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Understand funding liquidity and market liquidity in a regime-switching model

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Abstract
We investigate the time-varying relationship of funding liquidity (FL) and market liquidity (ML) in a Markov regime-switching model. By using a comprehensive U.S. TRACE dataset, we provide strong evidence that FL and corporate bond ML are interlinked, and their impact on each other is highly regime-dependent. We find that FL and ML exhibit a large-and-positive mutual impact when money market is tight and equity market is volatile. But in normal regimes, FL is found to have a negative impact on ML with a much smaller magnitude than those in stressed regimes. Furthermore, FL is more stable than ML with less regime changes. Our article offers insight on the important mechanism by which central banks can improve ML through the funding market.

KEYWORDS
funding liquidity, market liquidity, Markov regime-switching model

JEL CLASSIFICATION
C1; E5; G1

1 | INTRODUCTION

Financial time series occasionally display dramatic breaks in their behaviour, due to, for example, financial crises. Therefore, the idea of the financial market finding itself in different states at different times becomes appealing. Focusing on the recent academic and policy interests, our study elaborates the time-varying relationship of funding liquidity and market liquidity across stressed and normal regimes in the U.S. corporate bond market, where the switch between the two regimes is governed by the outcome of a Markov process. Our finding therefore builds a channel that central banks can use to improve market liquidity through funding markets.

It is common that firms finance their securities trading through borrowing on either an unsecured or a secured basis. The ease with which they can obtain funding affects their willingness and ability to provide market liquidity (i.e., the ease with which securities are traded). In recent decades, several financial crises have been triggered by liquidity shocks. For example, the 2008 financial crisis illustrates that a sharp de-leveraging of dealers' repo books coincided with an increase in Treasury bonds' bid-ask spreads (see Dudley, 2016). The Russian default and the LTCM collapse in 1998 is another example of fragility of liquidity where a relatively small liquidity shock had an unexpectedly large impact.

The co-movement of market liquidity (ML) and funding liquidity (FL) has received growing attention of market participants, central bankers and academics in recent years (see, e.g., Brunnermeier & Pedersen, 2009; Dudley, 2016). One of the main reasons is the desire to learn lessons from the financial crises of the recent decades, including the crises following the collapse of LTCM in 1998 and Lehman Brothers in 2008. It is observed that sudden drying-up of funding liquidity, triggered by demise of several major financial institutions' ability to finance their long-dated illiquid assets, led to much reduced overall market liquidity and a high degree of systemic stress.

A second reason is that central banks, acting as the lender-of-last-resort, desire to gain a better understanding of the dynamics of both funding liquidity and market liquidity, and a better awareness of how central banks can provide a funding liquidity 'backstop' in order to improve market liquidity when markets are experiencing negative shocks. Finally, with the expectation of the end of a near zero-interest-rate monetary policy in the United States and other advanced economies, rising interest rates will generate selling pressure and cause bond prices to fall. In this case, maintaining a liquid market is pivotal to financial market stability.

In this study, we take a different step to investigate the relationship of funding liquidity and market liquidity. We use a Markov regime-switching model in the analysis. In this model, the interaction of funding liquidity and market liquidity is assumed to follow a non-linear stationary process. By Markov properties, the current value of the variable depends only on its immediate past value. This means that a structure in the series may prevail for a random period of time, before being replaced by another structure when a switching takes place. In this way, the Markov regime-switching model is able to capture the more complex dynamic patterns (Hamilton, 1989, 2005), for example, the *time-varying* relationship of funding liquidity and market liquidity. Moreover, we focus our study in the U.S. corporate bond market because it is the largest corporate bond market in the world[1] and the availability of the associated Trade Reporting and Compliance Engine (TRACE) transaction-level data. The TRACE data is the most comprehensive and unique data source for an OTC corporate bond market. Our sample covers all U.S. corporate bond transactions in the secondary market in the period of 2004–2013, hence it allows for a more accurate calculation of liquidity measures (Dick-Nielsen, Feldhütter, & Lando, 2012).

Measuring liquidity is well-known to be a challenge in literature, as liquidity consists of a few dimensions including the breadth and depth of markets, transaction cost, transaction speed and resiliency (price impact). If the market is perfectly liquid, a trader can easily trade his desired quantity, immediately, without moving the market price. But if liquidity is less than perfect, the trader must sacrifice one or more of these dimensions (see Moulton, 2005). To tackle this issue, we follow Dick-Nielsen et al. (2012) to construct a first principle component market liquidity measure that combines the dimensions of price impact and transaction costs. The first principal component funding liquidity measure is calculated in a similar manner based on the TED spread and Libor-OIS spread.

We proceed in three steps. First, we construct a composite market liquidity measure for U.S. corporate bonds by using the first principal component of two market liquidity measures—the Amihud (2002) price-impact measure and the Roll (1984) measure of effective bid-ask spreads. Each of the two measures is first calculated using the TRACE transaction-level data on individual bonds, and then aggregated across all individual bonds. The composite funding liquidity measure for the U.S. funding market is constructed in the similar manner based on the first principal component of two funding liquidity measures—Libor-OIS spread and TED spread. Second, by controlling the aggregate bond market credit-rating change,[2] we investigate the drivers of the correlation between funding liquidity and market liquidity among the main macroeconomic variables, and use the significant driving factor in the Markov regime-switching model to predict and define regimes. Finally, we specify a Markov regime-switching model to investigate the time-varying relationship between funding liquidity and market liquidity, where the two regimes are determined/characterized by the bond market volatility (i.e., TYVIX)[3] and money market liquidity (i.e., funding liquidity).

Our results show that funding liquidity and market liquidity have a large-and-positive mutual effect when money market is tight and bond market volatility is high, but this mutual effect is much smaller or insignificant in normal regimes. Specifically, the impact of FL on ML in stressed regimes is greater than that in normal regimes, by a factor of 2.7; and the impact of ML on FL is significant in stressed regimes instead of normal regimes. The mutually reinforcing impact of FL and ML in downside markets is predicted in Brunnermeier and Pedersen (2009). Furthermore, FL is negatively related to ML in normal regimes. We also find that the frequency of being in a large-and-positive ML-to-FL impact state (i.e., a stressed regime) is much less than that of being in a large-and-positive FL-to-ML impact state (i.e., a stressed regime). This reflects that funding liquidity (i.e., money market liquidity) is more stable than bond market liquidity with less regime changes.

Our study depicts the market mechanism in depth on the time-varying relationship of funding liquidity and market liquidity. In normal regimes, more information (both public and private) is available in the market. If informed traders access capital or loans more easily, adverse selection can deter uninformed traders to trade, thus high funding liquidity can lower market liquidity, though this negative effect on market liquidity is small. However, when the market has had a negative shock, market participants (including financiers who provide capital or loans) encounter high uncertainty. They may be inclined to interpret price volatility as fundamental volatility, thus, raising capital and borrowing becomes difficult and costly. In this circumstance, all traders are reluctant to warehouse bonds and supply liquidity to the market, and market illiquidity picks up. The 2008 financial crisis is a typical example: at that time banks stopped lending to each other, and market liquidity suddenly dried up.

There is a regime-dependent feedback effect of market liquidity on funding liquidity too. The intuition is straightforward. Traders tend not to carry excess capital as it is expensive. While a market-wide fire sale is less likely in normal regimes, this is common during downturns since traders have to de-leverage their positions by selling part of their assets. The liquidation of a trader's position can reduce other investors' net worth through price effects. Therefore, declines in market liquidity may further impair funding liquidity (see Dudley, 2016).

We add to the growing literature in two aspects. First, the empirical literature has documented the relationship of funding liquidity and market liquidity in linear frameworks (see Boudt, Paulus, & Rosenthal, 2017; Chung, Ahn, Baek, & Kang, 2017); in linear frameworks, choosing the threshold value to classify regimes is a difficult and usually subjective task. We complement the literature by using a Markov regime-switching model to investigate the dynamic relationship of funding liquidity and market liquidity. The regime classification in this model is probabilistic and is endogenously determined by a Markov process. This approach is suitable to capture complex dynamic patterns of the relationship between FL and ML, which features with nonlinear stationarity and structural breaks. Through this approach, we add new findings to the literature (e.g., funding liquidity negatively influences market liquidity in normal times but this turns to be positive in stressed times). Second, this article directly explores the dynamic interaction of FL and ML in the U.S. corporate bond market, which is the largest corporate bond market in the world that attracts global investors.[4]

Our article relates to two strands of the literature. First, recent theoretical developments arguing that market liquidity is driven by funding liquidity. For instance, Gromb and Vayanos (2002) propose that market liquidity depends on the capital of financial intermediaries, that a liquidation of arbitrageurs' positions does not only reduce other arbitrageurs' net worth through price effects, but also can be detrimental to other investors through a reduction in market liquidity. Brunnermeier and Pedersen (2009) show that market and funding liquidities can reinforce each other in different ways under different market conditions. Second, our article is close to the empirical works of Boudt et al. (2017) and Chung et al. (2017) in which a linear framework is adopted in the analyses. The former examines the effect of the bid-ask spread of S&P 500 index on stock loan rates, and the later examines the relationship between liquidity discount rate and the floating-rate bonds in the Japanese market. Both works provide evidence that market liquidity and funding liquidity are strongly and positively related during market stress.

The remainder of the article is organized as follows. Section 2 discusses the related literature and establishes the hypothesis. Section 3 describes the data, the cleaning of TRACE data, and the method to calculate the ML measure and FL measure. Section 4 investigates the driving factors of the relationship of FL and ML. Section 5 explores the time-varying relationship of FL and ML in a Markov regime-switching model, and Section 6 briefly concludes the findings.

2 | LITERATURE REVIEW AND HYPOTHESES

In his 2010 AFA presidential address, Duffie (2010) indicates that financial crises and slow movement of investment capital increase the cost of intermediation, and thus lead to increases in trading spreads. Moreover, Duffie (2012) points out that the 2008 financial crisis not only affected banks' lending function, but also had a major impact on market liquidity. He further argues that investors and issuers of securities would find it more costly to borrow, raise capital, invest, hedge risks and obtain liquidity for their existing positions during any financial crisis.[5]

In the theoretical literature, the idea that rapid market declines cause asset illiquidity has been developed in various ways. For instance, the collateral-based models argue that traders finance their trades by posting margins and collateralizing the securities they hold. Thus, a negative shock in the market can hit traders' margin constraints, and force them to liquidate their assets. In this category, Gromb and Vayanos (2002) propose that market liquidity depends on the capital of financial intermediaries. When financial intermediaries are less well capitalized, they cannot fully absorb other investors' supply shocks (thus providing market liquidity to them). Gârleanu and Pedersen (2007) provide an explanation for the fact that sudden drops in prices and liquidity are related to higher volatility and lower risk-bearing capacity of institutions. Brunnermeier and Pedersen (2009) argue that a huge market-wide decline in prices reduces the ease with which market makers can obtain funding, which further restricts market makers from providing market liquidity during these downturns. Gârleanu and Pedersen (2011) show that a funding liquidity crisis gives rise to a price gap between securities with identical cash-flows but different margins.

In inventory models of market making, D'Souza and Lai (2006) and Lescourret and Robert (2011) discuss how funding capital may impact the behaviour of dealers and thus market liquidity in the context of bank consolidation or order preferencing. Other theoretical models also predict that large market declines cause agents to liquidate their positions across many assets and reduce liquidity supply, as liquidity providers hit their capital or funding constraints (for a detailed review, see Hameed, Kang, & Viswanathan, 2010).

While the theoretical literature has laid out the time-varying connection between market liquidity and funding liquidity (i.e., traders' funding constraints), the extant empirical literature is limited and mainly investigate this in a linear approach, focusing on stock and foreign exchange (FX) markets. For example, Chordia, Sarkar, and Subrahmanyam (2005) explore liquidity movements in stock and Treasury bond markets over a period of more than 1800 trading days, and establish a link between mutual fund flows and transaction liquidity. Hameed et al. (2010) find that negative market returns decrease stock liquidity in 1988–2003, especially during times of tightness in the funding market in that period. Their finding is consistent with recent theoretical models where binding capital constraints lead to sudden liquidity dry-ups. Karolyi, Lee, and van Dijk (2012) find that commonality in stock market liquidity is greater in countries with and during times of high market volatility (especially, large market declines). However, there is little evidence that commonality is greater in times of higher local interest rates, which represent tighter credit conditions when financial intermediaries are more likely to hit their capital constraints. In the FX market, Mancini, Ranaldo, and Wrampelmeyer (2013) show that negative shocks in funding liquidity lead to significantly lower FX market liquidity. Boudt et al. (2017) examine the effect of market liquidity on equity-collateralized funding liquidity. They document that market liquidity can affect funding liquidity in a stabilizing (destabilizing) manner in a state characterized by low (high) yield spread of Eurodollars over T-bills. Chung et al. (2017) have documented similar findings in the Japanese floating-rate bond market.

To contribute to the growing literature on funding liquidity and market liquidity, we investigate the relationship of funding liquidity and market liquidity in the U.S. corporate bond market in a non-linear Markov regime-switching model. The hypothesis that we are testing is as follows:

Hypothesis. *Funding liquidity and market liquidity are interlinked in the U.S. corporate bond market. The relationship between them is time-varying and depends on the market conditions, such as the tightness of the money market and bond market volatility.*

3 | DATA AND LIQUIDITY MEASURES

In this section, we first describe the TRACE data, money market liquidity data and other macroeconomic data used in the study, then we explain how we calculate corporate bond market liquidity measures and funding liquidity measures.

3.1 | Data

We compute market liquidity measures using corporate bond transaction-level data from the U.S. TRACE Enhanced database, which has the most comprehensive coverage of the bond market in the United States.[6] This database was the result of regulatory initiatives more than a decade ago to increase price transparency in the U.S. corporate bond market. The Trace database was initially limited to selected investment-grade bonds during its first phase, and it became comprehensive since October 2004 when its final phase was fully implemented and transactions of essentially all U.S. corporate bonds were reported. The Enhanced Historic TRACE database covers transactions up to September 2013 at the time of our data collection, including those that qualify for delayed dissemination.

Before usage, the data requires some cleaning. In particular, we remove transaction reports that are subsequently withdrawn or corrected as well as transactions with spurious prices (above $1,000 or below $0.01). We also search for transactions reported by both counterparties and delete one report for each of these pairs. Across calendar years of the dataset, 2–3.5% of transaction reports are dropped. These proportions are similar to those reported by Dick-Nielsen (2009, 2014), who used the same data filters. Table 1 presents the number of transactions in our data before and after filtering.

We further exclude non-business dates from the sample, following the Securities Industry and Financial Markets Association (SIFMA) U.S. Holiday

TABLE 1 TRACE dataset before and after the error filtering

Year	2004	2005	2006	2007	2008
No. of original transactions	7,630,171	8,106,863	7,300,388	6,700,012	8,982,733
No. of transactions after filtering	7,356,939	7,847,110	7,070,415	6,514,108	8,758,683
Removed transactions (%)	3.6	3.2	3.2	2.8	2.5
Year	**2009**	**2010**	**2011**	**2012**	**2013**
No. of original transactions	15,509,598	16,196,361	14,865,946	16,353,092	12,535,053
No. of transactions after filtering	15,151,480	15,760,565	14,558,377	15,849,214	12,153,785
Removed transactions (%)	2.3	2.7	2.1	3.1	3

Recommendations. The following regression analyses involve variables of bond market volatility (i.e., CBOE/CBOT 10-Year U.S. Treasury Note Volatility Index—TYVIX), aggregate credit-rating change (i.e., CDS index—CDX), short-term interest rate (i.e., Federal Fund Rate) and default spread of U.S. corporate bonds (i.e., the difference between BAA and AAA-rated corporate bond yields). We obtain the data from Bloomberg and Datastream.

3.2 | Market liquidity measures

For the U.S. corporate bond market, we compute the following two measures of market liquidity using transaction-level TRACE dataset for individual bonds. All the metrics are computed at daily frequency, and higher values indicate lower liquidity.

- Amihud measure: Amihud (2002) measures liquidity as the ratio of the daily absolute return to the daily trading volume. This measure proxies the price impact of trades. Following Dick-Nielsen et al. (2012), we estimate the price impact at the level of individual trades for each bond, and take the average over the trade-level values each day to obtain a measure at daily frequency for that bond. The Amihud measure is defined as follows. For a given bond on a given day t, $r_{i,t}$ is the return, $Q_{i,t}$ is the trade size (in \$ million) of the ith trade, and N_t is the number of trades. The Amihud measure is then the daily average of the absolute returns divided by the corresponding trade sizes:

$$Amihud_t = \frac{1}{N_t - 1} \sum_{i=2}^{N_t} \frac{|r_{i,t}|}{Q_{i,t}}.$$

The aggregate Amihud measure on day t is the median over individual bonds' Amihud measure on day t. Bonds that have no Amihud measure on day t (due to less than 2 transactions on day t) are excluded from the median calculation on day t. A high level of the Amihud measure implies a low liquidity.

- Roll measure: Roll (1984) shows that under certain assumptions, the percentage bid-ask spread is equal to two times the square root of the negative first-order serial covariance of returns. The intuition is that the transaction price will tend to bounce between the bid and ask prices, so that returns on consecutive trades are negatively correlated, and that this negative correlation will be larger if the bid-ask spread is wider. For a given bond on a given day t, $r_{i,t}$ is defined as the return on the ith trade. Our implementation of the Roll measure is then defined as:

$$Roll_t = 2\sqrt{\max\{0, -cov(r_{i,t}, r_{i-1,t})\}}.$$

Similar to the aggregate Amihud measure, the aggregate Roll measure on day t is the median over individual bonds' Roll measure on day t. Bonds that have no Roll measure on day t (i.e., less than four transactions on day t) are excluded from the median calculation on day t. A high level of the Roll measure also implies a low liquidity.

Figure 1a presents the Amihud measure and the Roll measure over the sample period 2004–2013. Both measures show that liquidity deteriorated markedly during the 2008 financial crisis, but it has recovered to around or slightly below pre-crisis levels in the past few years.

Although the Amihud and Roll measures focus on different dimensions of market liquidity, both measures can be captured by a few latent factors. Following Dick-Nielsen et al. (2012), we extract the first principal component of the Amihud and Roll measures within a principal component analysis, and combine them into a composite measure. Both measures are standardized before their principal component is extracted. We label this composite

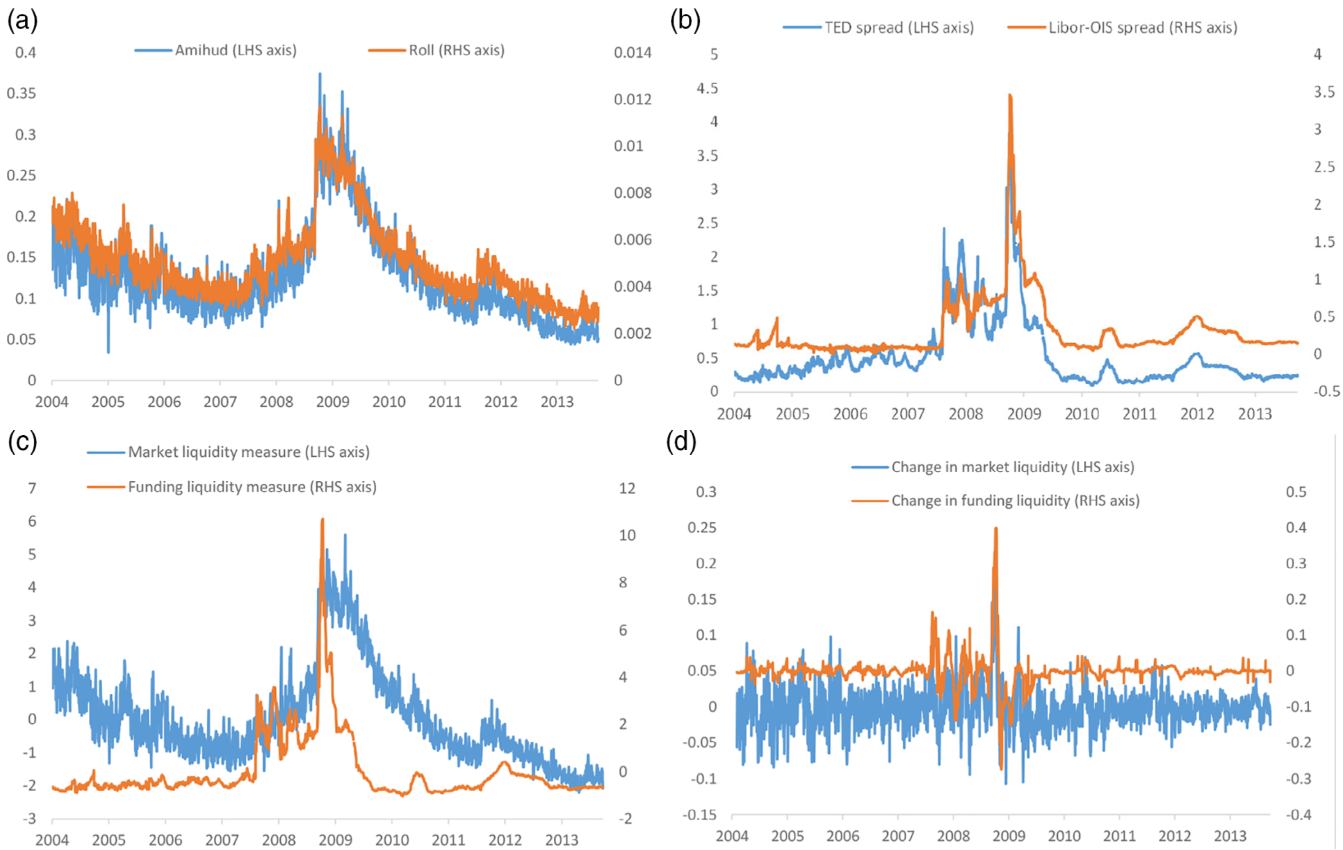


FIGURE 1 The market liquidity and funding liquidity measures. This figure illustrates the U.S. corporate bond market liquidity measures and funding liquidity measures from 1 January 2004 to 30 September 2013. (a) Plots the daily corporate bond market liquidity of Amihud and Roll measure. The Amihud measure is aggregated by the median across the daily mean value of individual bond's Amihud measure. The Roll measure is aggregated by the median across the individual bond's daily Roll measure. (b) Illustrates the United States daily funding liquidity measures of TED spread and Libor-OIS spread. (c) Shows the daily composite market liquidity measure (*ML*) and the daily composite funding liquidity measure (*FL*) and (d) shows the changes in ML (ΔML) and the changes in FL (ΔFL) on a 22-day moving average [Colour figure can be viewed at wileyonlinelibrary.com]

market liquidity measure as Market Liquidity measure (*ML*). A high level of *ML* implies a low market liquidity. We will use this definition of market liquidity in the rest of the article.

3.3 | Funding liquidity measures

We use the following funding liquidity measures:

- TED spread: TED spread is the difference between the 3-month USD Libor[7] and the 3-month U.S. Treasury bill rate. In times of uncertainty, banks charge higher interest for unsecured loans, which increases the LIBOR rate. Further, banks want to get first-rate collateral, which makes Treasury bonds more attractive and pushes down the Treasury bond rate. For both reasons, the TED spread widens in times of crises. Hence, TED spread is widely used as a measure of tightness in the interbank market (see Gârleanu & Pedersen, 2007; Nyborg & Östberg, 2014). We obtain the data from the Federal Reserve Bank in St. Louis.
- Libor-OIS spread: Libor-OIS spread is the difference between 3-month USD Libor and the 3-month USD overnight index swap rate. Libor-OIS spread also reflects tightness in the interbank market. Compared to TED spread, 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 (see Nyborg & Östberg, 2014).

Figure 1b shows the TED spread and Libor-OIS spread over the sample period. Both funding liquidity measures feature a sharp pick-up during the 2007–2008 crisis period, but they remained low and stable in pre- and post-crisis periods.

Following the same method as the construction of the composite market liquidity measure, we derive the composite funding liquidity measure using the first principal component of the Libor-OIS spread and TED spread. We label this composite funding liquidity measure as Funding Liquidity measure (*FL*). Similarly to the composite market liquidity measure (*ML*), a high level of *FL* implies a low funding liquidity. We will use this definition of funding liquidity in the rest of the article.

Figure 1c shows the daily composite funding liquidity measure (*FL*) and the composite market liquidity measure (*ML*) over the sample period. While both *FL* and *ML* became very volatile with sharp rises (i.e., more illiquid) during the 2007–2008 crisis period, they tended to move opposite way in the pre- and post-crisis period. In the pre-crisis period, *ML* exhibited a downward trend (i.e., more liquid), whereas *FL* showed a slightly upward trend though mainly remained stable. In the post-crisis period, *FL* returned to pre-crisis level much more quickly than *ML*. This provides the first evidence to the Hypothesis. Figure 1c also shows that FL is less volatile than ML over the sample period, implying that funding liquidity (i.e., money market liquidity) could be more stable than corporate bond market liquidity. This will be elaborated in the following Markov regime-switching analysis, where funding liquidity has less regime changes than market liquidity. Figure 1d further displays the change in ML (*ΔML*) and FL (*ΔFL*) on a 22-day moving average (i.e., equivalent to a monthly average), which will be used in the following Markov regime modelling.[8]

Visually, while FL spikes up during the 2007–2008 financial crisis period but maintains a low level in the pre- and post-crisis periods, ML has a tendency of decline over the sample period, though it also spikes up during the crisis period. The decline of ML in the post-crisis period relative to the pre-crisis period may be due to the U.S. Quantitative Easing (QE) programme implemented from 1 December 2008, in which the U.S. Fed increased money supply by purchasing mortgage- and treasury-backed bonds. It has been documented in the literature that QE can improve market liquidity (see, e.g., Christensen & Gillan, 2018). We therefore include QE as a control variable in the following Markov regime-switching analysis on the relationship of funding liquidity and market liquidity.

TABLE 2 Summary statistics

	Mean	*SD*	Min	Max
ML	0.000	1.398	−2.207	6.052
FL	−0.002	1.368	−1.033	10.735
ΔML	−0.001	0.028	−0.107	0.238
ΔFL	0.001	0.042	−0.273	0.400
ΔCDX	0.013	0.811	−3.773	4.499
TYVIX	6.756	2.102	3.620	14.720
ΔDEF	0.000	0.024	−0.170	0.350
ΔFed	0.000	0.082	−0.880	1.010

Note: This table presents the summary statistics of the variables. *ML* is the composite bond market liquidity and *FL* is the composite funding liquidity that are defined in Sections 3.1 and 3.2. *ΔML*, *ΔFL* and *ΔCDX* are the 22-day moving averages of the *ML*, *FL* and credit default swap spread (*CDX*), respectively. *TYVIX* is the United States Treasury note volatility index. *ΔDEF* and *ΔFed* are the daily changes of the default spread (i.e., the difference between the United States BAA and AAA-rated corporate bond yields) and Federal Fund Rate, respectively.

4 | DRIVING FACTORS OF THE RELATIONSHIP OF FUNDING LIQUIDITY AND MARKET LIQUIDITY

Since funding liquidity and market liquidity are hypothesized to correlate with each other regardless of market conditions, a natural question to ask is what drives this correlation. In this section, we try to answer this question by considering some main macroeconomic variables. The findings can help to specify the subsequent Markov regime-switching model, in which different regimes of the relationship can be predicted/characterized by these determinants.

The macroeconomic variables include bond market volatility index (TYVIX), changes in default spread

TABLE 3 Correlation matrix

	ML	*FL*	*ΔML*	*ΔFL*	*ΔCDX*	*TYVIX*	*ΔDEF*
FL	.57						
ΔML	.23	.31					
ΔFL	.00	.35	.41				
ΔCDX	.07	.24	.38	.19			
TYVIX	.76	.60	.17	.01	.22		
ΔDEF	.06	.19	.21	.21	.22	.06	
ΔFed	−.04	−.09	−.07	−.06	−.03	−.05	.00

Note: This table presents the correlation coefficients of the variables defined in Table 2.

(ΔDEF) and changes in the Federal Fund Rate (ΔFed). In addition, Bond market liquidity is closely related with its credit quality. Studies on bond market liquidity normally control for the credit quality by categorizing bonds into groups of different credit ratings (see, e.g., Bao, Pan, & Wang, 2011; Chen, Lesmond, & Wei, 2007; Díaz & Escribano, 2019; Dick-Nielsen et al., 2012; Helwege, Huang, & Wang, 2014).[9] Since Hull, Predescu, and White (2004) indicate that credit default swap (CDS) spreads track credit-rating changes, we use CDS spreads to control for the market-wide credit rating changes. Specifically, we employ the Barclays CDX index[10] in the United States market as a control variable.

Tables 2 and 3 present the summary statistics and correlation matrix of the variables. As expected, market liquidity and funding liquidity are highly correlated, either as changes (i.e., ΔML and ΔFL) or as levels (i.e., *ML* and *FL*).

We regress the correlation coefficient of *FL* and *ML* on the above mentioned macroeconomic variables and a dummy variable that indicates the presence or absence of the implementation of the U.S. quantitative easing programme (*QE*). Equation (1) presents the regression model and the estimates. The *SDs* are in the parenthesis.

$$\begin{aligned} Corr_t = \; & \underset{(-3.56)^{***}}{-0.03} \; \underset{(2.88)^{***}}{+0.003TYVIX_t} \; \underset{(1.16)}{+0.11\Delta DEF_t} \; \underset{(-1.35)}{-0.04\Delta Fed_t} \; \underset{(0.83)}{+0.004QE_t} \; \underset{(1.12)}{+0.003\Delta CDX_t} \; + \gamma X_t \\ & \text{Adj.}R^2 = 0.93 \end{aligned} \tag{1}$$

where $Corr_t$ is the correlation coefficient of *ML* and *FL* calculated at a 22-day moving average window, *t* is the trading day, $TYVIX_t$ is the bond market volatility index, ΔDEF_t is the change in default spread (i.e., the difference between BAA and AAA-rated corporate bond yields), ΔFed_t is the change in Federal Fund Rate, QE_t is the dummy variable with value of 0 if trading date is in the period of 5 January 2004 to 30 November 2008 or 1 otherwise (i.e., from 1 December 2008 to 30 September 2013), ΔCDXt is the change in CDX spreads, X_t consists of two lags of the dependent variable to control potential residual autocorrelation.

The regression results show that bond market volatility index (*TYVIX*) is the only significant driving factor of the correlation coefficient of *FL* and *ML*, where an increase in bond market volatility will increase the correlation of funding liquidity and market liquidity. Since *TYVIX* is usually regarded as an indicator of market stress, our result implies that the level of market stress determines the strength of the correlation between funding liquidity and market liquidity. Our result is also consistent with Fleming, Kirby, and Ostdiek (1998), in which the authors find a strong volatility linkage between the stock, bond and money markets, especially after the 1987 stock market crash. In the following sections, we will elaborate this implication in a Markov regime-switching model, where bond market volatility serves as a regime predictor.

Before we investigate the non-linear relationship between FL and ML, we first estimate the linear relationship between them, where the results are presented in Table A1. The results confirm that FL and corporate bond ML are significantly interlinked. To further explore the regime-dependent relationship of FL and ML, we employ the Markov regime-switching approach.

5 | THE TIME-VARYING RELATIONSHIP OF FUNDING LIQUIDITY AND MARKET LIQUIDITY: A MARKOV REGIME-SWITCHING APPROACH

Although funding liquidity and market liquidity are often treated as distinct, they can be closely related, especially during a financial crisis (see Dudley, 2016). Specifically, market liquidity is strongly affected by funding liquidity in a state of deteriorating market conditions (e.g., when the money market becomes illiquid and the bond market volatility increases), while this impact is much smaller in a normal state. Dudley (2016) provides some intuitive explanation of market liquidity as a function of funding liquidity. Since funding liquidity is the ability of a financial entity to borrow, it can be regarded as the shadow cost of capital. If funding liquidity declines because of market stress, this may cause intermediaries to become less willing to provide market liquidity (see Dudley, 2016).

The Hypothesis calls for two important features of the empirical model: regime-dependent relationship of funding liquidity and market liquidity, and the use of market stress indicators, that is, funding liquidity and bond market volatility index to classify stressed and normal regimes. We follow Watanabe and Watanabe (2008) to use a Markov regime-switching model to accommodate these features in our empirical investigation. Section 5.1 lays out the analysis for the impact of FL on ML, and Section 5.2 lays out the analysis for the impact of ML on FL.

5.1 | The impact of funding liquidity on market liquidity

In this section, we investigate the impact of FL on ML. We specify the Markov regime-switching model as follows[11]:

$$\Delta ML_t = \alpha_{S_t} + \beta_{S_t}\Delta FL_t + \delta QE_t + \gamma\Delta CDX_t + \varepsilon_{S_t,t}, \tag{2}$$

where $s = 1,2\, and\, \varepsilon_{S_t,t} \sim N\left(0, \sigma^2_{S_t}\right)$,

where ΔML_t, ΔFL_t, ΔCDX_t and QE_t are defined in the previous section, s = 1, 2 represents the states. We assume that the state transition for Equation (2) is governed by a Markov switching probability:

$$\begin{aligned}&\Pr(s_t = s|s_{t-1}; Predictor_{t-1})\\ &\quad= \frac{\exp(c_{s_t} + d_{s_t}\cdot Predictor_{t-1})}{1+\exp(c_{s_t} + d_{s_t}\cdot Predictor_{t-1})}, s = 1,2,\end{aligned} \tag{3}$$

where $Predictor_{t-1}$ is $TYVIX_{t-1}$ and FL_{t-1}, respectively, c_{s_t} and d_{s_t} are scalars. *Predictor* is used as a state variable to help predict and classify the FL–ML relationship states. The exponential transformation ensures that the transition probability always falls between 0 and 1. Following Watanabe and Watanabe (2008), we define that day t is in State 2 if the associated estimated probability of being in State 2 is higher than 0.75, and that day t is in State 1 otherwise. To avoid the daily time series being too volatile to define market regimes, we use ΔFL and ΔML in Equations (2) and (3) in a 22-day moving average (i.e., equivalent to a monthly average). Estimating Equations (2) and (3) gives a way of examining how market liquidity is affected by funding liquidity in the two different states.

Let us first look at the results on how funding liquidity affects market liquidity, that is, the estimates for Equations (2) and (3) where ΔML is the dependent variable. Panel A in Table 4 presents the estimated parameters of the Markov regime-switching model where the state indicator is *TYVIX*. Out of 2,299 days from January 2004 to September 2013, there were 764 days in the stressed State 2, characterized by high funding illiquidity (the mean of *FL* in State 2 is greater than in State 1), high market illiquidity (the mean of *ML* in State 2 is greater than in State 1), high bond market volatility (the mean of *TYVIX* in State 2 is greater than in State 1, $\sigma_2 > \sigma_1$), and high credit risk (i.e., high risk of credit-rating downgrade; the mean of CDX in State 2 is greater than in State 1). We observe a negative impact of FL on ML in normal times (State 1) and a much stronger positive impact of FL on ML in stressed times (State 2). Both estimated impact coefficients are statistically significant. The likelihood ratio test (LR test) strongly rejects the null hypotheses that $\beta_1 = \beta_2$ and $\sigma_1 = \sigma_2$.

Most importantly, the magnitude of β_2 exceeds that of β_1, by a factor of 2.7 (i.e., $0.332/|-0.124| = 2.7$), implying that FL affects ML more strongly in stressed regimes than in normal regimes. This supports the Hypothesis that the impact of funding liquidity on market liquidity is highly regime-dependent. While FL has a small impact on ML when the bond market volatility is low, it has a large impact when bond market volatility is high.

Furthermore, bond market volatility significantly predicts the two FL-to-ML impact state: large-and-positive impact state and the small-and-negative impact state. The significant d_1 coefficient (−0.403) of *TYVIX* implies that high bond market volatility tends to reduce the probability of staying in the small-and-negative FL-to-ML impact state and consequently moves to the large-and-positive FL-to-ML impact state. The LR test strongly rejects the null hypothesis that $d_1 = d_2 = 0$ with p-value of zero. This finding supports our Hypothesis.

Panel A in Figure 2 plots the estimated probability of being in the stressed State 2 (i.e., the large-and-positive FL-to-ML impact state), in which the bond market volatility index *(TYVIX)* is the state indicator. It is visually clear that the high probability of being in State 2 clusters in the 2007–2008 crisis period, and around 2010–2011 period coinciding with the Euro-debt crisis. This is consistent with the Hypothesis, that a tightened funding market deteriorates market liquidity when the market is in stress. Furthermore, the high probability of being in State 2 is visually less frequent in the post-crisis period relative to the pre-crisis period. This is associated with the significant coefficient of QE (−0.003). That said, the post-crisis United States QE program has improved market liquidity, and market liquidity is higher in the post-crisis period than the pre-crisis period when no QE was implemented. It is worth noting that the coefficient of ΔCDX is significantly positive, implying that an increase in credit risk (i.e., probability of credit-rating downgrade) dampens bond market liquidity.

Alternatively, we use funding liquidity (*FL*) as an indicator of market stress to predict the FL-to-ML impact states. Panel B in Table 4 presents the estimated parameters of the Markov regime-switching model, where the state indicator is *FL*, and Panel B in Figure 2 plots the associated estimated probability of being in State 2. Out of 2,299 days from January 2004 to September 2013, there were 784 days in the stressed State 2. Not surprisingly, the days in the stressed State 2 predicted by *FL* largely overlap with those predicted by *TYVIX*, that is, an overlap of 754 days in State 2. As a consequence, the characteristics of State 2 indicated by *FL* are the same as those by *TYVIX*, that is, high funding illiquidity (the mean of *FL*

TABLE 4 Estimates of the Markov regime-switching model on the FL-to-ML impact

Parameters Panel A State predictor: *TYVIX*		**Common parameters**		**Parameters Panel B State predictor: Funding liquidity (*FL*)**		**Common parameters**	
α_1	**.001**	c_1	**6.406**	α_1	.001	c_1	**3.632**
α_2	−.003	c_2	**3.279**	α_2	**−.003**	c_2	**3.381**
β_1	**−.124**	d_1	**−0.403**	β_1	**−.124**	d_1	**−0.954**
β_2	**.332**	d_2	0.009	β_2	**.334**	d_2	−0.119
σ_1	**0.015**	*QE*	**−0.003**	σ_1	**0.015**	*QE*	**−0.003**
σ_2	**0.031**	ΔCDX	**0.011**	σ_2	**0.030**	ΔCDX	**0.011**
LR tests		Common LR tests		LR tests		Common LR tests	
$\beta_1 = \beta_2$	**112**	$d_1 = d_2 = 0$	**15**	$\beta_1 = \beta_2$	**112**	$d_1 = d_2 = 0$	**19**
$\sigma_1 = \sigma_2$	**401**			$\sigma_1 = \sigma_2$	**402**		
Max LK (per period)		**5,588 (2.41)**		Max LK (per period)		**5,590 (2.41)**	
Daily means of selected variables by states				Daily means of selected variables by states			
	All	State 1	State 2		All	State 1	State 2
ML	−0.01	−0.42	0.81	*ML*	−0.01	−0.42	0.78
FL	0.01	−0.26	0.54	*FL*	0.01	−0.28	0.55
TYVIX	6.74	6.31	7.59	*TYVIX*	6.74	6.33	7.54
CDX	88.71	85.86	94.43	*CDX*	88.71	86.16	93.64
No. days	2,299	1,535	764	No. days	2,299	1,515	784
Sample period (No. obs)		200,401:201309 (2322)					

Note: This table presents the estimates of the impact of funding liquidity (*FL*) to market liquidity (*ML*) using Equations (2) and (3). Panels A and B report the results in which the regime predictor is bond market volatility (*TYVIX*) and funding liquidity (*FL*), respectively. The variables are defined in Table 2. The sample period is from 5 January 2004 to 30 September 2013. The table also shows $\chi 2$ statistics for the likelihood ratio tests (LR Tests) on various parameter restrictions, and the maximized log likelihood (Max LK) of the model estimation. The estimates and test statistics in bold refer to an, at least, 5% significance level.

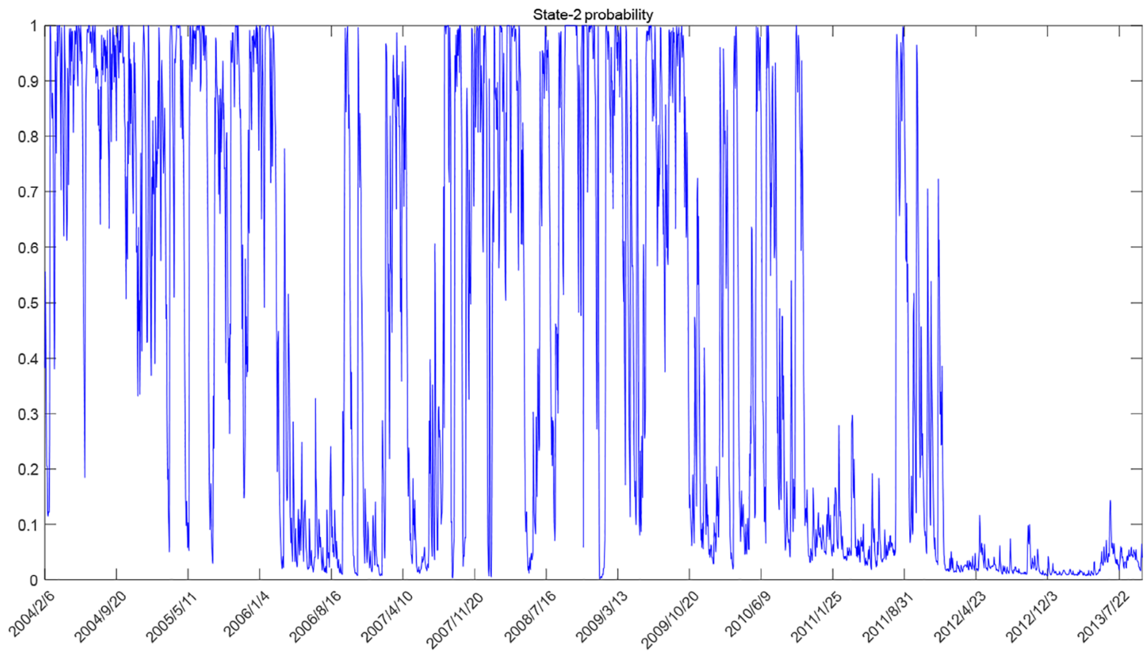
in State 2 is greater than in State 1), high corporate bond market illiquidity (the mean of *ML* in State 2 is greater than in State 1), high bond market volatility (the mean of *TYVIX* in State 2 is greater than in State 1, $\sigma_2 > \sigma_1$), and high credit risk (the mean of CDX in State 2 is greater than in State 1). The overall estimates are quantitatively similar to those where *TYVIX* is used as the state predictor.

The regime-switching of FL-to-ML impact between stressed and normal regimes may depict an interesting market mechanism. In normal regimes, there is usually more information (both public and private) available for evaluating securities. Hence the range of investors' expectation on fair prices is narrow. And this is reflected by a low-price volatility. In normal times, funding markets are generally liquid. For example, in our case, the mean of *FL* is −0.28 in the normal State 1 relative to 0.55 in the stressed State 2. If some traders have information advantage, and if they can access capital or loans easily when funding liquidity is high, then adverse selection can deter uninformed traders to trade, thus lowering market liquidity. However, in stressed regimes when the market has suffered a negative shock with high uncertainty, there is less information available. All traders, as well as financiers who provide them with capital or loans, are relatively uninformed about fundamentals. They are inclined to interpret price volatility as fundamental volatility, hence raising capital and borrowing becomes difficult and costly. In this circumstance, all traders are reluctant to warehouse bonds and supply liquidity to the market, that is, market liquidity gets much worse.

The 2008 financial crisis provides a typical example for this large-and-positive impact of FL on ML due to insufficient information. During the crisis, the lack of information about the true financial position of borrowers made banks reluctant to lend to each other (see, e.g., Calomiris, 2009). The fact that interlinkages between banks are so complex further deteriorated the transparency and sufficiency of information, and banks have to worry not only about the counterparty risk of their neighbours, but also of their neighbours' neighbours (see Caballero & Simsek, 2013).

It is worth noting that our estimate of the negative impact of FL on ML in normal regimes differ from Chung et al. (2017) and Moinas, Nguyen, and Valente (2018), where the authors find that a worsen funding liquidity either has no significant impact on the market, or if it

Panel A. State predictor: *TYVIX*



Panel B. State predictor: Funding liquidity (*FL*)

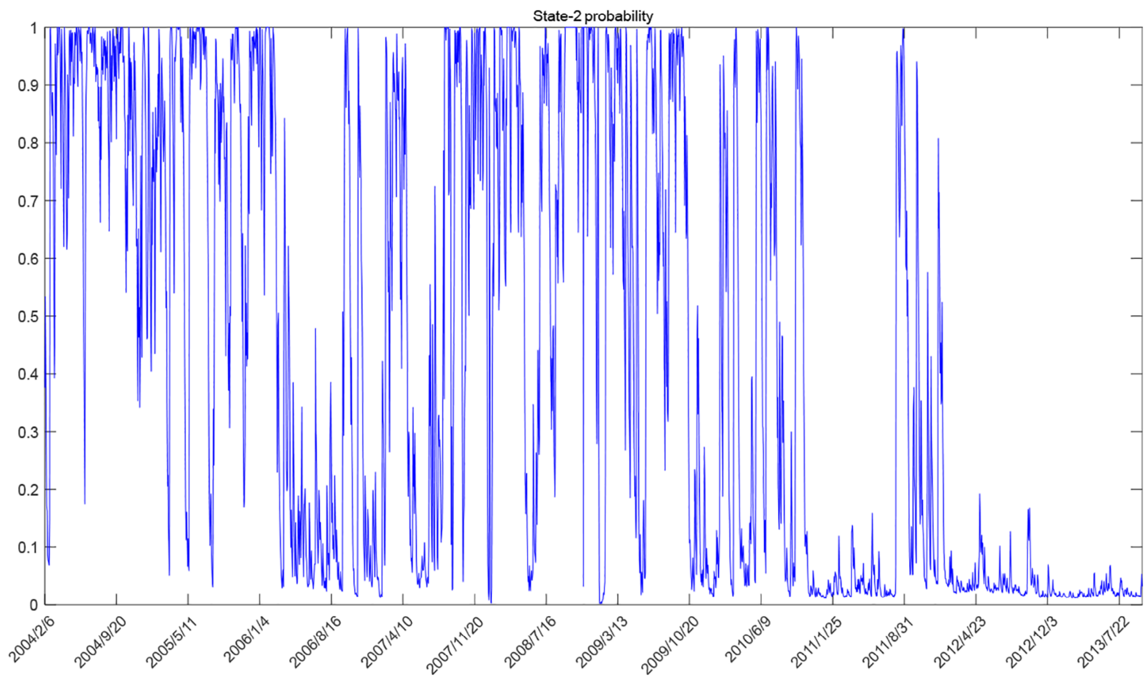


FIGURE 2 The estimated probability of being in State 2 on the FL-to-ML impact. This figure shows the probability of being in State 2 estimated by Equations (2) and (3), where Panels A and B are for the state predictors of bond market volatility (*TYVIX)* and funding liquidity (*FL*), respectively [Colour figure can be viewed at wileyonlinelibrary.com]

does impact, that impact is positive. This might be attributed to the high frequency data we use in the study that capture the fast-changing feature of liquidity. Chordia, Roll, and Subrahmanyam (2001) finds that daily changes in market averages of liquidity are highly volatile, and liquidity plummets significantly in down markets.

5.2 | The impact of market liquidity on funding liquidity

The time-varying feedback effect from ML to FL is another concern, which is explored in this section. We specify the Markov regime-switching model as follows[12]:

TABLE 5 Estimates of the Markov regime-switching model on the ML-to-FL impact

Parameters Panel A State predictor: *TYVIX*		Common parameters		Parameters Panel B State predictor: Funding liquidity (*FL*)		Common parameters	
α_1	**.002**	c_1	**7.087**	α_1	**.002**	c_1	**4.560**
α_2	−.001	c_2	1.880	α_2	−.001	c_2	**2.853**
β_1	.005	d_1	**−0.352**	β_1	.006	d_1	**−1.112**
β_2	**1.210**	d_2	0.175	β_2	**1.215**	d_2	**0.489**
σ_1	**0.007**	*QE*	**−0.002**	σ_1	**0.007**	*QE*	**−0.002**
σ_2	**0.073**	ΔCDX	**0.005**	σ_2	**0.074**	ΔCDX	**0.005**
LR tests		Common LR tests		LR tests		Common LR tests	
$\beta_1 = \beta_2$	**183**	$d_1 = d_2 = 0$	**9**	$\beta_1 = \beta_2$	**182**	$d_1 = d_2 = 0$	**25**
$\sigma_1 = \sigma_2$	**4,186**			$\sigma_1 = \sigma_2$	**1931**		
Max LK (per period)		**7,029 (3.03)**		Max LK (per period)		**7,037 (3.03)**	
Daily means of selected variables by states				Daily means of selected variables by states			
	All	State 1	State 2		All	State 1	State 2
ML	−0.01	−0.29	1.16	*ML*	−0.01	−0.28	1.16
FL	0.01	−0.40	1.73	*FL*	0.01	−0.41	1.79
TYVIX	6.74	6.21	8.96	*TYVIX*	6.74	6.22	8.99
CDX	88.71	80.21	124.63	*CDX*	88.71	80.28	125.36
No. days	2,299	1859	440	No. days	2,299	1869	430
Sample period (No. obs)		200,401:201309 (2322)					

Note: This table presents the estimates on the impact of market liquidity (*ML*) to funding liquidity (*FL*) using Equations (4) and (5). Panels A and B report the results in which the regime predictor is the bond market volatility index (*TYVIX)* and funding liquidity (*FL*), respectively. The variables are defined in Table 2. The sample period is from 5 January 2004 to 30 September 2013. The table also shows χ2 statistics for the likelihood ratio tests (LR Tests) on various parameter restrictions, and the maximized log likelihood (Max LK) of the model estimation. The estimates and test statistics in bold refer to an, at least, 5% significance level.

$$\Delta FL_t = \alpha_{S_t} + \beta_{S_t}\Delta ML_t + \delta QE_t + \gamma \Delta CDX_t + \varepsilon_{S_t,t}, \quad (4)$$

where $s = 1, 2$ represents the states, ΔML_t, ΔFL_t, ΔCDX_t and QE_t are defined in the previous section, $\varepsilon_{S_t,t} \sim N\left(0, \sigma^2_{S_t}\right)$.

Similar to the previous section, we assume that the state transition for Equation (4) is governed by a Markov switching probability:

$$\Pr(s_t = s|s_{t-1}; Predictor_{t-1}) = \frac{\exp(c_{s_t} + d_{s_t}\cdot Predictor_{t-1})}{1+\exp(c_{s_t} + d_{s_t}\cdot Predictor_{t-1})}, s = 1, 2, \quad (5)$$

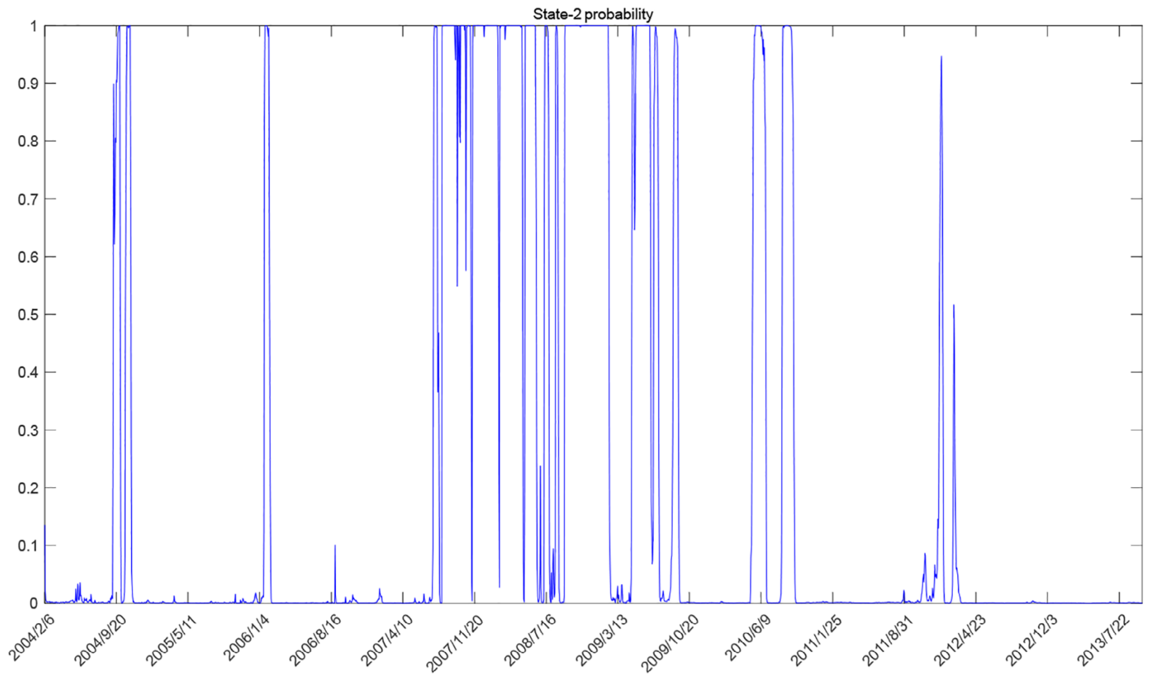
where Equation (5) is defined the same as Equation (3).

Panel A in Table 5 shows the estimated parameters where the state is predicted by bond market volatility index *TYVIX*. Out of 2,299 days from January 2004 to September 2013, 440 days were in the stressed State 2, characterized by high funding illiquidity (the mean of *FL* in State 2 is greater than in State 1), high market illiquidity (the mean of *ML* in State 2 is greater than in State 1), high bond market volatility (the mean of *TYVIX* in State 2 is greater than in State 1, $\sigma_2 > \sigma_1$) and high credit risk (the mean of CDX in State 2 is greater than in State 1). We observe a significantly positive impact of ML on FL in state 2 (i.e., stressed regimes), whereas this is insignificant in state 1 (normal regimes).

Usually, traders tend not to carry excess capital as it is expensive. During downturns in particular, traders have to de-leverage their positions by selling part of their assets. The liquidation of a trader's position can reduce other investors' net worth through price effects. Thus, declines in market liquidity may further impair funding liquidity (see Dudley, 2016). Our finding supports the Hypothesis that the feedback effect of market liquidity on funding liquidity is highly regime-dependent, where a much stronger feedback effect occurs when bond market is volatile and money market is tight.

TYVIX significantly predicts the regime-switching of ML-to-FL. The coefficient of d_1 is −0.352 and is statistically significant, implying that high bond market volatility tends to reduce the probability of being in the small-and-positive impact state of ML-to-FL, and consequently moves to the large-and-positive impact state of ML-to-FL. Meanwhile, the coefficient of d_2 is positive and insignificant, implying that high bond market volatility tends to increase the probability of staying in the large-and-positive impact state of ML-to-FL, though this is less significant. The LR test strongly rejects the null hypothesis that $d_1 = d_2 = 0$ with p-value of zero.

Panel A. State predictor: *TYVIX*



Panel B. State predictor: Funding liquidity (*FL*)

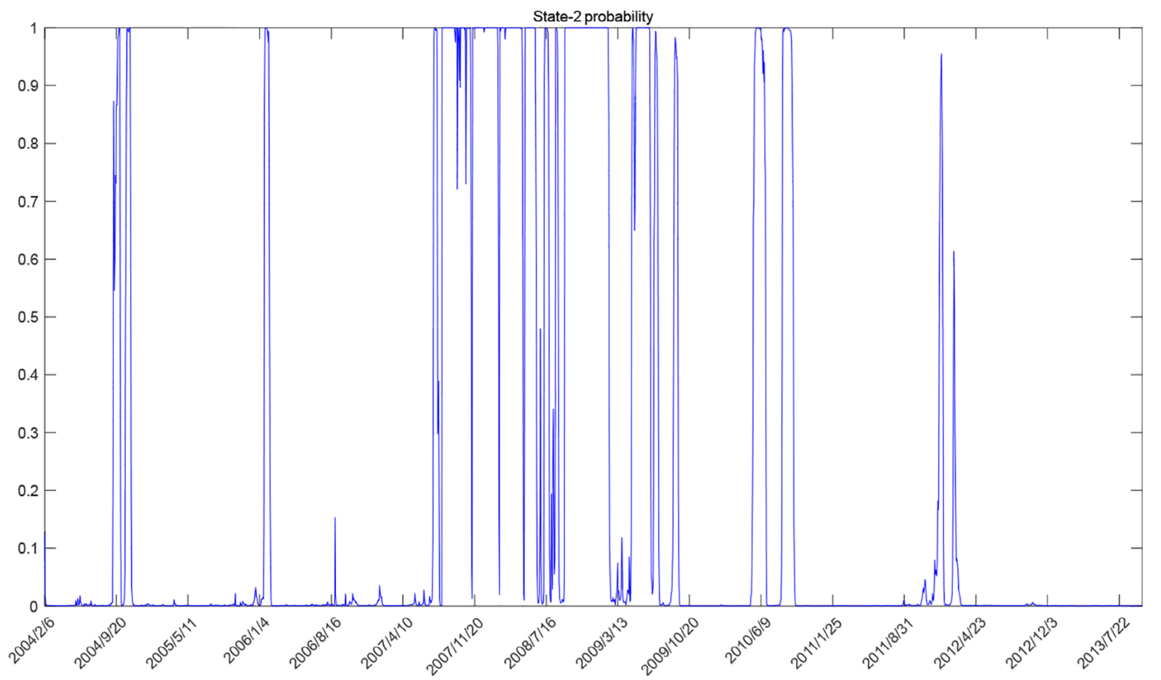


FIGURE 3 The estimated probability of being in State 2 on the ML-to-FL impact. This figure shows the probability of being in State 2 estimated by Equations (4) and (5), where Panels A and B are for the state predictors of bond market volatility (*TYVIX)* and funding liquidity (*FL*), respectively [Colour figure can be viewed at wileyonlinelibrary.com]

This finding supports the Hypothesis that bond market volatility is a critical condition of regime changes in the relationship of market liquidity and funding liquidity.

Panel A in Figure 3 plots the estimated probability of being in the large-and-positive ML-to-FL impact state (i.e., stressed regime), in which the bond market volatility index *TYVIX* is the state predictor. Similarly to the large-and-positive FL-to-ML impact state (i.e., stressed regime), a high probability of being in the large-and-positive ML-to-FL impact state clusters in the 2007–2008 crisis period and the 2010–2011 Euro-debt crisis period. However, high probabilities of being in the large-and-positive ML-to-FL impact state (i.e., stressed regimes in Figure 3) are predicted much less frequently than that for the large-and-positive FL-to-ML impact state (i.e., stressed regimes in Figure 2). This is true even during the post-2008 crisis period, when funding liquidity has been improved thanks to the U.S. QE program (i.e., the estimated coefficient of the regime-independent variable QE is −0.002 and significant). This indicates that money market liquidity (i.e., funding liquidity) is more stable than bond market liquidity with less regime changes. We also note that the coefficient of ΔCDX to ΔFL is significantly positive (0.005), and is smaller than the coefficient of ΔCDX to ΔML (0.011) as shown in Table 4. This implies that the influence of credit risk (i.e., credit-rating changes) is more associated with bond market liquidity rather than funding liquidity.

Panel B in Table 5 presents the estimated parameters of the Markov regime-switching model where the state predictor is funding liquidity, and Panel B in Figure 3 plots the associated estimated probability of being in State 2. The overall estimates are quantitatively and qualitatively similar to those where the *TYVIX* is used as the state predictor.

6 | CONCLUSIONS AND IMPLICATIONS

Inspired by the recent debates and theoretical development on funding liquidity and market liquidity, we investigate the time-varying relationship of funding liquidity and market liquidity. By using a Markov regime-switching model to capture the complex dynamic patterns of financial time series, and the U.S. TRACE transaction-level data for corporate bonds from 2004 to 2013, we find that funding liquidity and corporate bond market liquidity are interlinked, and their impact on each other is highly regime-dependent, even controlling for the bond market credit-rating change. The impact of FL on ML in stressed regimes is greater than that in normal regimes, by a factor of 2.7. We further find that the influence of FL changes signs between the two regimes: while FL has a positive impact on ML in stressed regimes, it has a negative impact on ML in normal regimes. This may reflect the adverse selection effect caused by informed traders in normal regimes.

The feedback effect of market liquidity on funding liquidity is highly regime-dependent too. A worsened ML reduces FL in stressed regimes, yet has no significant impact in normal regimes. The regime-switching is driven by the tightness of the money market and the bond market volatility. Furthermore, funding liquidity is more stable than bond market liquidity with less regime changes.

Our article offers interesting findings to market participants, since markets are more tightly interconnected in recent decades and liquidity factors play an increasingly important role in asset pricing (O'Hara, 2015). Our article offers useful policy implication too. Central bank monetary policy operations typically focus on the funding market. For instance, on 12 December 2007, the Bank of Canada, the Bank of England, the European Central Bank (ECB), the Federal Reserve and the Swiss National Bank jointly announced a set of measures designed to address elevated pressures in the funding markets, and to assess the effect of the establishment of these central bank liquidity facilities on the corporate bond market liquidity. Our article provides evidence that funding liquidity affects market liquidity in different magnitude and direction between stressed and normal regimes, and market liquidity affects funding liquidity in different magnitude but in the same direction between stressed and normal regimes. Thus, we offer further insight on the important mechanism by which central banks can improve market liquidity through the funding market.

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DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from FINRA, REFINITIVE EIKON Datastream and Bloomberg. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with the permission of FINRA, REFINITIVE EIKON Datastream and Bloomberg.

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ENDNOTES

[1] The U.S. corporate bond market has $8.5 trillion issues outstanding in 2016 (SIFMA Research, 2017).

[2] This is proxied by the change in the Barclays credit default swap spreads index in the US market.

[3] This is proxied by the CBOE/CBOT 10-Year U.S. Treasury Note Volatility Index.

[4] Macchiavelli and Zhou (2019) and Rapp (2018) investigate the impact of dealers' funding constraints on their liquidity provision in the U.S. corporate bond market. Differ to their studies, our article focuses on how the market-wide funding liquidity (i.e., money market liquidity), as a general financial market condition, is related to the U.S. corporate bond market liquidity.

[5] There are a number of studies review the role of liquidity in the 2007–2008 financial crisis. See, for example, Brunnermeier (2009), Chiu, Chung, Ho, and Wang (2012), Dick-Nielsen et al. (2012) and Rösch and Kaserer (2013).

[6] The finalization of the TRACE system has been through several stages. At the beginning stage, only trades of all investment-grade issues and a limited amount of high yield bonds were required to be reported. More high yield bonds were included in the system in the later stage and by 2004, 99% of all trades were disseminated.

[7] USD Libor is the average interbank interest rate at which a large number of banks on the London money market are prepared to lend one another unsecured funds denominated in US Dollars.

[8] Both ΔML and ΔFL are stationary in the Dickey–Fuller test unit root test, making the use of the time series fits in the assumption of Markov regime-switching model.

[9] We are very grateful to the reviewer for the suggestion of including credit rating of bonds as a control factor in our model.

[10] The data is from Bloomberg Barclays CDX.NA.IG.

[11] The Wald test on the linear regression of Equation (2) without QE shows a significant structure break of the estimated coefficients on 7 August 2007, coinciding with the 2007 subprime mortgage market crisis.

[12] The Wald test on the linear regression of Equation (4) without QE shows a significant structure break of the estimated coefficients on 16 October 2008, coinciding with the 2008 financial market meltdown.

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APPENDIX A.

TABLE A1 Estimates of the linear regressions on the FL-to-ML impact and ML-to-FL impact

Independent variable	FL-to-ML impact		ML-to-FL impact	
	ΔML	**Coefficients**	***ΔFL***	**Coefficients**
	ΔFL	**0.239**	*ΔML*	**0.581**
	ΔCDX	**0.011**	*ΔCDX*	0.001
	QE	−0.001	*QE*	**−0.008**
	Constant	−0.001	Constant	**0.006**
	Adj_R^2	0.27	Adj_R^2	0.18

Note: This table presents the estimates of a linear regression version of Equations (2) and (3). The variables are defined in Table 2. The estimates in bold refer to an, at least, 5% significance level.