Time-varying Funding Liquidity and the Corporate Bond Market Liquidity: An Non-linear Approach

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Abstract

The time-varying relationship of funding liquidity (FL) and market liquidity (ML) postulated in theoretical literature calls for a non-linear empirical examination. By using a Markov regime-switching model and the US transaction-level TRACE data of corporate bonds from 2004 to 2013, we find that high funding liquidity risk decreases market liquidity risk in normal times, but increases it in times of market stress. The impact of funding liquidity risk on market liquidity risk in stressed times is much greater, by a factor of 4.5, than in normal times. The regime-switching relationship between funding liquidity risk and market liquidity risk is driven by the tightness of the funding market and by the equity market volatility. Further linear robustness tests not only confirm the findings of the non-linear approach, but also show that FL risk and ML risk exhibit Granger causality, and that FL risk can drive ML risk for periods up to one week.

Keyword: Funding Liquidity, Bonk Market Liquidity, Market Volatility, Markov Regime-switching Model.
JEL Codes: C1, E5, G1

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1. Introduction

Firms that invest in securities finance their trades through borrowing on either an unsecured or a secured basis. The ease with which they can obtain funding affect their willingness and ability to provide market liquidity (i.e. the ease with which securities are traded). The textbook example of the 2008 financial crisis illustrates that a sharp deleveraging of dealers' repo books coincides with an increase in Treasury bonds' bid-ask spreads (see Dudley 2016). Several financial crises in recent decades have been triggered by liquidity shocks. However, no sufficient attention has been paid to the interactions of market and funding liquidity until recent years, given that the co-movement of the two would potentially make the financial system more fragile.

Theoretical works elaborate the time-varying relationship of funding liquidity (FL) and market liquidity (ML) (see, for example, Brunnermeier and Pedersen 2009), which calls for a non-linear approach in the empirical examination. In this respect, we employ a Markov regime-switching model to investigate the linkage of FL and ML in the US corporate bond market in the period of 2004 – 2013, during which the market went through both normal and stressed times. Another challenge in the literature is that ML is hard to capture, since ML consists of a few dimensions. That said, how easily a trader can trade his desired quantity, immediately, without moving the market price. If liquidity is less than perfect, the trader must sacrifice on one or more of these three dimensions (see Moulton 2005). To tackle this issue, we construct a composite ML measure that combines the dimensions of price impact and transaction cost of ML through a principal component analysis. We calculate a composite FL measure in the similar manner based on the TED spread and Libor-OIS spread.

We find that the risks of FL and ML, indeed, exhibit Granger causality. Most importantly, the way that the two types of liquidity risk interact in stressed times contrasts to that of in normal times. The result of the Markov regime-switching model shows that high funding liquidity risk lowers market liquidity risk in normal times, whereas it increases market liquidity risk in stressed times with a magnitude exceeding that of in normal times at a factor of 4.5. Those time-varying impacts of FL risk on ML risk are both statistically and economically significant. For example, the coefficients of FL risk in low/high VIX market conditions is -0.091 （t-statistic -4.907） and 0.41（t-statistic 17.557), respectively.

Consistent with the literature, the regime-switching is indicated by the tightness of funding liquidity and equity market volatility. Further linear tests not only confirm the finding in the Markov regime-switching model, but also show that, overall, FL risk can drive ML risk for periods up to one week.

The contributions of our study are threefold. Firstly, we use a Markov regime-switching model with regime indicators to examine the dynamic relationship of FL risk and ML risk, where regime classification in this model is probabilistic and determined by data. A handful of empirical studies have investigated the relationship of FL and ML, but only within a linear framework - in that framework, choosing the threshold value to classify regimes is a difficult and usually subjective task. Secondly, using Markov regime-switching model also allow us to estimate the probability of regime change. Hence, we can demonstrate the market conditions that will induce being in a positive FL and ML relationship. Thirdly, we utilise a new composite measure for FL and ML based upon a principal component analysis, which allows us to capture the most significant features of liquidity with a single measure. Finally, our study is the first paper to explore the dynamic relationship of FL and ML in the bond market during the period in which the market has experienced the dramatic changes associated with the 2008 financial crisis.

The co-movement of market liquidity and funding liquidity has received growing attention from central bankers and academics in recent years (see Dudley (2016) and Brunnermeier and Pedersen (2009) among others). One main reason is the desire to learn lessons from the financial crises of recent decades, for example, the crises following the collapse of Lehman Brothers in 2008 and LTCM in 1998. It was observed that the sudden drying-up of funding liquidity, triggered by the 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.

The second reason is the desire within central banks, acting as the lender-of-last-resort, to gain a much better understanding of the dynamics of both FL and ML, especially when markets are experiencing negative shocks. That should lead to a better awareness of how central banks can provide a funding liquidity "backstop" in order to improve market liquidity. Finally, with the expectation of the end of near zero-interest-rate monetary policy in the US and other advanced economies, rising interest rates will cause bond prices to fall and is expected to generate selling pressure. In this case, maintaining a liquid market is pivotal to financial market stability. Focusing on those academic and policy interests, our study elaborates the dynamic relationship of FL and ML, and attempts to demonstrate a channel that central banks can use to support market liquidity through funding markets.

Moreover, since equity financing is more expensive and speculators tend not to carry excess capital, higher margins (which is financed by capital) due to market stress force speculators to de-leverage their positions by selling part of their financial assets. The liquidation of a speculator's positions can reduce other investors' net worth through price effects, and deteriorate market liquidity. Declines in market liquidity, in turn may further impair funding liquidity, creating a negative feedback dynamic (see Dudley 2016).

We present our study as follows. Firstly, we use a composite ML measure for US corporate bonds, that is constructed by combining 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 calculated from 2004 to 2013 using TRACE data on individual bond transactions. Similarly, we construct a composite FL measure for US funding market by combining the first principal component of two funding liquidity measures - Libor-OIS spread and TED spread. We then define the first difference of the composite ML and FL measures as the ML risk (ΔML) and FL risk (ΔFL).

Secondly, we split the whole sample period into pre-crisis period (January 2002 – July 2007, a normal period), crisis period (August 2007 – December 2008, a stressed period) and post-crisis period (January 2009 – September 2013, a normal period), and conduct a 20-lagged VAR Granger causality test on ΔML and ΔFL in each sub-period. The result shows that market liquidity risk and funding liquidity risk Granger causes each other in each sub-period. In addition, with an attempt to select suitable regime indicators for the time-varying relationship of FL and ML, we regress the correlation coefficient of the composite ML and FL measures (in a 22-day moving average window) on a few state variables (i.e. default risk, the FED funds rate and a measure of the US quantitative easing scheme). We find that US equity market volatility (proxied by the VIX index) is the only significant factor that drives the correlation between ML and FL over the whole sample period.

Thirdly, we employ a Markov regime-switching model where FL and VIX are regime predictors, and find that ML risk decreases with FL risk in the normal regime featured with high FL or low market volatility. However, ML risk increases with FL risk in the stressed regime featured with low FL or high market volatility. The magnitude of FL risk impact on ML risk is greater than it is in normal regimes by a factor of 4.5. We further conduct a robust test by using a linear regression model, where a dummy variable referring to high/low FL in each of the three sub-periods. The result confirms the finding in the Markov regime-switching model, and also shows that FL risk can drive ML risk for periods up to one week.

Our study depicts the market mechanism in-depth on the time-varying relationship of FL and ML, as elaborated in Brunnermeier and Pedersen (2009). When the market is less volatile and it is easy to borrow money to trade, financiers - who set the margin – enjoy an advantage of accessing and evaluating information. Hence, they become more informed about fundamental values and expect that prices will likely equal fundamentals in the next period. They might set low margins (i.e. high funding liquidity) because they expect bond dealers can profit when prices return to fundamentals in the next period. This profit not only “cushions” dealers from losses due to price volatility, but also stimulates them to continuously supply liquidity to the bond market, resulting in a negative relation between FL risk and ML risk. However, a volatile market means there is a wider spectrum of investors’ expectation of the fair prices due to the greater uncertainty about price levels. Consequently, there is no substantial advantage for financiers from having information. They become less informed about fundamentals, tend to interpret price volatility as fundamentals, and set higher margin (i.e. higher funding costs). Since dealers have to pay more to warehouse bonds, they might reduce inventory and liquidity supply to the market.

Our paper is related to 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 can 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.

This paper proceeds as follows. Section 2 discusses the related literature. Section 3 describes the data, especially the cleaning of TRACE data, as well as the method to calculate the ML and FL measures. Section 4 conducts a VAR Granger causality analysis on the co-movement of ML and FL risk. Section 5 and Section 6 examine the time-varying relationship of ML and FL risk in a Markov regime-switching model and an OLS linear regression model, respectively. Section 7 briefly summarises our 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.

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 forces 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. Other theoretical models also predict that large market declines cause agents liquidate their positions across many assets and reduce liquidity supply, because liquidity providers hit their capital or funding constraints (see Hameed *et al*. (2010) for a detailed review).

While the theoretical literature has laid out the regime-dependant connection between market liquidity and funding liquidity (i.e. traders' funding constraints), the extant empirical literature mainly investigate this in a linear approach, focusing on stock and foreign exchange (FX) markets. For example, Chordia et al. (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 et al. (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 et al. (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 characterised 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 the best of our knowledge, none of the existing empirical studies examine the dynamic relationship of market liquidity and funding liquidity in a non-linear framework, and address this on the US bond market when the market has gone through dramatic changes in the pre- and post-2008 financial crisis. Inspired by the theoretical literature, we use both a Markov regime-switching model and a linear regression model to investigate the following hypotheses in the US corporate bond market:

Hypothesis 1: Funding liquidity risk and market liquidity risk Granger causes each other (i.e., they are interlinked).

Hypothesis 2: High funding liquidity risk decreases (increases) market liquidity risk in normal (stressed) regimes, when the regimes are characterised by the tightness of the funding market and by equity market volatility.

3. Liquidity measures and data

In this section, we first describe the TRACE data and other data used in the study, then we will show 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 US Trade Reporting and Compliance Engine (TRACE) Enhanced database, which has the most comprehensive coverage of the bond market in the US.[2] This database was the result of regulatory initiatives more than a decade ago to increase price transparency in the US corporate bond market. Reporting began in July 2002, but was at first limited to selected investment-grade bonds. However, it became comprehensive from October 2004. TRACE data is disseminated through two databases. 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 \$1000 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. We further exclude non-business dates from the sample, following the Securities Industry and Financial Markets Association (SIFMA) US Holiday Recommendations.

The following regression analyses involve variables of the Chicago Board Options Exchange Volatility Index (VIX), the Federal Fund Rate and the default spread of US corporate bonds (i.e. the difference between BAA and AAA-rated corporate bond yields). We obtain the data from Datastream.

3.2 Market liquidity measures

For the US corporate bond market, we compute the following two measures of market liquidity using transaction-level TRACE dataset, at the level of 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 trading volume that day. This measure is intended to indicate the price

[2]The finalisation 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.

impact of trades. Following Dick-Nielsen et al. (2012), we estimate the price impact at the level of individual trades for each bond, and average over the trade-level values each day to obtain a measure at daily frequency for that bond. More precisely, the Amihud measure that we construct is defined as follows. For a given bond on a given day t, define $r_{i,t}$ to be the return and $Q_{i,t}$ to be the trade size (in $ million) of the *i*-th trade, and define N_t to be 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 price, 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, define $r_{i,t}$ to be the return on the *i*-th trade. Our implementation of the Roll measure is then defined as:

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

Similarly 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 (due to less than 4 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 1. (a) shows the Amihud and Roll measures. Both measures develop in a similar time-series pattern over the sample period, showing that liquidity deteriorated markedly during the 2008 financial crisis, but 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 standardised before their principal component is extracted. We label this composite market liquidity measure as Market Liquidity (ML), and define the first difference of ML over time, i.e. $\Delta ML = ML_t - ML_{t-1}$, as market liquidity risk. We will use these definitions of market liquidity and market liquidity risk in the rest of the paper.

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[3] 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 and Pedersen 2011 and Nyborg and Östberg 2014). We obtain the data from the Federal Reserve Bank in St. Louis.

- Libor-OIS spread: Libor-OIS spread is the difference between three month USD Libor and the three 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 and Östberg 2014).

Figure 1 (b) 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 (FL), and define the first difference of FL, i.e. $\Delta FL = FL_t - FL_{t-1}$, as funding liquidity risk. We will use these definitions of funding liquidity and funding liquidity risk in the rest of the paper.

Figure 1 (c) shows the 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 Hypothesis 2.

Figure 1 (d) further displays the risks of ML and FL on a 22-day moving average (i.e., equivalent to a monthly average). Visually, while FL risk spikes up during 2007 – 2008 financial crisis period but maintains a low level in the pre- and post-crisis periods, ML risk has a tendency of decline over the sample period, though it also spikes up during the crisis period. The decline of ML risk in the post-crisis period relative to the pre-crisis period may be due to the US Quantitative Easing (QE) programme implemented from 1-Dec-2008, in which the US 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, for example, Christensen and Gillan 2016). We therefore include QE as a control variable in the regression analysis for the relationship of ML and FL in the following sections.

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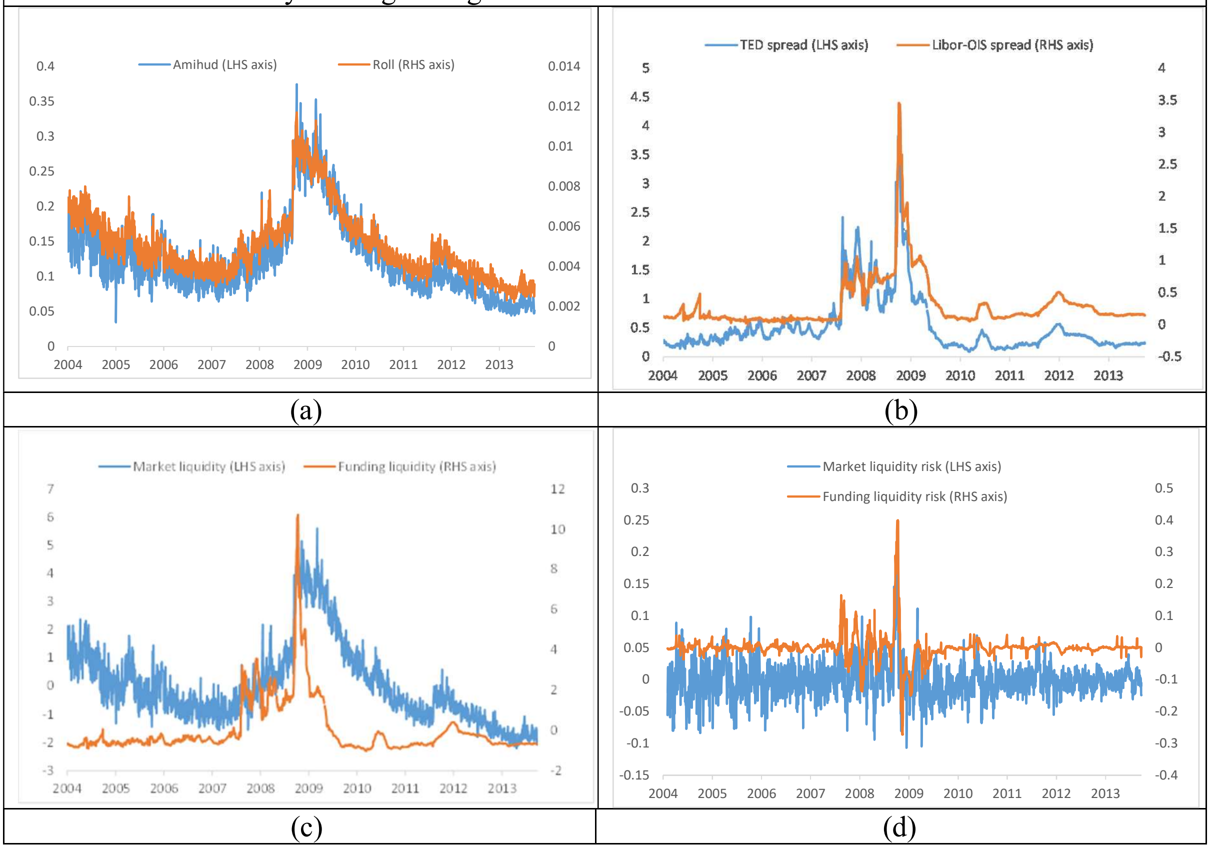
[3]USD Libor is the average interbank interest rate at which a large number of banks on the London money market are prepared to lend one another unsecured funds denominated in US Dollars.

Figure 1. The US corporate bond market liquidity measures and funding liquidity measures from January 1, 2004 to September30, 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 US 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 risks of ML and FL on a 22-day moving average.



4. The interlink of market and funding liquidity

In this section, we use a Vector Autoregression (VAR) Granger causality test to test Hypothesis 1 that FL and ML are interlinked. We specify the VAR as

$$Y_t = \alpha + \beta(L)Y_t + \delta VIX_t + \varepsilon_t \qquad (1)$$

where Y_t is 2×1 matrix specifying the endogenous VAR variables, i.e., market liquidity risk (ΔML) and funding liquidity risk (ΔFL) as defined in Section 3, (L) is the lag operator and the VAR is set to 20 lags, VIX is the exogenous variable, and t is trading day.

We investigate whether or not ΔFL Granger causes ΔML, and/or the other way round over 20 lags. In the VAR system that ΔFL is the causing variable, a rejection to the null hypothesis that all the coefficients on ΔFL lags equal to zero implies that ΔFL Granger causes ΔML. Similarly, in the VAR system that ΔML is the causing variable, a rejection to the null hypothesis that all the coefficients on ΔML lags equal to zero implies that ΔML Granger causes ΔFL.

Table 1 shows that, for each of the three sub-periods, the null hypothesis has been strongly rejected with very small p-values. The result provides evidence for Hypothesis 1 that funding and market liquidity risks are interlinked, regardless of the market conditions.

Table 1. VAR Granger causality test on the changes in Market Illiquidity (ΔML) and the changes in Funding liquidity (ΔFL). We use the VAR of equation (1) for a Granger causality test on ΔML and ΔFL:

$$Y_t = \alpha + \beta(L)Y_t + \delta VIX_t + \varepsilon_t \qquad (1)$$

where Y_t is 2×1 matrix specifying the endogenous VAR variables, (ΔML, ΔFL), (L) is the lag operator and the VAR is set to 20 lags, VIX is the exogenous variable, and t is trading day.

	pre-crisis period	crisis period	post-crisis period
Panel A. Test of ΔFL affects ΔML			
χ^2(All coefficients on ΔFL lags = 0)	38.38	37.61	34.00
p -value	0.01	0.01	0.03
Panel B. Test of ΔML affects ΔFL			
χ^2(All coefficients on ΔML lags = 0)	39.55	33.26	61.69
p -value	0.01	0.03	0.00

Since FL and ML risks are correlated to each other regardless of market conditions, a natural question is raised on what drives this correlation. We regress the correlation coefficient of FL and ML on the state variables of market volatility (VIX), default risk (ΔDEF), changes in Federal Fund Rate (ΔFed), and a dummy variable that refers to the period with the implementation of the US quantitative easing programme (QE). Equation (2) below presents the regression model and the estimation result.

$$\underset{(-5.22)^{***}}{Corr_t = -0.028} + \underset{(5.02)^{***}}{0.001VIX_t} + \underset{(1.27)}{0.113\Delta DEF_t} + \underset{(-1.28)}{0.033\Delta Fed_t} + \underset{(0.06)}{0.0002QE} + \gamma X_t \qquad (2)$$

$Adj.\ R^2 = 0.93$

where $Corr_t$ is the correlation coefficient of ML and FL calculated at a 22-day moving average window, t is the trading day, VIX_t is the Chicago Board Options Exchange Volatility Index, ΔDEF_t is the change in default yield spread (i.e., the difference between BAA and AAA-rated corporate bond yields), ΔFed_t is the change in Federal Fund Rate that is calculated as the difference between the returns on US long-term investment grade bond index and the US 10-year government bond index, QE is the dummy variable with value of 0 if trading date is before 01-Dec-2008 and of 1 otherwise, X_t consists of two lags of the dependent variable, which is sufficient to control residuals autocorrelation.

The regression result shows that market volatility (VIX) is the only significant driving factor of the correlation coefficient of FL and ML, in which an increase in VIX will increase the correlation of FL and ML. Since VIX is usually regarded as an indicator of equity market stress, our result implies that market stress conditions determine a positive correlation of FL and ML. Our result is also consistent with Fleming et al. (1998), in which the authors find a strong volatility linkage between the stock, bond and money markets, especially since the 1987 stock market crash. In the following sections, we will elaborate this implication in a Markov regime-switching model, where market volatility serves as a regime predictor.

5. The time-varying relationship of funding and market liquidity risks: A non-linear approach

Hypotheses 2 implies that funding and market liquidity risks have a state-dependent relationship, and high funding liquidity risk can deteriorate market liquidity risk in a state of high market volatility and/or funding illiquidity, but will increase or have no impact on market liquidity risk in a state of low market volatility and funding illiquidity.

Our hypothesis call for two important features of the empirical model: state-dependent relationship of funding liquidity risk (ΔFL) and market liquidity risk (ΔML), and the use of FL and VIX as indicators for the relationship states. In order to further elaborate the non-linear relationship of ΔFL and ΔML, we follow Watanabe and Watanabe (2007) and use a Markov regime-switching model to accommodate these features in our empirical investigation. We specify the model as follows:

$$\Delta ML_t = \alpha_{S_t} + \beta_{S_t}\Delta FL_t + \boldsymbol{\delta} QE_t + \varepsilon_{S_t,t}, \quad s = 1,2 \quad and \quad \varepsilon_{S_t,t} \sim (0, \sigma^2_{S_t}) \tag{3}$$

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

$$\Pr(s_t = s | s_{t-1}; Predictor_{t-1}) = \frac{\exp\left(c_{s_t} + d_{s_t} \cdot Predictor_{t-1}\right)}{1 + \exp\left(c_{s_t} + d_{s_t} \cdot Predictor_{t-1}\right)}, \qquad s = 1,2 \tag{4}$$

where $Predictor_{t-1}$ is $FL_{t-1}$and VIX_{t-1} respectively, c_{s_t} and d_{s_t} are scalars. $Predictor$ is used as a state variable to help predict the FL-ML relationship states. The exponential transformation ensures that the transition probability always falls between 0 and 1. To avoid the daily time series are too volatile to define market regimes, we define all the time series in Equations (3) and (4) as a 22-day moving average (i.e. equivalent to a monthly average).

Panel A in Table 2 presents the estimated parameters of the Markov regime-switching model where the state predictor is funding liquidity (FL). We observe significant negative (positive) relationship of FL risk and ML risk in state 1 (2), where state 2 is featured with high volatility ($\sigma_1 < \sigma_2$). The likelihood ratio test (LR test) strongly rejects the null hypotheses that $\beta_1 = \beta_2$ and $\sigma_1 = \sigma_2$. In addition, the magnitude of β_2 exceeds that of β_1 by a factor of 4.5, implying that FL risk hits ML risk more seriously when the funding liquidity is tight.

Furthermore, FL significantly predicts the negative- and positive-relationship states of FL and ML. The significant d_1 coefficient of FL implies that high funding illiquidity tends to reduce the probability of staying in the negative FL-ML relationship state and consequently moves to the positive FL-ML relationship state. The LR test strongly rejects the null hypothesis that $d_1 = d_2 = 0$ with p-value of zero. These findings support Hypotheses 2.

Panel A in Figure 2 plots the estimated probability of being in state 2 (i.e. a positive FL-ML relationship state), in which FL is the state indicator. It is visually clear that the high probability of being in state 2 clusters in 2007-2008 crisis period and around 2011, no doubt due to the Euro-debt crisis. This is consistent with Hypothesis 2 that a tightened funding market deteriorates market liquidity when market is in stress. In addition, the high probability of being in state 2 is visually less frequent in the post-crisis period relative to the pre-crisis period. Meanwhile, the estimated coefficient of the state-independent variable QE is -0.005 at the 1% significance level. This implies that the post-crisis US QE programme has improved market liquidity. Hence the market liquidity risk is lower in the post-crisis period than the pre-crisis period when no QE was implemented, leading to a less frequent high probability of being in state 2 during the post-crisis period.

Alternatively, we use market volatility as an indicator of market stress to predict ΔFL-ΔML relationship states. Panel B in Table 2 presents the estimated parameters of the Markov regime-switching model where the state predictor is market volatility index (VIX), and Panel B in Figure 2 plots the associated estimated probability of being in state 2. These results are quantitatively and qualitatively the same as those in which FL is the state predictor.

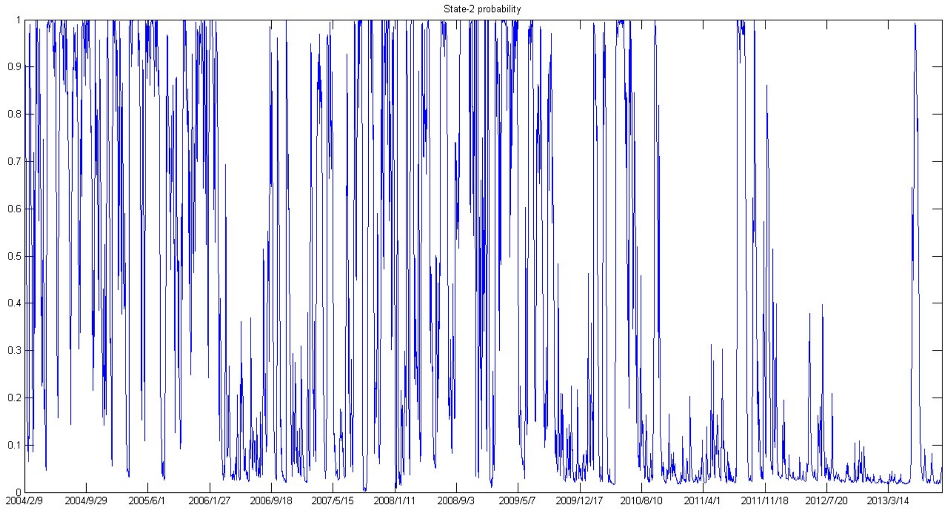
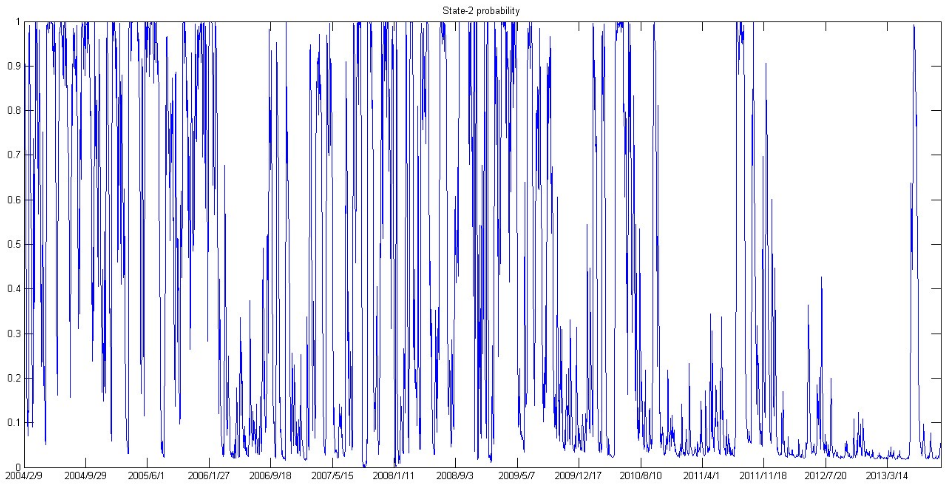
The result depicts an interesting market mechanism. Financiers (e.g. security lenders, brokers) - who set collateral lending margins – have the advantage of accessing and evaluating information efficiently. In normal times, there is sufficient information available to the market so that securities can be evaluated precisely. Hence the range of investors' expectation on fair prices is narrow. This is reflected by a low price volatility. Under these market condition, financiers are well-informed about fundamentals. They know that prices will be based on fundamentals in the next period, therefore they set lower margin (i.e. high funding liquidity) since they expect bond dealers, who buy low and sell high, can profit when prices return to fundamentals in the next period. This profit not only "cushions" dealers from losses due to fundamental volatility, but also stimulates them to continuously supply liquidity to the market, resulting in a negative relationship between FL risk and ML risk. However, in stressed times when the market has had a negative shock, there is less information available, and financiers are relatively ill-informed about fundamentals. They are inclined to interpret price volatility as fundamental volatility, thus set higher margin (i.e. low funding liquidity) to compensate for high price volatility. High margins increase dealers' funding costs to warehouse bonds, causing a reduction in the liquidity supply to the bond market. Our findings also lend evidence to Brunnermeier and Pedersen's (2009) prediction.

Table 2. Estimated parameters of the Markov regime-switching model

This table shows estimated parameters and corresponding t-statistics (in parentheses) of the Markov regime-switching model in Equation (3). The sample period is from January 5, 2004 to September 30, 2013. Panel A and Panel B report the results in which the regime predictor is Funding liquidity (FL) and VIX, respectively. T-statistics are in parentheses. The table also shows chi-square statistics and *p*-value (in parentheses) for the likelihood ratio tests (LR Tests) on various parameter restrictions; Max LK is the maximized log likelihood. ***, ** and * denote the significance level at 1%, 5% and 10%.

Parameters			Common Parameters		
Panel A. State predictor: Funding liquidity (FL)					
α_1	-0.002	(-1.523)	c_1	3.344	(15.640)***
α_2	0.001	(0.643)	c_2	2.897	(11.006)***
β_1	-0.092	(-4.827)***	d_1	-0.472	(-3.910)***
β_2	0.412	(17.49)***	d_2	-0.167	(-1.578)
σ_1	0.015	(32.639)***	QE	-0.005	(-4.093)***
σ_2	0.036	(28.873)***			
LR Tests			Common LR Tests		
$\beta_1 = \beta_2$	106.121	(0.000)***	$d_1 = d_2 = 0$	11.734	(0.000)***
$\sigma_1 = \sigma_2$	149.096	(0.000)***			
Max LK (Per Period)			5246.430 (2.352)		
Sample Period (N Obs)			200401:201309 (2322)		
Panel B. State predictor: VIX					
α_1	-0.002	(-1.526)	c_1	4.361	(9.468)***
α_2	0.001	(0.519)	c_2	3.514	(6.754)***
β_1	-0.091	(-4.907)***	d_1	-4.893	(-2.835)***
β_2	0.410	(17.557)***	d_2	-2.907	(-1.739)*
σ_1	0.015	(32.423)***	QE	-0.005	(-4.254)***
σ_2	0.036	(28.995)***			
LR Tests			Common LR Tests		
$\beta_1 = \beta_2$	106.915	(0.000)***	$d_1 = d_2 = 0$	6.410	(0.000)***
$\sigma_1 = \sigma_2$	150.273	(0.000)***			
Max LK (Per Period)			5243.768 (2.35)		
Sample Period (N Obs)			200401:201309 (2322)		

Figure 2. Time series plots of the estimated probability of being in State 2

Panel A. State predictor: Funding liquidity (FL)

Panel B. State predictor: VIX


6. The relationship of funding and market liquidity risks: A robust test in a linear approach

In this section, we conduct a robust test for the result presented in section 5. Our long sample period of 2004 – 2013 go through the crisis period of 2007-2008 when the market was in stress, as well as non-crisis period. This allows us to investigate the time-varying relationship of FL and ML across different market conditions. In section 4, we show that equity market volatility drives the correlation of FL and ML. We therefore split the sample period into three sub-periods: the pre-crisis period of 5-January-2004 to 31-July-2007, the crisis period of 1-August-2007 to 22-December-2008 and the post-crisis period of 5-January-2009 to 30-September-2013[4], of which the average daily value of VIX is 14, 29 and 22, respectively.

[4]We follow Drehmann and Nikolaou (2013) to define the pre-crisis period and crisis-period.

Obviously this implies that the market stress is high in the crisis period, but relatively low in the pre- and post-crisis periods.

To see how the relationship of the risks of FL and ML vary across market conditions, we regress ΔML on ΔFL in the three sub-periods. Equation (5) presents the regression model.

$$\Delta ML_t = \alpha + \sum_{k=0}^{3} \beta_k \, \Delta FL_{t-k} + \boldsymbol{\delta}(\Delta VIX_t, \Delta DEF_t, \Delta Fed_t, X_t) + \varepsilon_t \tag{5}$$

where ΔML and ΔFL are the market liquidity risk and funding liquidity risk that are defined in Section 3, the control variables of $\Delta VIX_t, \Delta DEF_t$ and ΔFed_t are suggested in the literature (see Pelizzon et al. 2016, Borio 2000, and Chordia et al. 2001) and are defined in Equation (2), X_t consists of 4 lags of the dependent variable in order to control the residual autocorrelation.

Table 3 presents the multiple regression results of Equation (5) in the pre-crisis period, where the control variables are included in the regressions sequentially. The estimated coefficients of FL risk (ΔFL_t) are consistent across the 6 sub-regresses in terms of the sign and significance level. We focus our discussion on the sub-regression (6) that obtains the highest value of the adjusted R^2. The estimated coefficient of ΔFL_t is -1.284 and significant at the 1% level, implying that a decrease in funding liquidity risk simultaneously comes with a higher market liquidity risk. The sum of the estimated coefficients of ΔFL up to lag 3 is -0.106, which means that, overall, a fall in funding liquidity risk could reduce market liquidity risk within one week. The result confirms our finding in section 5.

It is worth noting that the estimated coefficients of ΔFL_{t-2} and ΔFL_{t-3} are positive and significant at the 1% level. This implies that market liquidity risk over-reacts to funding liquidity risk on day t, then starts to adjust two or three days later. That said, while an increase in funding liquidity risk reduces market liquidity risk simultaneously or one day in advance, it pushes up market liquidity risk over a longer time (i.e., over a few days). The return to a positive relationship of the two liquidity risks over a longer time could be due to two reasons. Firstly, the value of information declines as time elapses, therefore, financiers may be better informed about the fundamentals over a shorter period but not so much over a longer period. Secondly, margins can be adapted to market conditions on a daily basis and margin lending is short term. Hence, it is likely that financers can set lower margins even if market liquidity risk is high in a shorter period, but not so over a longer period.

Table 3. The relationship of market and funding liquidity risks in the pre-crisis period
This table presents the coefficients estimates of Equation (5) in the pre-crisis period of January 5, 2004 to July 31, 2007. The dependent variable is market liquidity risk (ΔML_t) as defined in Section 3. Among the independent variables, ΔFL_t is the funding liquidity risk as defined in Section 3, ΔVIX_t is the change in VIX, ΔDEF_t is the change in default yield spread (i.e., the difference between BAA and AAA-rated corporate bond yields), and ΔFed_t is the change in Federal Fund Rate. T-statistics are in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔFL_t	-1.460	-1.398	-1.267	-1.263	-1.288	-1.284
	(-6.62)***	(-6.19)***	(-5.51)***	(-5.50)***	(-5.60)***	(-5.60)***
ΔFL_{t-1}	-0.365	-0.279	-0.138	-0.158	-0.173	-0.234
	(-1.61)	(-1.19)	(-0.58)	(-0.67)	(-0.74)	(-0.99)
ΔFL_{t-2}		0.434	0.633	0.642	0.635	0.626
		(1.90)*	(2.71)***	(2.75)***	(2.72)***	(2.69)***
ΔFL_{t-3}			0.783	0.762	0.770	0.786
			(3.41)***	(3.32)***	(3.36)***	(3.43)***
ΔVIX_t				2.975	2.793	2.762
				(2.06)**	(1.92)*	(1.91)*
ΔDEF_t					-1.551	-1.587
					(-1.47)	(-1.50)
ΔFed_t						0.575
						(2.17)**
Constant	-0.002	-0.002	0.000	-0.000	-0.000	-0.003
	(-0.13)	(-0.13)	(0.02)	(-0.00)	(-0.01)	(-0.25)
Adj. R^2	0.3464	0.3491	0.3615	0.3641	0.3651	0.3681

Table 4 presents the multiple regression results of Equation (5) in the crisis period. Similarly to Table 3, the control variables are included in the regressions sequentially. The estimated coefficients of FL risk (ΔFL_t) are consistent across the 6 sub-regresses in terms of the sign and significance level. We focus our discussion on the sub-regression (3) that obtains the highest value of the adjusted R^2. The estimated coefficient of ΔFL_t is 0.197 and significant at the 1% level, implying that an increase in funding liquidity risk simultaneously comes with an increase in market liquidity risk. The sum of the estimated coefficients of ΔFL up to lag 3 is 0.49, which means that, overall, a rise in funding liquidity risk could lift up market liquidity risk within one week. The result confirms our finding in section 5 too.

Table 4. The relationship of market and funding liquidity risks in the crisis period
This table presents the coefficients estimates of Equation (5) in the crisis period of August 1, 2007 to December 22, 2008. The dependent variable, i.e. market liquidity risk (ΔML_t) and all independent variables are defined in Table 3. T-statistics are in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔFL_t	0.170	0.191	0.197	0.181	0.181	0.181
	(2.27)**	(2.55)**	(2.60)***	(2.31)**	(2.31)**	(2.32)**
ΔFL_{t-1}	0.203	0.162	0.160	0.163	0.163	0.174
	(2.69)***	(2.09)**	(2.02)**	(2.07)**	(2.07)**	(2.18)**
ΔFL_{t-2}		0.152	0.161	0.166	0.156	0.153
		(2.03)**	(2.06)**	(2.12)**	(1.96)*	(1.92)*
ΔFL_{t-3}			-0.028	-0.032	-0.035	-0.038
			(-0.37)	(-0.42)	(-0.46)	(-0.49)
ΔVIX_t				0.620	0.473	0.375
				(0.80)	(0.59)	(0.47)
ΔDEF_t					-0.558	-0.562
					(-0.88)	(-0.89)
ΔFed_t						0.130
						(1.06)
Cons	0.019	0.019	0.021	0.021	0.017	0.019
	(0.79)	(0.79)	(0.89)	(0.88)	(0.70)	(0.79)
Adj. R^2	0.1674	0.1791	0.1793	0.1783	0.1777	0.1780

Table 5 presents the multiple regression results of Equation (5) in the post-crisis period. Similarly to Table 3, the control variables are included in the regression sequentially. The estimated coefficients of FL risk (ΔFL_t) are consistent across the 6 sub-regresses in terms of the sign and significance level. We focus our discussion on the sub-regression (5) that obtains the highest value of the adjusted R^2. Although the estimated coefficient of ΔFL_t is -0.220 and insignificant, the estimated coefficient of ΔFL_{t-1} is -0.945 and significant at the 1% level. This provides the same implication as in Table 3 though the implication is slightly weaker. Bear in mind that the daily average of VIX in the post-crisis period is higher than that of in the pre-crisis period (but lower than the crisis period), the finding in the post-crisis period is still consistent with the result in section 5. In addition, the impact of ΔFL_{t-3} on ΔML is positive, and the overall one-week reaction of market liquidity risk to funding liquidity risk is 0.134 (i.e. the sum of the estimated coefficients of ΔFL up to lag 3), with similar interpretation to that in the pre-crisis period in Table 3.

Table 5. The relationship of market and funding liquidity risks in the post-crisis period
This table presents the coefficients estimates of Equation (5) in the post-crisis period of January 5, 2009 to September 30, 2013. The dependent variable, i.e. market liquidity risk (ΔML_t) and all independent variables are defined in Table 3. T-statistics are in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔFL_t	0.136	0.014	-0.125	-0.125	-0.220	-0.209
	(0.53)	(0.05)	(-0.47)	(-0.47)	(-0.83)	(-0.79)
ΔFL_{t-1}	-0.534	-0.828	-0.908	-0.904	-0.945	-0.927
	(-2.09) **	(-3.09)***	(-3.36)***	(-3.35)***	(-3.51)***	(-3.43)***
ΔFL_{t-2}		0.858	0.669	0.683	0.644	0.633
		(3.33)***	(2.47)**	(2.51)**	(2.38)**	(2.34)**
ΔFL_{t-3}			0.692	0.694	0.655	0.669
			(2.68)***	(2.68)***	(2.54)**	(2.59)***
ΔVIX_t				0.406	0.391	0.374
				(1.01)	(0.97)	(0.93)
ΔDEF_t					-1.094	-1.090
					(-3.41)***	(-3.39)***
ΔFed_t						0.479
						(0.75)
Cons	-0.012	-0.010	-0.008	-0.008	-0.006	-0.006
	(-1.53)	(-1.25)	(-1.05)	(-1.01)	(-0.79)	(-0.78)
Adj. R^2	0.2630	0.2700	0.2769	0.2769	0.2842	0.2839

To conduct a robust test on Hypothesis 2 that the non-linear relationship between funding and market liquidity risks is driven by the tightness of funding markets, we regress ML risk on FL risk over the whole sample period, with a dummy variable ($D_{LowFL_{t-1}}$) referring to the lowest one third of the funding liquidity (i.e. the top one third of the FL) and a dummy variable ($D_{High\quad t-1}$) referring to the highest one third of the funding liquidity (i.e. the bottom one third of the FL). Equation (6) is the regression model.

$$\Delta ML_t = \alpha + \beta \Delta FL_t + \boldsymbol{\delta}\begin{pmatrix} \Delta VIX_t, \Delta DEF_t, \Delta Fed_t, \\ \Delta FL_t * D_{LowFL_{t-1}}, \Delta FL_t * D_{HighFL_{t-1}}, X_t \end{pmatrix} + \varepsilon_t \tag{6}$$

Table 6 shows the multiple regression results of Equation (6). Similarly, the control variables are included in the regressions sequentially. The estimated coefficients of FL risk (ΔFL_t) and the two dummy variables are consistent across the 6 sub-regresses in terms of the sign and significance level. We focus our discussion on the sub-regressions (5) and (6) that obtain the highest value of the adjusted R^2. In the sub-regression (5), low level of funding liquidity significantly increases market illiquidity by 1.864. The sum of the coefficient of ΔFL_t and $\Delta FL_t * D_{LowFL_{t-1}}$ is 0.107 (= -1.657 + 1.864). This implies a positive relationship when the funding market is tight. On the contrary, in the sub-regression (6), high level of funding liquidity significantly decreases market illiquidity by 1.329. The sum of the coefficient of ΔFL_t and $\Delta FL_t * D_{HighFL_{t-1}}$ is -1.216 (= -1.329 + 0.113). This implies a negative relationship when the funding market is liquid. Our finding supports Hypothesis 2 and the result presented in section 5.

Table 6. The relationship of market and funding liquidity risks in high/low funding risk conditions
This table presents the coefficient estimates of Equation (6) in the whole sample period of January 5, 2004 to September 30, 2013. The dummy variables $D_{LowFLt-1}$ and $D_{HighFLt-1}$ refer to the observations of funding liquidity (FL, as defined in Section 3.2) at the top one third and the bottom one third, respectively. The dependent variable, i.e. market liquidity risk (ΔML_t) and other independent variables are defined in Table 3. T-statistics are in parentheses. ***, ** and * denote the significance level at 1%, 5% and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
ΔFL_t	0.110	-1.652	0.136	0.087	-1.657	0.113
	(2.06)**	(-8.14)***	(2.52)**	(1.61)	(-8.19)***	(2.07)**
ΔVIX_t				0.651	0.546	0.661
				(1.69)*	(1.44)	(1.72)*
ΔDEF_t				-1.148	-1.130	-1.142
				(-3.88)***	(-3.88)***	(-3.87)***
ΔFed_t				0.112	0.117	0.118
				(1.28)	(1.37)	(1.37)
$\Delta FL_t * D_{LowFL\ t-1}$		1.880			1.864	
		(8.99)***			(8.94)***	
$\Delta FL_t * D_{HighFL\ t-1}$			-1.320			-1.329
			(-3.50)***			(-3.54)***
Cons	-0.006	-0.004	-0.003	-0.005	-0.004	-0.003
	(-0.79)	(-0.53)	(-0.43)	(-0.76)	(-0.50)	(-0.40)
Adj. R^2	0.2452	0.2711	0.2489	0.2513	0.2768	0.2551

7. Conclusion and policy implications

Inspired by the recent debates and theoretical development on funding and market liquidity, we employ a Markov regime-switching model to investigate the time-varying relationship of funding liquidity and market liquidity. We make use of the US TRACE transaction-level data for corporate bonds during the period of January 2004 to September 2013. We find that funding liquidity risk is negatively (positively) related to corporate bond market liquidity risk in normal (stressed) market conditions. In particular, the impact of funding liquidity (FL) risk on market liquidity (ML) risk in stressed times is much greater, by a factor of 4.5, than in normal times.

The regime-switching relationship between funding liquidity risk and market liquidity risk is driven by the tightness of the funding market and the equity market volatility. Further linear tests not only confirm this finding in the non-linear approach, but also shows that FL risk and ML risk exhibit Granger causality regardless of market conditions. FL risk overall influences ML risk for periods up to one week.

Our findings have interesting policy implications. Central bank monetary policy operations typically focus on the funding market. For instance, on December 12, 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 funding markets. This article assesses the effect of the establishment of these central bank liquidity facilities on the corporate bond market liquidity. Our study provides strong evidence on how and to what extent funding liquidity is linked to corporate bond market liquidity. Thus we have provided insight on this important mechanism by which central banks can improve market liquidity via the funding market, and some additional clarity as to the timing of that intervention.

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