when the TED spread breeches some threshold. Therefore, a financier will charge destabilizing rates: an increase in market illiquidity yields an increase in financing rates. Testing this hypothesis tests Brunnermeier and Pedersen's (2009) Proposition 3 "(destabilizing margins)" and the case in Gromb and Vayanos's (2010) Proposition 2 where $u > (W_0 + 2x_0\varphi_0)/2\bar{\varepsilon}$ and $W_0 + 2x_0\varphi_0 < 2\bar{\varepsilon}x_0$.

3 Data description

We use six variables in our two-regime, two-stage least squares estimation procedure. We proxy for funding liquidity as dependent variable with a market-based measure using stock loan rates for S&P 500 stocks. Our set of explanatory variables consists of bid-ask spreads for the S&P 500, S&P 500 implied volatility, and the TED spread. To account for the endogenous relationship of both market liquidity and volatility with the dependent variable, we introduce two natural instruments to isolate the exogenous variation in market liquidity: a variable representing the trend in inter-trade duration, and a measure for the change in short-term AAA corporate bond yields versus the change in Treasury bill rates. We also add lagged volatility and lagged TED spread as an internal instrument to handle any endogeneity of the VIX index and TED spread. Our sample period covers July 2006–May 2011.[2]

Throughout the paper, we speak of funding and market liquidity. However, the nature of these variables means that they measure funding and market *illiquidity*. Thus we refer to these illiquidities when working with the data.

3.1 Variables

Funding illiquidity (log of value-weighted average stock loan rate in basis points). For our measure of funding illiquidity, we use stock loan fees (in basis points, bp). Since the illiquidity measure is non-negative and heavily right-skewed, we take the log of the data to get a more symmetric distribution; thus a funding illiquidity measure of 2.5 corresponds to a loan fee of $e^{2.5} = 12.2$ bp.

[2] Data limitations prevent us from further extending the sample period. Stock loan data from Data Explorers is not available prior to July 2006, and alterations to the computation method of the CBOE-disseminated bid-ask spreads on the S&P 500 index prevent us from using data after May 22nd 2011.

Accurate measurement of the cost of equity-collateralized funding would require information on both the loan rate and the haircut applied to equity-collateralized loans.[3] However, such data is not publicly available. Fortunately, we can infer about fluctuations in the cost of borrowing against a portfolio of S&P 500 equities using a publicly available panel data set of stock lending transactions and stock loan rates *i.e.* the cost of borrowing a stock as part of a short-sell strategy.[4] We rely on the intuition that the cost of borrowing against equities will increase (decrease) whenever equities are perceived to be poorer (better) quality collateral, which, in turn, is reflected in increased (decreased) demand for shorting equities. Using similar stock loan data from a single institutional investor, Cohen et al. (2007) document that an increase in the shorting demand on average leads to a significant negative abnormal return of 2.98% in the following month. They also show that the shorting market is an important mechanism for private information revelation. In fact, an outward (inward) shift of the demand curve for shorting a specific stock implies more (less) capital is betting that its price will decrease, revealing the stock as worse quality collateral.

Since stock loan rates may be affected by simultaneous changes in supply and demand in the market for shorting stock, we need to isolate those stock loan rates that are informative about a shift in the demand curve for shorting stock. Such an identification requires information on both the price for borrowing stock and the quantities of stock on loan. Let $VWAF_{it}$ be the volume-weighted average stock loan fee for the S&P 500 stock i on day t and $TBQ_{i,t}$ be the corresponding total balance quantities (*i.e.* quantities of stock on loan). Table A.1 reports

[3]Recent survey evidence from the Bank for International Settlements (2010) reveals that these loan fees and haircuts are positively correlated and countercyclical. Market participants report that the practice of setting haircuts is institution-specific and involves decision-making from risk-management, global collateral management, and front-office units, as well as a committee of senior managers and chief risk officers. The bureaucratic nature of this process means that haircuts are less frequently revised, or revised through a blanket introduction of multipliers. Overall, this evidence suggests that haircuts are the slower-moving leg of the cost of funding, as opposed to the actual loan fees. Therefore, we believe the lack of publicly-available haircut data does not affect the validity of our fee-based analysis.

[4]The dataset is made available by DataExplorers.

summary statistics for these variables across all stocks (top panel) and across categories of stocks grouped by market capitalization quintile. We first note that only 3.5% of the lending transactions are related to the smallest stocks. We further observe that the mean VWAF and daily transaction count are higher for smaller stocks and that the mean TBQ is higher for larger stocks.

For each stock in our sample, we isolate shifts in the shorting demand curve by exploiting price-quantity pairs. For example, an increase in the reported VWAF (our price measure) coupled with an increase in the TBQ (our quantity measure) corresponds to an increase in shorting demand — as would be the case for any increase in price coupled with an increase in quantity for downward-sloping demand curves. As Cohen et al. (2007) note, this is not necessarily the only shift that occurred; however, for a shift of price and quantity into this quadrant, a demand shift outwards must have occurred. Similarly, we isolate a joint decrease of price and quantity from one day to the next as an inward shift of the demand curve. We keep only the changes which clearly involve demand shifts and disregard the observations which clearly involve supply shifts. The occurrence of demand and supply shifts in our dataset is tabulated, by year and market capitalization, in Table A.2. From July 2006–May 2011, we record a total of 603,552 shifts more or less equally distributed across the four largest size quintiles of the S&P 500. Only 20,000 observations can be attributed to the smallest stocks of the S&P 500 index.[5] Tables A.3 and A.4 describe these outward and inward shifts of the shorting demand curve in terms of the absolute and relative changes in the VWAF and TBQ of stock on loan. We observe that outward shifts are characterised by

[5]Since demand shifts dominate our dataset, an alternative specification of $fundilliq_t$ based on the full sample of stock loan rates differs little. Consequently, all results in Section 4 are qualititatively similar under such an alternative specification. We also investigated a specification of $fundilliq_t$ which weights stock loan fees (VWAF) by loan size instead of the number of transactions. The correlation between the two specifications of funding illiquidity is not strong, however, due to outliers in loan sizes and fees. Large stock loans may be negotiated over time, priced differently, or illiquid and thus not representative of a given day. Nevertheless, the two-regime model detects similar regimes for the two measures. For brevity, these results are omitted here but they are available from the authors on request.

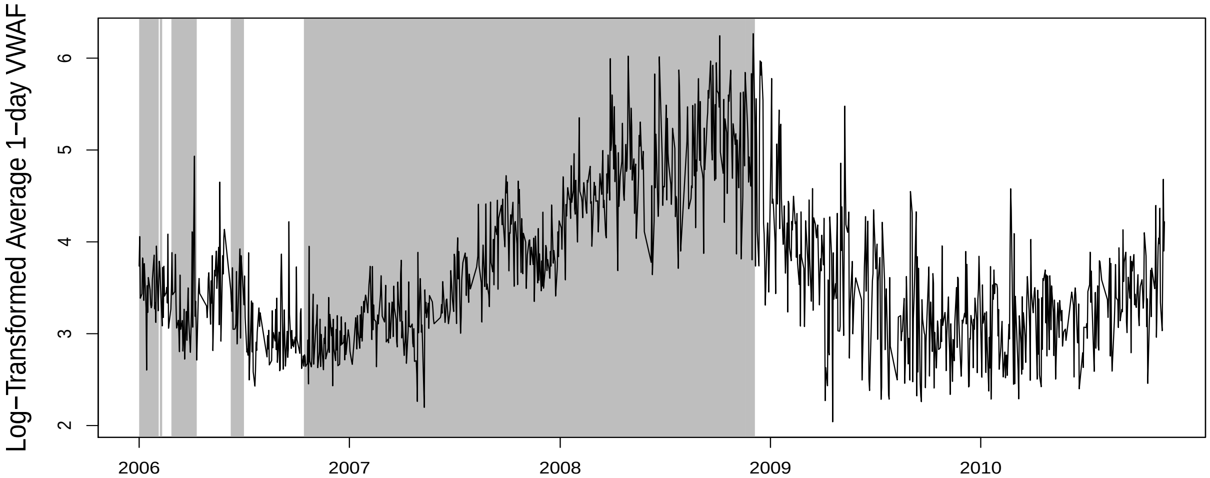

Figure 1: Log-transformed volume-weighted average fees ($fundilliq$) on S&P 500 stock loans over July 2006–May 2011. Shaded regions indicate time periods when the lagged TED spread exceeds 48 bp.

significantly larger price changes than inward shifts, and that the distribution of the price increases accompanying the outward shifts is heavily right-skewed.

We denote a shift in the demand curve for shorting stock i between day $t-1$ and day t with an indicator variable, $\mathbb{1}_{DS,it}$, defined as:

$$\mathbb{1}_{DS,it} = \begin{cases} 1 & \text{if } (VWAF_{i,t-1} < VWAF_{i,t}) \cap (TBQ_{i,t-1} < TBQ_{i,t}); \text{ (demand shift out)} \\ 1 & \text{if } (VWAF_{i,t-1} > VWAF_{i,t}) \cap (TBQ_{i,t-1} > TBQ_{i,t}); \text{ (demand shift in)} \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

For each day, we weight the VWAFs for known demand shifts by the number of transactions initiated that day for known demand shifts. Thus our daily measure of funding illiquidity for S&P 500 stocks is:

$$fundilliq_t = \log\left(\frac{\sum_{i=1}^{N} Trades_{it} \times VWAF_{it} \times \mathbb{1}_{DS,it}}{\sum_{i=1}^{N} Trades_{it} \times \mathbb{1}_{DS,it}}\right), \tag{2}$$

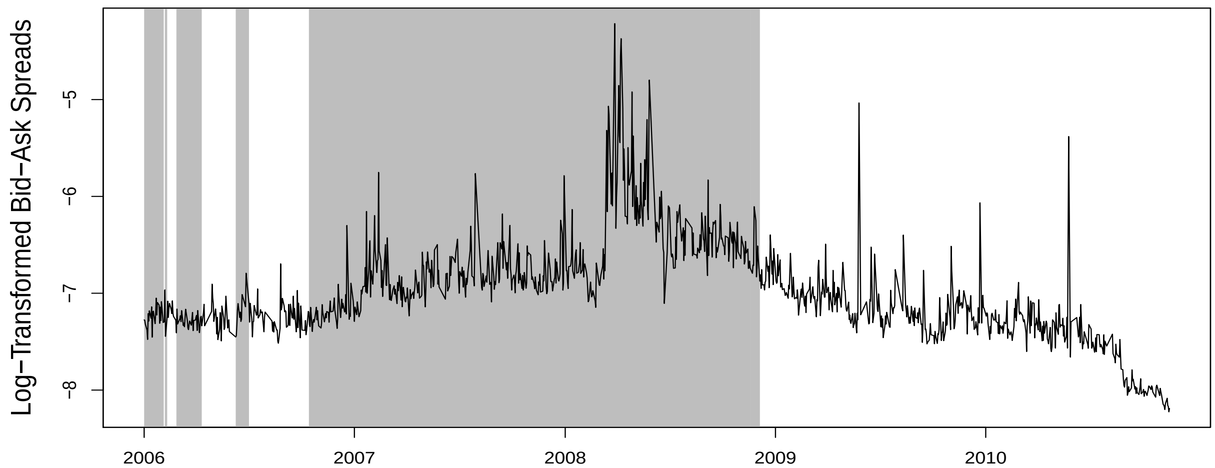

Figure 2: Log-transformed bid-ask spreads on the S&P 500 index (*mktilliq*) July 2006–May 2011. Shaded regions indicate time periods when the lagged TED spread exceeds 48 bp.

where i indexes the N members of the S&P 500 on a day t with stock loan activity and $Trades_{it}$ represents the number of transactions initiated for stock i on day t.

We filter the raw data from Data Explorers to exclude negative values for $VWAF_{it}$, observations for which either $VWAF_{it}$ or $Value_{it}$ is missing, and decompositions of aggregate figures due to dividend treatment. The average as per these filters and Equation (2) is plotted in Figure 1. The plot shows several spikes throughout the evolution of the credit crisis (2007–2009), indicating increased demand for borrowing stock as part of a short-sell strategy.

Market illiquidity (log of bid-ask spread in %). Pagano (1989) and Johnson (2006) define market liquidity as the average willingness of the market to accommodate trade at prevailing prices. This willingness may fluctuate as the underlying state of the economy changes. Bid-ask spreads, standardized via division by the midquote, are generally considered a good measure of market illiquidity as per Goyenko et al. (2009). The CBOE aggregates bid-ask spread data from the market for the S&P 500 index members; the resulting series is available through Bloomberg. We take the logarithm of the standardized S&P 500 bid-ask spreads to reduce the impact of extremes on estimation; thus a market illiquidity measure of -7 corresponds to a bid-ask spread of $e^{-7} = 0.0009 = 9$ bp.

We denote this illiquidity measure *mktilliq* since an increase in bid-ask spread corresponds to an increase in illiquidity. Since we expect a causal relationship of funding illiquidity on market illiquidity, we treat *mktilliq* as an endogenous regressor in our key estimations. We plot *mktilliq* across time in Figure 2 and observe a widening of bid-ask spreads for the S&P 500 index throughout the credit crisis.

Figure 3 presents scatter plots of $fundilliq$ on *mktilliq* in Panels A. Gray circles (black crosses) correspond to stable (stressed) market conditions (based on a TED spread threshold). We find that the gray circles reveal a linear pattern with a modest inclination whose magnitude is difficult to discern on a visual basis. Nevertheless, this suggests that market illiquidity only has a limited effect on funding illiquidity when market conditions are perceived as stable and financiers' willingness to lend funds seems little affected by asset liquidity.

We further note that the black crosses, corresponding to stressed market conditions, exhibit a distinctly different pattern. The black crosses in Panel A show a steep positive slope. This implies higher market illiquidity is associated with higher funding illiquidity when credit concerns are high (*i.e.* high TED spreads). Thus, Panel A of Figure 3 demonstrates the importance of distinguishing between stable and stressed markets when modeling the effect of market liquidity on equity-collateralized funding liquidity.

Volatility of stock collateral (in %): For a measure of the volatility of equity collateral,

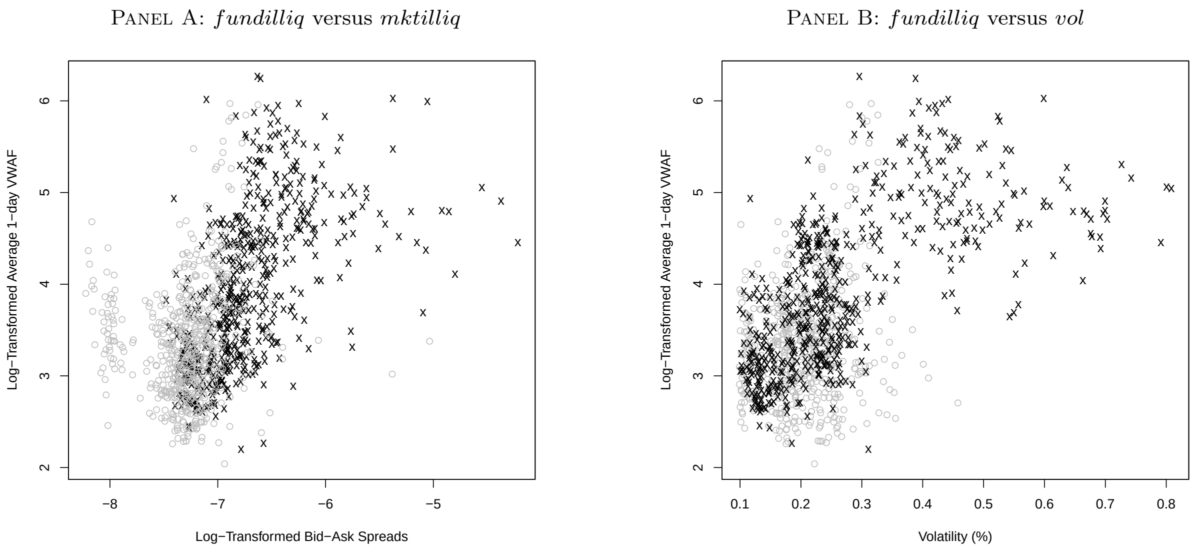

Figure 3: Scatter plots of funding illiquidity versus market illiquidity (*mktilliq*) and volatility (*vol*). Panel A (B) shows the log-transformed volume weighted average stock loan fee versus market illiquidity (volatility), with gray circles (black crosses) for observations when the lagged TED spread is below (above) 48 bp. The strong separation of gray circles (low TED spread) from black crosses (high TED spread) reveal the presence of two distinct regimes, differentiable on the basis of a TED spread threshold.

we use the CBOE implied volatility index (VIX) derived from options on the S&P 500 index. The series is denoted *vol* and plotted in Figure 4. While we are interested in estimating the effect of asset volatility on our two funding illiquidity measures, we believe it is reasonable that funding constraints may feed back into asset market volatility. Consequently, we treat the VIX index as an endogenous regressor in our key estimation.

We analyze the relationship between funding illiquidity proxies and the VIX index by means of scatter plots of $fundilliq$ on vol. These plots are represented in Panel B of Figure 3 and reveal that, if we do not distinguish between a normal and high credit risk regime, at least a quadratic function is needed to fit all data points well. For this reason and because risk tends to scale with variance, we also include the squared series $volsq$ in our model.

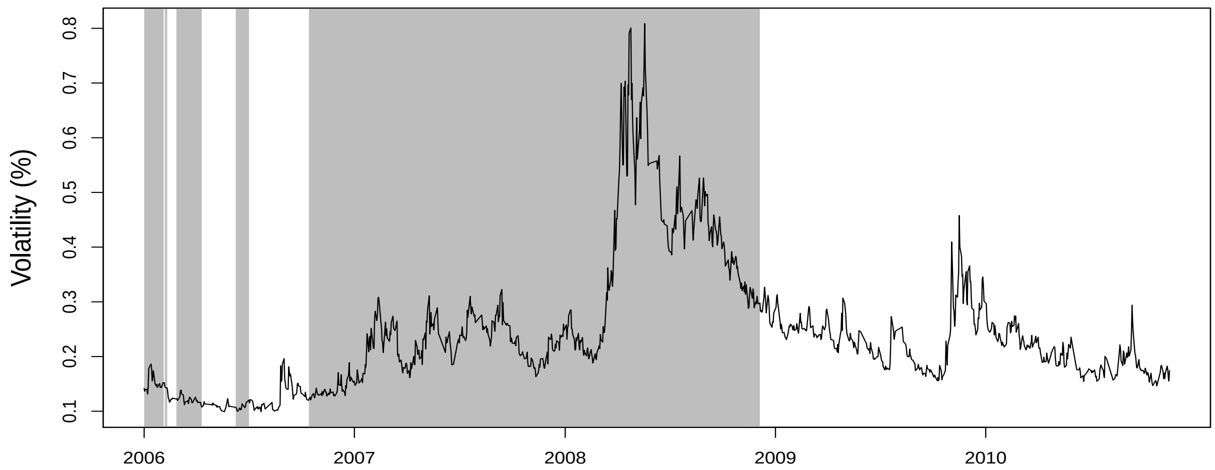

Figure 4: Daily volatility (in percent) as measured by the Chicago Board Options Exchange implied volatility index (VIX) July 2006–May 2011. Shaded regions indicate time periods when the lagged TED spread exceeds 48 bp.

TED spread (in %): The TED spread (*ted*) serves as a control variable in our funding illiquidity model. The TED spread is the difference in yields between three-month Eurodollar deposits (effectively LIBOR) and three-month US T-bills.[6] Thus it represents the risk premium charged on top-rated interbank loans versus risk-free loans to the US government. Historically, market observers have focused on the TED spread (Kawaller and Koch, 1992; Brunnermeier, 2009). Since both T-bills and Eurodollar futures are highly liquid and liquidity effects are pronounced at longer maturities, we believe the TED spread to be largely a measure of credit risk. Indeed, the TED spread is now generally used as an indicator of perceived credit risk in the economy: Taylor and Williams (2009) show that rises in LIBOR rate spreads compared to overnight federal funds can be attributed to increased counterparty

[6] Mollencamp and Whitehouse (2008) provides evidence that London banks have been manipulating the submissions which help determine LIBOR and Keenan (2012) gives anecdotal evidence of this happening as far back as 1991. For several reasons, we suspect that this does not greatly affect our analysis. First, initial indications are that the sizes of the manipulations are on the order of a few basis points — economically significant for the interest-rate swaps markets, but not compared to the thresholds we estimate. Second, these manipulations were not always of the same direction; therefore, we would expect the manipulations to add noise to LIBOR and our analysis. If anything, this would make our results appear weaker than they would otherwise be.

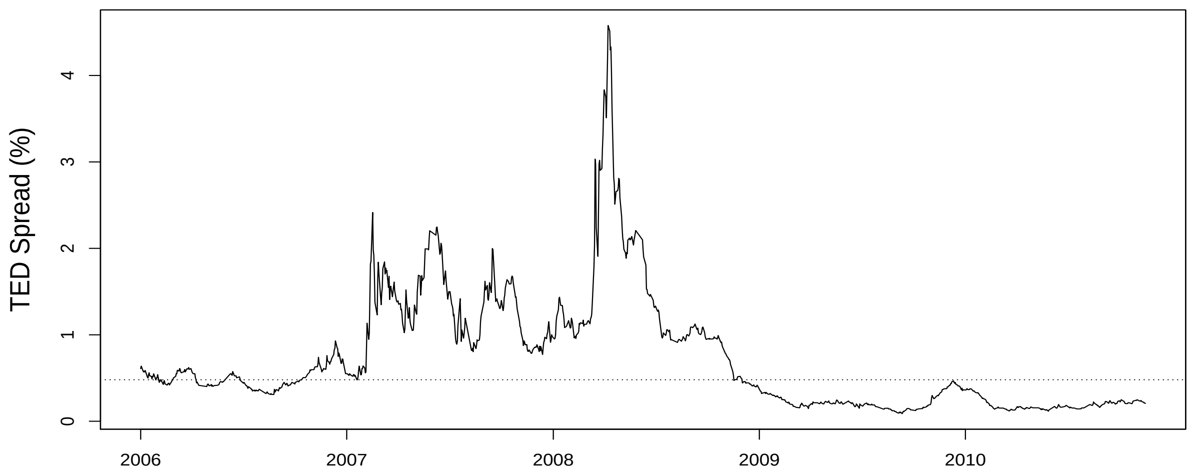

Figure 5: TED SPREAD AS AN INDICATOR FOR STABILIZING AND DESTABILIZING FUNDING LIQUIDITY CYCLES JULY 2006–MAY 2011. The dashed line marks a TED spread of 48 bp, above which the one-day ahead liquidity regime is stressed.

risk. We use the TED spread as a state variable to help distinguish between stabilizing and destabilizing regimes in the Brunnermeier and Pedersen model. Figure 5 displays the TED spread series over the sample period with noticeable spikes for the recent credit crisis. The dashed line marks the levels at which market participants' (48 bp) actions suggest they perceive a crisis.[7]

3.2 Instruments

The seminal models of Gromb and Vayanos (2002, 2010) and Brunnermeier and Pedersen (2009) illustrate the presence of a feedback effect between market illiquidity and funding illiquidity. This requires that our estimation handles such a simultaneous relationship. A possible remedy lies in using instrumental variables. These variables should have a high correlation with market liquidity and zero correlation with the error in predicting funding

[7]This threshold estimate is obtained through a two-regime, two-stage least squares estimation procedure detailed in Section 4.1 and is statistically significant at the 95% level.

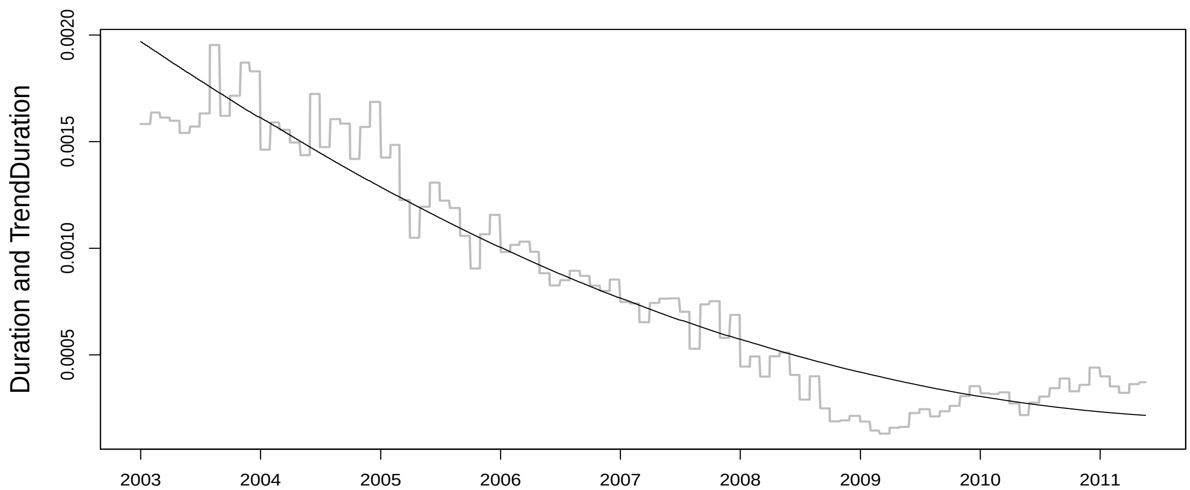

Figure 6: Duration between US stock trades and its long-term trend February 2001–May 2011. The gray line shows the inter-trade duration; the black line shows the trend.

liquidity using market liquidity and the control variables listed above. While little research exists on the determinants of funding liquidity, much more work has been done on market liquidity. This allows us to identify several natural instruments that isolate exogenous variation in the bid-ask spreads. Since asset market volatility is an important control variable in our regressions, we account for the possibility that funding liquidity could feed back into asset market volatility by completing our set of instruments with lagged volatility terms. Hence, we obtain (at least) exactly identified models. Such lagged volatility measures have previously served as internal instruments for stock volatility in Bloom et al. (2007).

Trend in inter-trade duration. We use the long term trend in the average time between trades on the Nasdaq as a second instrument. It is well known that there is a strong correlation between trading activity and market liquidity, see *e.g.* George and Longstaff (1993) and Chordia et al. (2001). Unfortunately, NYSE trade counts are not directly available, but for the purpose of constructing an instrument, it suffices to proxy the trading activity on the S&P 500 stocks by the monthly average time between trades (expressed in years) on the

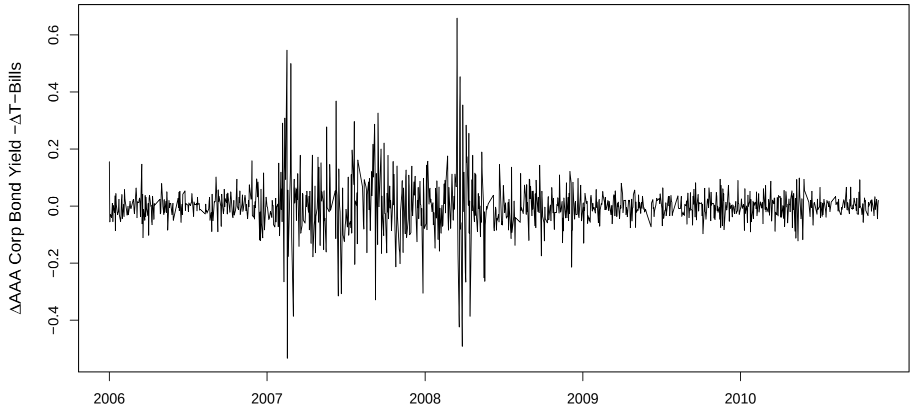

Figure 7: DIFFERENCE BETWEEN CHANGES IN SHORT-TERM AAA CORPORATE BOND YIELDS AND CHANGES IN TREASURY BILLS JULY 2006–MAY 2011. This difference captures bond market liquidity unrelated to credit issues.

Nasdaq.[8] The time series of *duration* is plotted in Figure 6. It has two components: a long term trend, driven by exogenous technological innovation, and stationary deviations from that trend.[9] Because the latter may be correlated with changes in funding illiquidity, we only use the trend in duration as an instrument. To extract the trend, we regress duration on a quadratic trend variable for a data sample staring in February 2001, after the NYSE completed its move to decimal pricing on 29 January 2001 (Portniaguina, Bernhardt, and Hughson, 2006) which lowered the tick size from eighths and sixteenths to pennies.[10] These deterministic variables were shown by Chordia et al. (2005) to be significant determinants of market liquidity as measured by the quoted spreads on NYSE stocks. The bold black line (*durtrend*) in Figure 6 is thus our first instrument.

[8]The monthly Nasdaq trade count can be retrieved from `http://www.nasdaqtrader.com/Trader.aspx?id=MonthlyMarketSummary`. We measure the time between trades in years assuming 390 trading minutes per day and 252 trading days in a year.

[9]The Augmented Dickey Fuller test with intercept and trend in the testing regression and lags selected by means of the AIC criterion rejects the presence of a unit root in the daily $fundilliq$, *mktilliq*, *vol*, *volsq* and *ted* series and the monthly *duration* series at a 95% confidence interval.

[10]While we do not believe that the effective trend is quadratic, we do believe that there was a nonlinear decrease in tick sizes: the changes were large at first and then smaller until the withdrawal of liquidity during the financial crisis led to an increase in tick sizes. A quadratic model is the most simple model which fits the data and is sufficient to extract a general trend.

Change in AAA corporate bond yields versus T-Bills. We use the change in yields for short-term (1-year or less) AAA-rated corporate bonds versus the change in US Treasury bill yields as our final instrument. We specifically want to know when money flows cause differential price movements between high-grade, short-maturity government and corporate credit, due to the lower liquidity of corporate bonds. We measure that by looking at the change in the yield spread between the two. Since both are top-rated credits, we expect money to flow into or out of both similarly; thus movement in the spread between the two would be primarily due to the lower liquidity of corporate bonds.

Therefore, this instrument isolates variation in bond market liquidity that is exogenous to variation driven by a flight to quality. Put differently: this instrument (*aaaliq*) is constructed to detect liquidity-driven action within the bond market that is exogenous to variations in credit risk that would be reflected in collateralized funding rates. Comparable spreads have been used for similar purposes by Chen et al. (2005) and Almeida and Philippon (2007). The instrument is computed using the Bloomberg AAA corporate bond yield index (C0011Y) and is shown in Figure 7.

3.3 Summary statistics

Table 1 presents summary statistics for the six variables. The statistics are presented for the full sample and subsamples for when the TED spread is below or above 48 basis points. We observe that the transition from a tranquil (low or moderate TED spreads) to a stressed regime (high TED spreads) is characterized by an overall increase in funding and market illiquidity as well as in volatility. These increases are both economically and statistically significant. Formally, the χ^2 test of median equality and the t-test of mean equality indicate that the medians and means of $fundilliq$, $mktilliq$, vol and ted are significantly different

Table 1: Summary statistics. The statistics are presented for the full sample and subsamples when the lagged TED spread is below or above 48 basis points.

Key: July 2006–May 2011 summary statistics for covariates (funding and market illiquidity, volatility, TED spread) and instruments (inter-trade duration trend, change in yield spread of AAA corporates over T-Bill rates). The yield spread is in percent ("0.5" = 0.5%); duration trend is in thousandths of years ("1" = 0.001 years). The omitted tick-size-change instrument is 0 before full decimalization (29 Jan 2001) and 1 otherwise. The χ^2 test of median equality and the t-test of mean equality indicate that the median and mean of $fundilliq$, $mktilliq$, vol and ted are significantly different between the two regimes at a 99% confidence level.

	Summary Statistics									
Jul 2006 – May 2011	**Full sample** (1130 obs)		**Lagged TED spread ≤ 48 bp** (559 obs)				**Lagged TED spread > 48 bp** (571 obs)			
	med	mean	min	med	mean	max	min	med	mean	max
$fundilliq$	3.50	3.66	2.04	3.34	3.39	5.97	2.20	3.81	3.94	6.27
$mktilliq$	-7.08	-7.00	-8.23	-7.27	-7.28	-5.04	-7.48	-6.80	-6.73	-4.22
vol	0.22	0.24	0.10	0.21	0.21	0.46	0.10	0.23	0.27	0.81
ted	0.48	0.73	0.09	0.21	0.26	0.47	0.55	1.04	1.21	4.58
$durtrend$	0.4	0.4	0.3	0.3	0.4	0.8	0.2	0.4	0.5	1
$aaaliq$	0.00	0.00	-0.21	0.00	0.00	0.12	-0.53	0.00	0.00	0.66

between the two regimes at a 99% confidence level.

4 Empirical analysis

4.1 Methodology

A simple approach to analyze the relation between funding and market illiquidity is to estimate an ordinary least squares model of funding illiquidity versus market illiquidity and the explanatory variables:

$$fundilliq_t = \beta_0 + \beta_1 mktilliq_t + \beta_2 vol_t + \beta_3 volsq_t + \beta_4 ted_t + \varepsilon_t. \tag{3}$$

This approach is followed by Drehmann and Nikolaou (2013) in a reduced form univariate setting. Our descriptive analysis of the funding and market liquidity proxies, however, indicates that two corrections are needed to properly decipher the connection between market and funding illiquidity.

First, consistent with the evidence in Table 1 and Figure 3 and in line with Balke (2000), we allow for a regime change if credit conditions cross a critical threshold. We implement this idea with an indicator variable $stress_t(\kappa)$ that equals 1 when the TED spread on day $t-1$ exceeds a threshold value κ and is zero otherwise. This variable represents the transition from a stable to a distressed market regime. Using this variable, we define the following two-regime regression model and estimate it naively by least squares

$$\begin{aligned} fundilliq_t = {} & \beta_0 + \beta_1 mktilliq_t + \beta_2 vol_t + \beta_3 volsq_t + \beta_4 ted_t \\ & + \beta_5 stress_t + \beta_6 stressmktilliq_t + \beta_7 stressvol_t + \beta_8 stressted_t + \varepsilon_t \end{aligned} \tag{4}$$

where $stressmktilliq_t = mktilliq_t \times stress_t(\kappa)$, $stressvol_t = vol_t \times stress_t(\kappa)$, and $stressted_t = ted_t \times stress_t(\kappa)$.[11]

Next, because of the endogeneity between $fundilliq$ and the explanatory variables $mktilliq$, vol, ted, $stressmktilliq$, $stressvol$ and $stressted$, we introduce an instrumental variables

[11] By not interacting $volsq_t$ with $stress_t$, Equation (4) imposes a linear relationship between volatility and funding illiquidity when credit risk is high. Adding this interaction term would exacerbate the problem of multicollinearity among the $stress$-variables, to the extent that the standard errors on the estimated coefficients increase substantially. Nevertheless, our threshold estimates $\hat{\kappa}$ are robust to the inclusion of $stress_t \times volsq_t$ in the model.

estimation. This yields the following set of first-stage equations

$$\begin{aligned} mktilliq_t &= \alpha_0 + \alpha_1 stress_t + \alpha_2 durtrend_t + \alpha_3 aaaliq_t + \alpha_4 vol_{t-1} + \alpha_5 volsq_{t-1} \\ &\quad + \alpha_6 ted_{t-1} + \alpha_7 stressvol_{t-1} + \alpha_8 stressted_{t-1} + \eta_t, \end{aligned} \tag{5}$$

$$\begin{aligned} vol_t &= \gamma_0 + \gamma_1 stress_t + \gamma_2 durtrend_t + \gamma_3 aaaliq_t + \gamma_4 vol_{t-1} + \gamma_5 volsq_{t-1} \\ &\quad + \gamma_6 ted_t + \gamma_7 stressvol_{t-1} + \gamma_8 stressted_{t-1} + \xi_t, \end{aligned} \tag{6}$$

$$\begin{aligned} volsq_t &= \delta_0 + \delta_1 stress_t + \delta_2 durtrend_t + \delta_3 aaaliq_t + \delta_4 vol_{t-1} + \delta_5 volsq_{t-1} \\ &\quad + \delta_6 ted_{t-1} + \delta_7 stressvol_{t-1} + \delta_8 stressted_{t-1} + \zeta_t, \end{aligned} \tag{7}$$

$$\begin{aligned} ted_t &= \phi_0 + \phi_1 stress_t + \phi_2 durtrend_t + \phi_3 aaaliq_t + \phi_4 vol_{t-1} + \phi_5 volsq_{t-1} \\ &\quad + \phi_6 ted_{t-1} + \phi_7 stressvol_{t-1} + \phi_8 stressted_{t-1} + \psi_t, \end{aligned} \tag{8}$$

$$\begin{aligned} stressmktilliq_t &= \alpha_0^s + \alpha_1^s stress_t + \alpha_2^s durtrend_t + \alpha_3^s aaaliq_t + \alpha_4^s vol_{t-1} + \alpha_5^s volsq_{t-1} \\ &\quad + \alpha_5^s ted_{t-1} + \alpha_7^s stressvol_{t-1} + \alpha_8^s stressted_{t-1} + \eta_t^s, \end{aligned} \tag{9}$$

$$\begin{aligned} stressvol_t &= \gamma_0^s + \gamma_1^s stress_t + \gamma_2^s durtrend_t + \gamma_3^s aaaliq_t + \gamma_4^s vol_{t-1} + \gamma_5^s volsq_{t-1} \\ &\quad + \gamma_6^s ted_{t-1} + \gamma_7^s stressvol_{t-1} + \gamma_8^s stressted_{t-1} + \xi_t^s. \end{aligned} \tag{10}$$

$$\begin{aligned} stressted_t &= \phi_0^s + \phi_1^s stress_t + \phi_2^s durtrend_t + \phi_3^s aaaliq_t + \phi_4^s vol_{t-1} + \phi_5^s volsq_{t-1} \\ &\quad + \phi_6^s ted_{t-1} + \phi_7^s stressvol_{t-1} + \phi_8^s stressted_{t-1} + \psi_t^s. \end{aligned} \tag{11}$$

We then re-estimate the benchmark linear model (3) and the two-regime model (4) by instrumental variables, using the trend in trade duration, change in short-term AAA corporate bond yields vs. T-Bill rates, lagged volatility, lagged squared volatility, lagged TED spread and the lagged interaction between volatility (TED spread) and stressed market conditions, as instruments for *mktilliq*, *vol*, *volsq*, *ted*, *stressmktilliq*, *stressvol* and *stressted*.

Thus we obtain four estimation approaches to relating market and funding liquidity: (i) the linear model in Equation (3) estimated by ordinary least squares (OLS); (ii) the linear model in Equation (3) fitted by instrumental variables (IV) estimation; (iii) the two-regime specification in Equation (4) estimated by OLS, and finally; (iv) the two-regime specification in Equation (4) by IV estimation.

Regardless of whether we are estimating a two-regime specification in Equation (4) by OLS or IV, the threshold κ (and its confidence interval) is always estimated by the methods of Hansen (2000) and Caner and Hansen (2004). The threshold estimate is asymptotically consistent but non-normally distributed. The Caner and Hansen (2004) likelihood ratio test rejects the null of no threshold effect ($\kappa = 0$) at a 99% confidence interval. The least squares estimates of the slope parameters follow directly from threshold estimation. Under the model with endogenous market illiquidity and volatility, we estimate by two stage least squares $\beta_0, \ldots, \beta_4$ on the subsample for which $ted_{t-1} \leq \hat{\kappa}$, and use the remainder of the sample to estimate $\beta_5, \beta_6, \beta_7, \beta_8$. Hansen (2000) and Caner and Hansen (2004) show that these estimators are asymptotically normal with asymptotic covariance matrix as if $\hat{\kappa}$ were fixed at κ. Finally, we follow these authors in using a Bonferroni method to construct parameter confidence bands that adjust for estimation uncertainty in $\hat{\kappa}$.

4.2 Results

The main results of our analysis are shown in Table 2.[12] Column 1 of Table 2 shows the results for the least squares estimation of the linear specification in Equation (3). We find a destabilizing effect of $mktilliq$ on $fundilliq$, suggesting that financiers charge higher rates when the liquidity of the stock that serves as collateral on the loans deteriorates.

[12] The (first-stage) instrument regressions are displayed in Table A.5. The F-tests for all these first-stage regressions indicate the instruments are relevant at the 99% confidence level.

In column 2, we re-estimate the same linear model by instrumental variables and obtain qualitatively equivalent results.

Column 3 of Table 2 shows the results for OLS estimation of the two-regime model in Equation (4). The estimates suggest a transition from stable to stressed markets when the TED spread exceeds 43 basis points. In the lower TED spread regime, market liquidity has no effect on funding liquidity, while in the higher TED spread regime, market liquidity has a destabilizing effect on funding liquidity. The asymptotic t-test rejects the null hypothesis that $\beta_1 + \beta_6$ is zero at a 99% confidence interval. But, in spite of the statistical significance, the destabilizing effect $\hat{\beta}_1 + \hat{\beta}_6 = 0.396$ is relatively small compared to the effect we obtain using the estimates that are corrected for the endogeneity of both market illiquidity, volatility and TED spread. These results are presented in Column 4.

Using the recommended instrumental variable estimation of the two-regime model, we estimate the value of the regime threshold κ to be a TED spread of 48 basis points. The 95% confidence interval is [0.438; 0.487]. For all coefficients, the instrumental variable estimation procedure seems to inflate standard errors and, hence, induces a lower power to detect significant impacts. Regarding the control variables, we find that, except for the stress dummy variable, only the linear volatility variable is significant at the 90% confidence level and has the expected positive sign. The coefficients on the squared volatility and the stress volatility variables are economically speaking large but small compared to their standard errors. Regarding our first hypothesis, we thus find only limited statistical evidence of the effect of volatility on funding liquidity. We further find no effect of the TED spread variable (beyond its important role as a state variable). As could be expected from the summary statistics in Table 1, the coefficient of the stress dummy variable is significantly positive, indicating a strong increase in funding illiquidity when the TED spread exceeds 48 basis points.

Table 2: Fitted Models of Funding Illiquidity, July 2006–May 2011.

Key: Both linear and two-regime models were estimated using OLS and 2SLS IV for data generated by shifts in the shorting demand curve. 95% confidence intervals are shown since they are asymmetric for the two-regime models (due to Bonferroni corrections). Variables significant at a 95% level are bolded; variables significant at a 90% level are italicized. The bottom panel reports the parameter combinations estimating the total effect in the stressed market regime, together with their asymptotic standard errors.

	Linear Model		**Two-Regime Model**	
Independent Variables	**OLS**	**IV**	**OLS**	**IV**
(*intercept*)	**4.732**	**8.399**	**2.594**	-26.327
	(0.516)	(2.746)	(0.665)	(18.332)
			[1.239 ; 4.054]	[-90.913 ; 25.638]
$mktilliq_t$	**0.323**	**0.790**	0.014	*-3.612*
	(0.0645)	(0.348)	(0.082)	(2.283)
			[-0.152 ; 0.202]	[-11.690 ; 2.788]
vol_t	**6.263**	**4.953**	**5.192**	*13.093*
	(0.655)	(1.290)	(0.652)	(7.240)
			[3.782 ; 6.776]	[-4.809 ; 33.909]
$volsq_t$	**-4.550**	**-3.627**	**-8.303**	-6.818
	(0.894)	(1.206)	(0.924)	(6.712)
			[-10.458 ; -6.150]	[-26.888 ; 16.820]
ted_t	0.012	-0.174	**0.717**	3.965
	(0.042)	(0.134)	(0.292)	(1.962)
			[0.117 ; 1.468]	[-4.100 ; 12.460]
$stress_t$			**2.466**	*40.553*
			(0.977)	(13.222)
			[0.002 ; 4.535]	[-14.790 ; 144.736]
$stressmktilliq_t$			**0.382**	*5.210*
			(0.124)	(1.685)
			[0.064 ; 0.642]	[-1.881 ; 18.471]
$stressvol_t$			**4.824**	-6.267
			(0.649)	(4.853)
			[3.256 ; 6.206]	[-39.343 ; 13.580]
$stressted_t$			**-1.055**	-4.599
			(0.296)	(1.617)
			[-1.792 ; -0.449]	[-14.292 ; 3.289]
Threshold κ			**0.429**	**0.479**
			[0.417 ; 0.443]	[0.438 ; 0.487]
Stressed regime coefficients				
$mktilliq_t + stressmktilliq_t$			**0.396**	1.598
			(0.094)	(2.435)
$vol_t + stressvol_t$			**10.016**	6.826
			(0.7569)	(9.613)
$ted_t + stressted_t$			**-0.338**	-0.633
			(0.050)	(0.579)

Regarding our variable of interest, we find that the effect of $mktilliq$ on $fundilliq$ for low TED spreads is -3.612. This implies that, under stable market conditions (TED spread < 0.48), a 1% increase in bid-ask spreads causes a 3.6% decrease in the value-weighted average stock loan fee. Under the one-sided alternative, we can conclude with a 90% confidence, that financiers act in a stabilizing manner when credit risk is low. Under stressed market conditions (TED spread > 0.48), however, the effect of market illiquidity on funding illiquidity is 1.598; *i.e.* financiers typically charge 1.6% higher rates in response to a 1% increase in bid-ask spreads. This is an economically important result, considering the average absolute change in market illiquidity between July 2006 and May 2011 is 19.36%. An average-sized increase in market illiquidity implies a $1.6 \times 19.36\% = 30.98\%$ increase in funding illiquidity. Because of the large standard errors associated with this estimate, $\hat{\beta}_1 + \hat{\beta}_6$ (the estimated effect in the stressed regime) is statistically insignificant at the 90% confidence level. However, since $\hat{\beta}_6$ is statistically significant at the 90% confidence level, we find that the effect is less stabilizing in the stressed regime (high TED spreads) than in the stable regime (low TED spreads).

4.3 Synthesis

The conclusions drawn from the point estimates in Table 2 for the models in Equations (4)–(6) are remarkable: they translate market-watchers' beliefs of a TED spread-based transition from a stable to a stressed market, to Brunnermeier and Pedersen's notion of a risk-averse financier deciding between charging *stabilizing* or *destabilizing* rates on equity collateralized funding. The two-regime model provides evidence in favor of our first hypothesis that financiers set the loan rate on a collateralized loan given expectations for the value-evolution of equity collateral and that these expectations are influenced by market liquidity and market volatility. The TED spread impacts the funding rates significantly as a state variable separating a normal and stressed market regime under which funding liquidity has different dynamics. When TED spread values are lower than 48 basis points, market participants are soothed: they believe that a decrease in market liquidity is only temporary, and hence they do not change the risk-factor of equity collateral for broker loans. In this situation *stabilizing* rates are chosen. In contrast, TED spread values higher than 48 basis points signal a stressed market situation to market participants; this leads them to act in a less stabilizing manner. According to the point estimates, financiers would even increase the premium they charge to brokers on stock collateral loans in response to a deterioration in market liquidity when TED spreads values are above 48 basis points. This course of action fits the description of *destabilizing* rates and provides evidence consistent with the existence of self-feeding liquidity spirals that can result in a system-wide liquidity dry-up. Our finding of TED-spread based transition from a stable to a destabilising liquidity regime therefore has diagnostic value to policy-makers, aiming at steering the financial system away from systemically risky states.

Jointly, these observations highlight what we believe are the two key contributions of this paper. First, we propose a novel two-regime specification to analyze the effects of asset market liquidity on funding liquidity across different levels of credit risk in the economy. This handles the endogeneity issues which have affected previous analyses. Second, we estimate this two-regime specification with the techniques of Hansen (2000) and Caner and Hansen (2004). This enables us to infer the threshold between stable and unstable markets while still accounting for the bidirectional relationship between funding liquidity, market liquidity, and asset volatility.

5 Allowing for Autoregressive Effects

In the preceding analyses, we have highlighted the dual importance of allowing for a threshold effect and controlling for endogeneity, in quantifying the effect of market illiquidity on funding illiquidity. In this section, we investigate whether our results are robust to adding autoregressive effects to the model. Formally, we re-estimate Equation (4) by 2SLS, controlling for 1-day lagged values of funding illiquidity, both below and above the critical TED-spread threshold κ. The results are presented in Column 4 of Table 3. Columns 1-3 of Table 3 present the results of the simpler estimation strategies, exactly as in the main analysis presented in Table 2.

Column 1 of Table 3 shows the results for the OLS estimation of the single-regime model. As in prior results, we find a destabilizing effect of market liquidity on funding liquidity: when market illiquidity increases, funding illiquidity increases. However, this model does not account for endogeneity nor for two regimes.

Column 2 of Table 3 shows the results for the instrumental variable estimation of the linear model. As in prior results, we note that the coefficient for market illiquidity is negative — suggesting shocks to the illiquidity of equities get absorbed through the financing channel. The autoregressive coefficient is estimated as 1.002, indicating a possible unit root. This may be another indication of model misspecification, *i.e.* the lack of a second regime.

Column 3 of Table 3 shows the results for the OLS estimation of the two-regime model. While this model does not fully account for endogeneity, the $lagfundilliq$ variable might correct for some of the endogeneity issues. However, in this model the effect of market liquidity on funding liquidity is statistically insignificant (with a destabilizing sign) in both regimes. Despite that insignificance, the net effect in a stressed market is significant at a

Table 3: Fitted Models of Funding Illiquidity with Lagged Funding Illiquidity, July 2006–May 2011.

Key: Both linear and two-regime models were estimated using OLS and 2SLS IV for data generated by shifts in the shorting demand curve. 95% confidence intervals are shown since they are asymmetric for the two-regime model (due to Bonferroni corrections). Variables significant at a 95% level are bolded; variables significant at a 90% level are italicized.

	Linear Model		Two-Regime Model	
Independent Variables	**OLS**	**IV**	**OLS**	**IV**
(*intercept*)	**1.953**	*-0.111*	*1.574*	-19.440
	(0.193)	(0.061)	(0.581)	(14.204)
			[-0.24 ; 3.39]	[-58.5 ; 41.0]
$mktilliq_t$	**0.129**	*-0.014*	0.024	-2.573
	(0.003)	(0.008)	(0.070)	(1.747)
			[-0.24 ; 0.20]	[-7.44 ; 4.71]
$fundilliq_{t-1}$	**0.574**	**1.002**	**0.449**	**0.528**
	(0.001)	(0.001)	(0.037)	0.071
			[0.13 ; 0.54]	[-0.15 ; 0.75]
vol_t	**2.665**	0.021	2.585	*8.887*
	(0.313)	(0.026)	(0.574)	(5.221)
			[-1.10 ; 4.54]	[-13.4 ; 24.4]
$volsq_t$	**-1.918**	-0.009	**-3.893**	-4.804
	(0.539)	(0.025)	(0.858)	(3.721)
			[-5.76 ; -0.37]	[-18.4 ; 13.4]
ted_t	**0.010**	*0.005*	0.382	*2.669*
	(0.001)	(0.003)	(0.239)	(1.532)
			[-0.51 ; 4.79]	[-5.42 ; 6.46]
stressintercept			0.312	**20.706**
			(0.879)	(8.448)
			[-1.61 ; 3.42]	[-10.7 ; 56.1]
$stressmktilliq_t$			0.107	**2.631**
			(0.108)	(1.086)
			[-0.12 ; 0.54]	[-1.53 ; 7.85]
$stressfundilliq_{t-1}$			*0.107*	0.010
			(0.051)	(0.074)
			[-0.02 ; 0.50]	[-0.16 ; 0.86]
$stressvol_t$			2.109	3.169
			(0.600)	(2.554)
			[-2.08 ; 4.00]	[-18.2 ; 10.6]
$stressted_t$			*-0.523*	**-2.809**
			(0.243)	(1.171)
			[-4.84 ; 0.39]	[-5.41 ; 3.64]
Threshold κ			**0.439**	**0.478**
			[0.214 ; 0.471]	[0.460 ; 0.486]
Stressed regime coefficients				
$mktilliq_t + stressmktilliq_t$			*0.131*	0.058
			(0.083)	(1.920)
$vol_t + stressvol_t$			**4.694**	5.718
			(0.752)	(5.793)
$ted_t + stressted_t$			**-0.141**	-0.140
			(0.045)	(0.478)

90% level. In line with this, the threshold estimate is also significant (at a 95% level) and suggests a transition in model behavior at a TED spread of 44 bp.

Column 4 of Table 3 shows the IV estimation for the two-regime model. This model corrects for endogeneity and accounts for two regimes; however, segmenting the data reduces the power of some coefficient inferences and instrumental variable regression reduces that power further. Nonetheless, the market illiquidity coefficients have the expected signs: negative for periods of market tranquility (ted <48 bp); positive for periods of market stress (ted >48 bp). Unlike in the improperly-specified models, the effect of market illiquidity is destabilizing in times of stress. Furthermore, we note that the lagged funding illiquidity variable $lagfundilliq$ is not significant which is a strong indicator that the first-stage regressions adequately address the endogeneity of market and funding liquidity.

The effect of $mktilliq$ on $fundilliq$ for low TED spreads is -2.573 which implies that under stable market conditions (TED spread < 0.48), a 1% increase in bid-ask spreads causes a 2.6% decrease in the value-weighted average stock loan fee. However, we cannot conclude with typical levels of statistical significance that financiers act in a stabilizing manner when credit risk is low.

The results in Column 4 of 3 do give us stronger support for the hypothesis of the existence of a destabilizing equilibrium than those in Table 2. Without controlling for autoregressive effects, the $stressmktilliq$ coefficient was insignificant and marginally significant whereas in this model it is significant at a 95% level. Under this specification, when economy-wide credit risk is high, the differential effect of market illiquidity on funding illiquidity is 2.631; *i.e.* financiers typically charge 2.6% higher rates in response to a 1% increase in bid-ask spreads versus in a stable market regime. This is an economically significant result in addition to being statistically significant at the 95% level.

6 Conclusion

This study investigates the determinants of funding liquidity, broadly defined as financiers' willingness to provide loans against equity collateral. This willingness should naturally depend on the quality of the assets that serve as collateral: in particular, on their liquidity and volatility. We empirically test for the validity of this economic intuition on a 5-year sample period from 2006 to 2011 using a proxy for equity-collateralized funding liquidity. We find that a deterioration of S&P 500 stock market liquidity causes (equity-collateralized) funding liquidity to increase when market-wide credit conditions are favorable, and otherwise does not affect or even reduces funding liquidity. This finding holds after controlling for endogenous stock volatility and accounting for the endogeneity of market liquidity.

Recent theoretical models such as Gromb and Vayanos (2002, 2010) and Brunnermeier and Pedersen (2009) strongly emphasize the endogeneity of market liquidity and volatility on the one hand, and funding liquidity on the other hand. Despite that strong emphasis, this paper is the first empirical investigation of funding liquidity that explicitly accounts for this endogeneity.

We further argue that a standard linear model, even when estimated by instrumental variables, is insufficient to model the relationship between market liquidity and funding liquidity. Scatterplots of funding liquidity versus market liquidity easily reveal the presence of two distinct regimes, differentiable on the basis of a TED spread threshold. We believe this observation is consistent with Brunnermeier and Pedersen's (2009) proposition that a stabilizing relation between funding illiquidity and market illiquidity should (only) be present when there is no contemporaneous flight to quality. Thus, we propose a two-regime specification that distinguishes between stable and stressed market regimes on the basis of the TED spread. This specification for funding illiquidity, properly estimating both regimes and the threshold by the method of Caner and Hansen (2004) and using instrumental variables to address the endogeneity of market liquidity and volatility, provides us with robust inference about two regimes.

We find that the dynamic model linking market liquidity to funding liquidity changes when the TED spread surpasses a 48 bp threshold, whereby the impact of market liquidity on funding liquidity becomes significantly less stabilizing than in the regime with TED spreads below 48 bp. In ongoing work, we exploit the setting developed in this paper to analyze the effects of central-bank funding rates on liquidity regimes. In spite of data challenges, preliminary results suggest a similar transition from a stabilizing to destabilizing liquidity regime for values of the TED-spread exceeding a critical threshold of around 50 bp. Whether our findings call for further active policy maker intervention in the secondary funding market is a question we leave for future research. However, we conclude from our analysis that the TED spread should be considered an informative market barometer for liquidity regimes in equity markets.

A Appendix

Table A.1: Lending Activity Sample Summary Statistics

Key: This table reports lending summary statistics for the 'Total Balance Quantities' (TBQ), the 'Volume Weighted Average Fees' (VWAF) and the 'Number of Transactions per Day' (Trades) for an individual stock on loan in Data Explorers' dataset. These are the variables that are used to construct the funding illiquidity measure in Equation (2). The statistics are presented for the entire sample and per S&P 500 market capitalization quintile for the full sample period July 2006–May 2011. S&P 500 quintile allocation is evaluated on a monthly basis. The minimum and maximum market capitalization ranges overlap because these monthly-determined boundaries vary across time.

	Summary Statistics				
	Mean	**Std. Dev.**	**Min.**	**Median**	**Max.**
Full Sample ($N = 603,552$)					
market capitalization (billion \$)	20.90	30.66	0.04	9.88	561.2
total balance quantity (million shares)	13.50	26.90	0.00	6.46	604.00
volume weighted average fee (bp pa)	26.61	200.87	0	9.65	12,447.38
number of transactions per day	3.63	32.22	1	15	1061
Q1 ($N = 20,859$)					
market capitalization (billion \$)	2.19	0.92	0.04	2.30	3.82
total balance quantity (million shares)	1.29	1.59	0.01	7.56	198.00
volume weighted average fee (bp pa)	75.60	397.39	0	14.51	12,447.38
number of transactions per day	34.79	54.11	1	18	633
Q2 ($N = 121,146$)					
market capitalization (billion \$)	3.77	1.35	0.58	3.81	7.17
total balance quantity (million shares)	12.00	17.72	0.00	6.05	305.00
volume weighted average fee (bp pa)	36.05	290.88	0	10.13	10,018.51
number of transactions per day	26.09	37.59	1	16	884
Q3 ($N = 148,502$)					
market capitalization (million \$)	7.24	1.98	2.50	7.15	12.90
total balance quantity (million shares)	12.02	23.90	0.00	5.85	44.30
volume weighted average fee (bp pa)	28.62	203.36	0	9.85	8,527.10
number of transactions per day	25.17	31.39	1	16	1061
Q4 ($N = 163,425$)					
market capitalization(billion \$)	13.90	3.99	4.51	13.62	25.90
total balance quantity(million shares)	13.30	33.20	0.01	6.11	604.00
volume weighted average fee (bp pa)	22.47	153.90	0	9.32	8,802.51
number of transactions per day	22.35	30.18	1	14	802
Q5 ($N = 149,890$)					
market capitalization(billion \$)	58.51	58.70	11.72	36.33	561.2
total balance quantity(million shares)	16.60	29.00	0.04	7.91	43.50
volume weighted average fee (bp pa)	14.76	71.02	0	8.47	9,079.48
number of transactions per day	19.96	25.02	1	14	986

Table A.2: Supply and Demand Shifts: Summary Statistics

Key: This table reports summary statistics for shifts in shorting supply and demand per S&P 500 market capitalization quintile. S&P 500 quintile allocation is evaluated on a monthly basis. Statistics are reported for the full sample period and per year. Shifts are constructed by checking each day if there was a shift in shorting supply or demand compared to the previous day (based on changes in loan fees and changes in the total balance quantities) for each individual stock. We place stocks into shift categories: demand out (DOUT), supply out (SOUT), demand in (DIN), and supply in (SIN). The data on stock lending is from Data Explorers for July 2006–May 2011.

		Summary Statistics				
Time	**Quintile**	**DOUT**	**SOUT**	**DIN**	**SIN**	**Total**
Jul 2006–May 2011	$Q1$	3,961	3,842	8,838	3,948	20,589
	$Q2$	22,261	22,579	52,880	23,426	121,146
	$Q3$	26,656	27,410	65,506	28,930	148,502
	$Q4$	28,462	29,430	74,050	31,483	163,425
	$Q5$	25,281	25,848	70,900	27,861	149,890
Jul 2006–Dec 2006	$Q1$	917	845	2,141	988	4,981
	$Q2$	1,935	1,911	4,579	2,200	10,625
	$Q3$	2,329	1,153	5,540	2,665	12,787
	$Q4$	2,491	2,501	6,128	2,829	13,949
	$Q5$	2,332	2,495	5,886	2,757	13,470
2007	$Q1$	1,555	1,549	3,447	1,555	8,106
	$Q2$	4,372	4,248	9,429	4,342	22,391
	$Q3$	4,897	4,830	11,215	5,224	26,166
	$Q4$	5,416	5,409	12,765	5,830	29,420
	$Q5$	5,029	5,103	12,266	5,328	27,726
2008	$Q1$	1,085	1,080	2,388	1,024	5,577
	$Q2$	4,127	4,089	9,893	4,130	22,239
	$Q3$	4,242	4,262	10,645	4,288	23,437
	$Q4$	4,621	4,786	12,714	4,891	27,012
	$Q5$	3,925	3,978	11,996	4,230	24,129
2009	$Q1$	274	285	614	261	1,434
	$Q2$	3,394	3,650	9,268	3,822	20,134
	$Q3$	3,889	4,167	11,083	4,442	23,581
	$Q4$	4,116	4,392	12,914	4,679	26,101
	$Q5$	3,284	3,374	11,716	3,694	22,068
2010	$Q1$	114	68	215	102	499
	$Q2$	4,067	4,194	9,477	4,396	22,134
	$Q3$	5,052	5,156	11,616	5,393	27,127
	$Q4$	5,439	5,524	12,897	6,019	29,879
	$Q5$	5,155	4,124	12,896	5,758	28,934
2011	$Q1$	16	15	33	18	82
	$Q2$	3,576	3,650	8,446	3,762	19,434
	$Q3$	5,011	5,299	12,289	5,472	28,071
	$Q4$	5,066	5,405	13,369	5,768	29,608
	$Q5$	4,400	4,554	12,937	4,809	26,700

Table A.3: Shorting Demand Curve, Outward Shifts: Summary Statistics.

Key: This table reports summary statistics for outward shifts of the shorting demand curve (DOUT) for the entire sample and per S&P 500 market capitalization quintiles. S&P 500 quintile allocation is evaluated on a monthly basis. Shifts are constructed by checking each day if there was an outward shift in shorting demand compared to the previous day for each individual stock; this is identified through observing simultaneous increases in loan fees and total balance quantities. We report the average increase in the volume weighted average fee in absolute and relative terms and the average increase in total balance quantities in absolute and relative terms. We also report the average number of stocks subject to an outward shift of the shorting demand curve per day, the average number of transactions for such a stock, and the average total number of transactions per day for all stocks undergoing outward shifts of the shorting demand curve. The data on stock lending is from Data Explorers for July 2006–May 2011.

		Summary Statistics				
Subset	**Statistic**	**Mean**	**Std. Dev.**	**Min.**	**Median**	**Max.**
Full Sample	*dvwaf (bp pa)*	16.62	57.16	1.142	8.68	1,830.30
	dvwaf (%)	3.65	9.33	0.03	1.49	153.15
	dtbq (million shares)	0.66	0.39	0.00	0.58	6.75
	dtbq (%)	0.09	0.07	0.00	0.08	1.51
	# stocks	91.05	34.29	1	94	271
	# transactions/stock	28.26	11.40	1	27.10	101
	total # transactions	2,583.079	1,478.24	1	2,360	10,230
Quintile 1	*dvwaf (bp pa)*	57.49	370.88	0.01	10.43	7,218.86
	dvwaf (%)	2.44	14.08	0.00	0.55	272.54
	dtbq (million shares)	0.51	0.71	0.00	0.32	8.82
	dtbq (%)	0.06	0.06	0.00	0.04	0.50
	# stocks	5.34	4.24	1	4	24
	# transactions/stock	38.89	28.05	1	32.21	207.25
	total # transactions	218.02	275.24	1	122.50	1,867
Quintile 2	*dvwaf (bp pa)*	17.34	38.56	0.91	6.50	603.91
	dvwaf (%)	3.05	17.90	0.09	0.72	426.69
	dtbq (million shares)	0.50	0.30	0.00	0.392	4.42
	dtbq (%)	0.08	0.13	0.00	0.06	3.92
	# stocks	19.49	7.28	1	19	51
	# transactions/stock	30.40	14.19	1	28.33	112.72
	total # transactions	597.47	380.22	1	526	3,426
Quintile 3	*dvwaf (bp pa)*	13.44	32.63	0.01	5.51	672.11
	dvwaf (%)	2.97	16.53	0.00	0.82	420.66
	dtbq (million shares)	0.48	0.32	0.00	0.41	3.81
	dtbq (%)	0.01	0.21	0.00	0.06	6.87
	# stocks	23.28	8.43	1	23	55
	# transactions/stock	30.31	13.11	1	28.33	88.85
	total # transactions	698.16	393.05	1	645	3,218
Quintile 4	*dvwaf (bp pa)*	12.14	24.74	0.42	5.07	499.60
	dvwaf (%)	3.45	10.15	0.03	1.11	135.13
	dtbq (million shares)	0.60	0.49	0.02	0.50	8.99
	dtbq (%)	0.09	0.08	0.00	0.08	1.39
	# stocks	24.86	9.27	1	25	71
	# transactions/stock	26.79	11.80	1	24.76	102.30
	total # transactions	667.81	390.79	1	596	3,038
Quintile 5	*dvwaf (bp pa)*	12.04	16.38	0.06	5.02	180.85
	dvwaf (%)	4.82	16.38	0.02	1.80	297.58
	dtbq (million shares)	1.10	0.87	0.00	0.89	10.50
	dtbq (%)	0.11	0.07	0.00	0.10	0.93
	# stocks	21.93	9.84	1	22	81
	# transactions/stock	24.32	11.13	1	22.74	140
	total # transactions	534.84	322.73	1	489	2,228

Table A.4: Shorting Demand Curve, Inward Shifts: Summary Statistics.

Key: This table reports summary statistics for inward shifts of the shorting demand curve (DIN) for the entire sample and per S&P 500 market capitalization quintiles. S&P 500 quintile allocation is evaluated on a monthly basis. Shifts are constructed by checking each day if there was an inward shift in shorting demand compared to the previous day for each individual stock; this is identified through observing simultaneous decreases in loan fees and total balance quantities. We report the average decrease in the volume weighted average fee in absolute and relative terms and the average increase in total balance quantities in absolute and relative terms. We also report the average number of stocks that are subject to an inward shift of the shorting demand curve per day, the average number of transactions for such a stock, and the average total number of transactions per day for all stocks undergoing inward shifts of the shorting demand curve. The data on stock lending is from Data Explorers for July 2006–May 2011.

		Summary Statistics				
Subset	**Statistic**	**Mean**	**Std. Dev.**	**Min.**	**Median**	**Max.**
Full Sample	*dvwaf (bp pa)*	-14.57	21.45	-208.15	-7.60	-0.36
	dvwaf (%)	-0.34	0.10	-0.87	-0.32	-0.02
	dtbq (million shares)	-0.66	0.52	-11.60	-0.55	0.00
	dtbq (%)	-0.06	0.02	-0.29	-0.06	0.00
	# stocks	183.77	126.50	1	130	482
	# transactions/stock	20.62	9.05	1	19.16	63.85
	total # transactions	4,062.78	3,810.22	1	2,627	24,658
Quintile 1	*dvwaf (bp pa)*	-40.20	222.43	-5,594.89	-10.41	-0.02
	dvwaf (%)	-0.31	0.18	-1	-0.28	-0.00
	dtbq (million shares)	-0.51	0.80	-13.40	-0.32	-0.00
	dtbq (%)	-0.05	0.04	-0.36	-0.04	-0.00
	# stocks	8.71	9.84	1	6	49
	# transactions/stock	31.37	23.75	1	26.90	221
	total # transactions	289.78	441.98	1	131	3,288
Quintile 2	*dvwaf (bp pa)*	-17.16	41.82	-750.19	-6.03	-0.86
	dvwaf (%)	-0.0	0.11	-0.88	-0.27	-0.04
	dtbq (million shares)	-0.42	0.29	-3.14	-0.35	-0.00
	dtbq (%)	-0.05	0.02	-0.26	-0.05	-0.00
	# stocks	36.02	26.15	1	25	97
	# transactions/stock	23.11	12.76	1	21.09	174.22
	total # transactions	893.75	911.90	1	541	5,670
Quintile 3	*dvwaf (bp pa)*	-13.22	28.89	-595.75	-5.75	-0.24
	dvwaf (%)	-0.31	0.11	-0.97	-0.29	-0.02
	dtbq (million shares)	-0.46	0.34	-7.06	-0.38	0.00
	dtbq (%)	-0.06	0.02	-0.21	-0.05	0.00
	# stocks	44.56	31.71	1	31	121
	# transactions/stock	22.56	10.78	1	20.78	80.85
	total # transactions	1,058.78	1,005.09	1	673.5	6,886
Quintile 4	*dvwaf (bp pa)*	-12.53	28.45	-458.80	-5.13	-0.60
	dvwaf (%)	-0.34	0.11	-0.89	-0.32	-0.10
	dtbq (million shares)	-0.59	0.59	-15.90	-0.48	0.00
	dtbq (%)	-0.07	0.03	-0.39	-0.06	0.00
	# stocks	50.41	34.29	1	37	128
	# transactions/stock	19.81	9.21	1	18.07	68.25
	total # transactions	1,061.88	982.20	1	677	6,689
Quintile 5	*dvwaf (bp pa)*	-11.30	22.27	-478.49	-4.96	-0.36
	dvwaf (%)	-0.41	0.13	-1	-0.39	-0.02
	dtbq (million shares)	-1.13	1.08	-15.40	-0.85	0.00
	dtbq (%)	-0.08	0.03	-0.29	-0.07	0.00
	# stocks	47.94	31.12	1	36	121
	# transactions/stock	17.17	7.04	1	16.39	50.67
	total # transactions	875.27	759.53	1	614	5,137

Table A.5: Fitted First-Stage Instrumental Variable Regressions, July 2006–May 2011.

Key: Results in Panel A are for the linear model, while results in Panel B are for the two-regime model with a TED spread threshold ($\kappa \approx 48$ bp) reported in Table 2. Variables significant at a 95% level are bolded. For all first stage regressions, the F-test indicates relevance of the instrumental variables at the 99% confidence interval.

	Panel A			
Dep. Variable:	$mktilliq_t$	vol_t	$volsq_t$	ted_t
(intercept)	**-8.38**	0.00	-0.01	-0.03
	(0.10)	(0.01)	(0.01)	(0.02)
$durtrend_t$	**587.88**	-11.08	0.87	29.34
	(104.79)	(7.75)	(7.28)	(26.49)
$aaaliq_t$	-0.11	**-0.04**	**-0.03**	**0.57**
	(0.11)	(0.01)	(0.01)	(0.03)
vol_{t-1}	**4.76**	**1.02**	**0.09**	0.18
	(0.40)	(0.03)	(0.03)	(0.10)
$volsq_{t-1}$	**-3.73**	**-0.09**	**0.82**	**-0.25**
	(0.49)	(0.04)	(0.03)	(0.12)
ted_{t-1}	**0.33**	**0.00**	**0.00**	**0.99**
	(0.02)	(0.00)	(0.00)	(0.00)
Adjusted R^2	**0.64**	**0.96**	**0.94**	**0.99**
F-statistic	**408.64**	**5794.31**	**3330.55**	**17985.73**

	Panel B						
Dep. Variable:	$mktilliq_t$	vol_t	$volsq_t$	ted_t	$stressmktilliq_t$	$stressvol_t$	$stressted_t$
(*intercept*)	**-8.03**	0.01	-0.01	-0.01	0.12	-0.00	0.03
	(0.11)	(0.01)	(0.01)	(0.03)	(0.07)	(0.01)	(0.03)
(*stressintercept*)	**0.12**	-0.01	**-0.01**	**0.00**	**-7.38**	**0.08**	**0.24**
	(0.06)	(0.00)	(0.00)	(0.01)	(0.04)	(0.00)	(0.02)
$durtrend_t$	64.27	-17.04	3.54	-1.92	**-546.25**	**-69.01**	**-243.71**
	(134.95)	(10.14)	(9.52)	(34.75)	(88.78)	(11.29)	(38.73)
$aaaliq_t$	-0.10	**-0.04**	**-0.03**	**0.57**	0.03	**-0.03**	**0.59**
	(0.10)	(0.01)	(0.01)	(0.03)	(0.07)	(0.01)	(0.03)
vol_{t-1}	**3.35**	**1.00**	**0.09**	0.09	-0.03	-0.04	**-0.33**
	(0.45)	(0.03)	(0.03)	(0.12)	(0.29)	(0.04)	(0.13)
$volsq_{t-1}$	**-3.08**	**-0.13**	**0.77**	-0.23	**-0.92**	**0.19**	**0.75**
	(0.54)	(0.04)	(0.04)	(0.14)	(0.35)	(0.04)	(0.15)
ted_{t-1}	**0.69**	0.01	0.01	**1.01**	**0.57**	**0.11**	**0.36**
	(0.12)	(0.01)	(0.01)	(0.03)	(0.08)	(0.01)	(0.04)
$stressvol_{t-1}$	**0.87**	**0.05**	0.04	0.07	**2.23**	**0.80**	**-0.42**
	(0.25)	(0.02)	(0.02)	(0.06)	(0.16)	(0.02)	(0.07)
$stressted_{t-1}$	**-0.45**	-0.01	0.00	**-0.33**	**-0.11**	-0.02	**0.62**
	(0.13)	(0.01)	(0.01)	(0.08)	(0.01)	(0.03)	(0.04)
Adjusted R^2	**0.66**	**0.96**	**0.94**	**0.99**	**0.99**	**0.98**	**0.99**
F-statistic	**164.74**	**3758.05**	**2157.82**	**6596.42**	**331.67**	**2525.90**	**5140.07**

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