Liquidity transmission and the subprime mortgage crisis: a multivariate GARCH approach

Ling Xiao1 • Gurjeet Dhesi2 • Eduard Gabriel Ceptureanu3 • Kevin Lin4 • Claudiu Herteliu3 • Babar Syed2 • Sebastian Ion Ceptureanu3

Abstract
This paper examines the liquidity transmission across the interbank money market by investigating four liquidity measurements. We detect an empirical evidence of the increase in conditional correlation across different liquidity channels during the subprime mortgage crisis. Two structural breaks are observed, and the break dates correspond to the critical events that happened at the beginning of the subprime mortgage crisis. Furthermore, two out of three significant pairwise liquidity transmissions involved the TED liquidity spread.

Keywords Financial crisis • Multivariate GARCH • Liquidity transmission • Subprime mortgage crisis

1 Introduction

Usually, the term financial crisis refers to a situation in which financial institutions or assets suddenly suffer from significant losses of their value. The effects of a crisis of financial markets may be increased by systemic risk; furthermore, they may impact on whole sectors of the economy. The scope and severity of the consequences of the Subprime Mortgage Crisis (SMC) in the USA have been well studied. Still, the sentence “When Belgium sneezes, Europe gets the cold” (Garas et al. 2010; Rotundo and D’Arcangelis 2016; Varela Cabo et al. 2015) evidences well that, in principle, the failure of a single domestic market can almost lead to the destruction of the global financial system. Policymakers and economists continue to study the cause and effects of the financial crisis, but the controversy over its nature remains unresolved.

The SMC 2007 severely damaged the global financial system (IMF Global Financial Stability Report 2008) but—at the same time—it offers an opportunity for further investigation on main triggering factors and intrinsic weaknesses of the system. For instance, the application of the originate-to-distribute (OTD) model—where the originator of a loan sells it to third parties and demands fees that the banks adopted—has been criticised for the nature of its information asymmetry. Mark-to-market accounting standards have been questioned for its adequacy of asset valuation under extreme market conditions. The interbank market and its liquidity transmission (LT) mechanisms are quite a key factor of the crisis. The literature reports many empirical tests for its significance in relation to multiple bank failures.

The application of the OTD model to the interbank lending market can be improved by the information on the source of liquidity shock transmission and capture the dynamics of the interbank linkages during the crisis period. Actually, several liquidity requirements are necessary to banks for obtaining short-term funding through the interbank lending market. However, the SMC shows the fragility of such system under extreme circumstances. Empirical studies have been drawn upon on the evaluation of the transmission mechanism and dynamics of liquidity shocks to identify the liquidity risk in relation to multiple bank defaults. Frank et al. (2008) estimate the transmission of liquidity shocks by applying a multivariate generalised
autoregressive conditional heteroscedasticity (GARCH) model during the SMC period. The SMC clearly demonstrates the impacts of liquidity shock transmissions through different lending channels. The collapse of one financial institution causes others to fail because of the liquidity shortage. This has raised the question whether some unknown forms of LT mechanisms were developed during the crisis period.

The transmission mechanisms of liquidity shocks during the subprime mortgage crisis is described as reinforcing liquidity spirals, perceived as a temporary liquidity shock in the beginning, but eventually becoming severe financial distress. These transmission mechanisms were detected in the US financial market, as well as in other advanced and emerging markets. Frank and Hesse (2009) use multivariate GARCH model to analyse the financial spillover effect between advanced economies and emerging markets during the crisis period. Their findings suggest that the links between funding liquidity stress and equity markets in both the developed and emerging economies are highly correlated.

It is prominent during certain crisis moments where a number of liquidity stress indicators leap significantly, such as the asset-backed commercial paper (ABCP) spread and the overnight indexed swap (OIS) spread [see Bordo and Murshid (2001), Demirgüç-Kunt et al. (2005), Strahan (2008), Adrian and Shin (2008) and Dell’Ariccia et al. (2008) for bank liquidity in relation to financial crisis]. The mechanisms of liquidity shock transmission are dynamic and interconnected to each of the liquidity channels. The complexity of interbank holdings prevents banks from assessing the accurate quantity of risk to which they are exposed and means they often underestimate the potential risk they might be bearing. Understanding the interbank market structure and the relationships amongst and implications of different interbank exposures may improve banks’ risk assessment.

This paper advances the discussion of the IMF Global Financial Stability Report (2008) and Frank et al. (2008). We make further improvements in the research design by providing detailed LT specifications with updated datasets. The Dynamic Conditional Correlation (DCC) (Engle 2002) is also applied to our analysis which enables us to acquire the knowledge of dynamic links between LT across different liquidity channels over the period of 2004–2010. We also introduce the difference between 3-month LIBOR and 3-month Treasury bill (TED) spread as a new liquidity measurement. It serves as a proxy measurement of banks’ attitude towards lending and overall credit risk within the interbank market. This spread supplements other quantitative measurements in the previous work. Furthermore, the multivariate BEKK model (Baba et al. 1989) is used to investigate the pairwise transmissions between the liquidity measures. In particular, the off-diagonal elements in the conditional variance–covariance matrix implied in the BEKK offer the quantities and directions of the transmission across liquidity measurements.

Finance as a complex system in a computational framework can be evidenced in works (Arinaminpathy et al. 2012; Bougheas and Kirman 2015; Brunnermeier 2009; Cristescu 2020; Ionescu et al. 2009; Hesse et al. 2008; Marinescu and Ijacu 2014; May 2013; Rampone and Russo 2012; Rotundo 2013; Varela Cabo et al. 2015). In addition, studies and recent researches in liquidity shocks and transmissions are still of paramount interest (León et al. 2018; Bluhm 2018). There is an increasing interest in applying soft computational methodology to address the liquidity transmission (Zhang et al. 2018; Shen and Tzeng 2015; Wu et al. 2018). This paper will contribute to the existing SMC and liquidity risk literatures in three main aspects. The dataset (2004–2010) covers both pre-crisis (04.10.2004 to 01.06.2007) and post-crisis (10.03.2009 to 20.10.2010) periods of the financial crisis of 2007–2008. This assists us to scrutiny a broader picture of the financial crisis. The empirical analysis uses the DCC model and provides evidence of structural breaks. Furthermore, we employ the bivariate BEKK estimation to measure pairwise LT across the four liquidity measurements. Section 4 provides the results, and conclusions are in Sect. 5.

2 Literature review

International financial markets have become increasingly interconnected as a result of the strong international financial flows interactions. Hence, investors are exposed to higher international exchange risks and equity price fluctuations. Return and volatility spillovers are often examined to better understand the interdependence across financial markets. The abundant literature modelling volatility dynamics of time-series data exist, here for brief we mention (Billio and Caporin 2009; Burda and Maheu 2012; Ding and Engle 2001) the previous research on a similar topic using multivariate GARCH models such as McAleer (2005) and McAleer et al. (2009). The BEKK and DCC models are the most widely employed ones of conditional covariances and correlations in multivariate GARCH models (Engle and Kroner 1995; Caporin and McAleer 2012). This is due to the good results of GARCH models in catching the fluctuation characteristics and volatility spillovers between financial time series (Kang et al. 2013; Constantinides and Savelev 2013; Chang et al. 2013; Bentes 2015). The multivariate GARCH is the natural extension of GARCH which can be applied to deal with multivariate dimension dataset and the interrelationships between variables. Most studies examined the cross-
Liquidity transmission and the subprime mortgage crisis: a multivariate GARCH approach

market volatility spillover effects from the time perspective; still others focused on the frequency perspective (Lee 2004; Ghosh et al. 2011; Huang 2011; Huang et al. 2015; Chakrabarty et al. 2015).

Short-term market illiquidity shocks may create arbitrage opportunities for investors. However, the liquidity shocks might be amplified via different transmission mechanisms under crisis periods. Adrian and Shin (2008), Degryse and Nguyen (2004) and Upper and Worms (2002) investigate the connections and mechanisms in relation to liquidity shock and financial crisis based on balance sheet information from an interbank market exposures perspective. The interconnections of the liquidity market examined in these studies are the source of the shocks during the SMC. Allen and Gale (2006) argue that the completeness of the interbank market is an important factor in a liquidity crisis, where the term “complete” has to be interpreted in a network framework. Each bank is connected to all the other banks. The amount of interbank deposits that any bank holds is evenly spread over a number of banks. Frank et al. (2008) estimate the transmission of liquidity shocks by applying a multivariate GARCH model during the SMC period. The GARCH model allows for the evaluation of the transmission of the liquidity shock that spreads from credit market to equity market as well as modelling the conditional heteroscedasticity exhibited by the data.

Moreover, the multivariate GARCH model explicitly addresses the linkages between market and funding liquidity and it is able to capture the dynamics of banks’ liquidity pressures within the interbank market. The DCC maintains the plausibility of the constant correlation (CC) model, while allowing for time-varying conditional correlation. Sheppard (2001) has improved the viability of the DCC model estimation by reducing the estimation of multivariate GARCH to a series of univariate GARCH processes, with an additional correlation estimator. The specification of the univariate GARCH is generous to any GARCH process with normally distributed errors that satisfy non-negative constraints and stationary conditions. The question that remains is where and what are the sources of financial shocks and to what extent are they transmitting from one channel to the others. The DCC specification allows us to capture possible structural breaks in the unconditional correlation amongst the variables. In contrast, the multivariate BEKK model is able to provide more detailed transmission information apart from the conditional correlation. The off-diagonal elements in the variance–covariance matrix show the transmission percentage across liquidity measurements. Considering the difficulty of discerning the large number of coefficients obtained from the multivariate BEKK model, the pairwise bivariate BEKK model is used to investigate the LT between different measurements. The transmission mechanisms of liquidity shocks during the SMC have been described as reinforcing liquidity spirals, where it can be perceived that temporary liquidity shock in the beginning eventually causing severe financial distress.

In the present analysis, the data collection ranges from 4 October 2004 until 20 December 2010, which includes the period of the SMC. This sample period allows us to evaluate the dynamics of the interbank market prior to the collapse of the financial system and the persistence of the liquidity shocks in the post-crisis period. We choose four liquidity measurements to investigate the transmission mechanism within the interbank market. The funding liquidity condition in the ABCP is measured by the spread between the yield of the 3-month ABCP and the 3-month US Treasury bill (T-bill). The second variable is the spread between the OIS and the 3-month LIBOR rate which is considered as a strong indicator of credit and liquidity risk in the money market. We use the TED spread as our third variable to measure the credit risk during the crisis period. Lastly, the S&P 500 is considered as a proxy for market volatility measurement.

3 Materials and methods

For the BEKK model, we use the autoregressive moving average model ARMA (1, 1) to define the conditional mean of returns.

The model takes the following form:

\[ r_{it} = \alpha_i + \varphi_i r_{it-1} + \theta_i e_{it-1} + e_{it} \]

\[ \forall i = 1, \ldots, k; \forall t = 1, \ldots, T \quad (1) \]

where \( k = 4, r = (r_{it}) \in \mathbb{R}^{k \times T} \) is a matrix of asset returns, and \( e_{it} = (e_{i1t}, \ldots, e_{ikt}) \) represents the randomness due to the innovation. \( e_{it} \) conditioned to the matrix of previous information set, \( \Omega_{t-1} \), follows a multivariate Gaussian distribution with mean 0 and a time-dependent variance–covariance matrix \( H_t \in \mathbb{R}^{k \times k} \)

\[ e_{it} | \Omega_{t-1} \sim N(0, H_t) \]

where \( H_t \) describes the second moment of the model, and it is used to examine the relationship in terms of volatility. \( H_t \) is given by the evolution equation

\[ H_t = C_0 C_0 + A' \tilde{e}_{t-1} \tilde{e}_{t-1}' A + G H_{t-1} G \quad (2) \]

The BEKK model is well suitable for investigating volatility spillover effects (Xiao and Dhesis 2010). In fact, in the BEKK model, the conditional variance is not only a function of all lagged conditional variances and squared returns, but also a function of conditional covariance and cross-product returns: \( C_0 \in \mathbb{R}^{k \times k} \) is a matrix positive definite, \( A \in \mathbb{R}^{k \times k} \) modulates the ARCH regression, and \( G \in \mathbb{R}^{k \times k} \) modulates the GARCH regression.
$R^{k \times k}$ collects the coefficients of the GARCH. The diagonal elements in the parameter matrix $G$ measure the effect of lagged volatility; the off-diagonal elements capture the cross-market effects. The apostrophes indicate the transpose of the matrix.

The joint log-likelihood function of BEKK model is given by

$$L = \sum_{t=1}^{T} L_t$$

where $T$ is the total number of the observations and $L_t$ is the log-likelihood of the observation $t$ given by

$$L_t = -Tn/2 + \ln(2\pi) - \frac{1}{2} \sum_{i=1}^{T} (\ln|H_t|) + e'_t|H_t^{-1}|e_t),$$

$$t = 1,\ldots,T$$

The apostrophe indicates the operation of transposition, and $n$ is the number of variables in the model ($n = 42$, in this case).

The DCC model (Engle and Sheppard 2001) assumes that the returns from $k$ assets are conditionally multivariate normal with zero mean and covariance matrix $H_t$. The returns can be either zero mean or the residuals from a filtered time series:

$$r_t \sim N(0, H_t), \text{ where } H_t = D_t R_t D_t$$

and $D_t \in R^{k \times k}$ is a diagonal matrix of time-varying standard deviations from the univariate GARCH model with $\sqrt{h_{it}}$ on the $i$th diagonal. $R_t$ is the time-varying correlation matrix. The log-likelihood of this estimator is

$$L(R_t) = -\frac{1}{2} \sum_{t=1}^{T} (k \log 2\pi) + 2 \log|D_t| + \log(|R_t|) + e'_t R_t^{-1} e_t)$$

where $e_t \sim N(0, R_t)$ are the residuals standardised by their conditional standard deviations.

Engle and Sheppard (2001) propose to rewrite the elements in $D_t$ through the univariate GARCH in the following way:

$$h_{it} = \omega_i + \sum_{p=1}^{P_i} \alpha_{ip} e^2_{it-p} + \sum_{q=1}^{Q_i} \beta_{iq} h_{it-q}, \quad \forall i = 1,2,3,4$$

with the usual GARCH constraints for non-negativity and stationary:

$$\sum_{p=1}^{P_i} \alpha_{ip} + \sum_{q=1}^{Q_i} \beta_{iq} < 1, \quad i = 1,\ldots,4$$

The subscripts are present in the individual $P_i$ and $Q_i$ for each series to indicate the lag length chosen which need not to be the same.

The proposed dynamic correlation structure is:

$$Q_t = \left(1 - \sum_{m=1}^{M} a_m - \sum_{n=1}^{N} b_n\right) \overline{Q} + \sum_{m=1}^{M} a_m \left(e_{t-m} e'_{t-m}\right) + \sum_{n=1}^{N} b_n Q_{t-n}$$

The second component of the Engle and Sheppard (2001) framework consists of a specific $DCC(M,N)$ structure, which can be expressed as:

$$R_t = Q^{'-1}_t Q_t Q^{'-1}_t$$

where $Q_t$ is the conditional variance–covariance matrix of residuals with its unconditional (time-invariant) variance–covariance matrix $\overline{Q}$ resulting from Eq. (8). $Q^{'*}_t$ is a diagonal matrix with the square root of the diagonal elements on the diagonal:

$$Q^{'-1}_t = \left[\begin{array}{cccc}
\frac{1}{\sqrt{q_{11}}} & 0 & 0 & 0 \\
0 & 1 & 0 & 0 \\
0 & 0 & \frac{1}{\sqrt{q_{33}}} & 0 \\
0 & 0 & 0 & \frac{1}{\sqrt{q_{44}}} \end{array}\right]$$

In detail, Engle (2002) specifies the DCC model through the GARCH $(1, 1)$-type process:

$$q_{ij} = \rho_{ij}(1 - \alpha - \beta) + \alpha q_{i,j-1} + \beta q_{i,j-1} + \chi_{i,j-1} \quad \forall i = 1, 2, 3, 4$$

where $\rho_{ij}$ is the constant correlation between the two time series $\{ e_{i,t-1} \}$ and $\{ e_{j,t-1} \}$, $\alpha$ is the coupling coefficient and $\beta$ is the decay coefficient. The model is mean reverting if $\alpha + \beta < 1$. The typical element of $R_t$ will be the form $\rho_{ij}$, and the quantity $\rho_{ij}$ is normalised using

$$\rho_{ij} = \frac{q_{ij}}{\sqrt{q_{ii} q_{jj}}}$$

This value—which can be either positive or negative—is the main interesting result which represents the conditional correlation between different liquidity transmission measurements.

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4 Results

We applied the models described in the previous section to the time series of the volatilities of OIS, ABCP, TED and S&P500 sampled since October 2004 till December 2010.

In this section, we summarise our main findings and discuss the implications of these results. Please note that for the sake of brevity, only the results significant for the performed tests are included in this paper.

The implied conditional correlations extracted from the DCC model are graphically represented in Fig. 1. Further liquidity transmission effects are analysed using the results obtained from applying the bivariate BEKK model. Figure 1 provides the selected DCC graphs. These graphs show the conditional correlation which are generated by using the multivariate DCC model.

There is clear evidence of an increase in the correlations during the SMC period. Several interesting evolutions can be observed. First of all, dynamic conditional correlations widely exist across different liquidity channels. This confirms the reason for our earlier strategy of choosing the ABCP, OIS, TED and S&P500 volatility as the representatives of liquidity channels are appropriate. Also this fact shows a macro-picture of the different liquidity channels tend to affect each other. Moreover, the first structural break is found during mid-2007 which is consistent with the results of Frank et al. (2008). In addition, another structural break occurred in September 2008, likely to be explained by the effect from the collapse of the Lehman Brothers in September 2008. The failure of Lehman Brothers intensified the fragile liquidity market and led to significant liquidity shortages across different interbank markets. Thirdly, we observe a mean reverting process in...
the conditional correlation prior to the structural breaks. The implication is that after a liquidity shock occurs, the correlations tend to immediately return to the long-term unconditional level.

Due to curse of dimensionality in the BEEK model (we recall that with \( k = 4 \) time series the number of parameters in formula (4) lifts to \( n = 42 \), formulas (1) and (2) are applied in its bivariate form, posing \( k = 2 \), examining only the pairwise LT mechanism. The maximum likelihood function in Eq. (4) calibrates the parameters.

Table 1 displays three pairwise results which exhibit significant liquidity transmission. Our findings and comments are as follows. Firstly, the liquidity shocks significantly transmit across the four liquidity measurements. This may indicate that to some extent, there is a systemic LT in the financial market. In other words, once liquidity shortage happens in one of the liquidity channels, it tends to spillover to the others and thus induces the whole market to collapse. Secondly, as an indicator of the whole financial markets the S&P 500 volatility transmits 6.38% to OIS and 6.26% to TED, respectively. Although there is no direct transmission between S&P500 and ABCP, we remark that the TED transmits 9.55% to the ABCP spread. Also it is interesting to note that the transmission is bidirectional but not symmetrical. For example, the S&P500 transmits 6.38% to OIS spread but only about 1% the other way around. A similar pattern is observed for pairwise comparison of S&P500 and TED. It suggests to us that the S&P500 volatility may have a significant impact on the LT mechanism. Thirdly, the new measurement TED we introduced for this study has been involved in two of the three significant LT pairs. This empirical evidence confirms our choice of the TED and also guides us to undertake further investigation of the role of TED playing in the LT.

5 Conclusions

The lending mechanism under the OTD model describes the degree of complexity in interbank holdings between financial institutions. The cross-holdings of structured products within the banking system might not pose a problem during normal economic conditions. However, in the event of financial distress such as the subprime mortgage crisis, liquidity shocks can be transmitted through these lending channels. Based on quantitative analysis, this study has found evidence of the existence of liquidity shock transmission during the SMC.

The DCC analysis shows two structural breaks. The first one is matched with the finding of Frank et al. (2008), and the second structural break is found in September 2008 which can be explained by the collapse of Lehman Brothers and that the general market perception of financial distress leads to higher market volatility. The results from the bivariate BEKK estimation show that there are three exceptionally significant LTs pairwise across the four liquidity measurements and, moreover, two of them involve the TED indicator. The dynamics of LT within the interbank market found significant evidence that there were liquidity shocks spillovers in the four different liquidity measurements across the US market. Banks are able to obtain short-term funding from the ABCP market under normal market condition. However, in the event of bank failures the confidence of the interbank market reduced significantly. Banks with an unhealthy balance sheet such as high leverage ratio may become illiquid but still solvent, where they possess sufficient assets against their liabilities but are unable to meet the short-term financial obligations. This is demonstrated by the drying up of the ABCP market during the crisis period. In addition, as the interbank market was intensified by a series of negative events during the SMC, the TED spread jumped up significantly.

### Table 1: Implied transmission implied in the bivariate BEKK model

| LT Description                              | LT   | Se(LT)         |
|---------------------------------------------|------|----------------|
| Liquidity transmit from ABCP to TED         | 0.3% | (2.0468e−6)    |
| Liquidity transmit from TED to ABCP         | 9.55%| (0.0057)       |
| Log-likelihood: 4909.8                     |      |                |
| Liquidity transmit from OIS to S&P500 Volatility | 0.84%| (6.4862e−6)    |
| Log-likelihood: 8159.4                     |      |                |
| Liquidity transmit from S&P500 Volatility to OIS | 6.38%| (4.7621e−6)    |
| Log-likelihood: 7066.8                     |      |                |
| Liquidity transmit from S&P500 Volatility to TED | 6.26%| (0.0001)       |
| Log-likelihood: 7066.8                     |      |                |
| Liquidity transmit from TED to S&P500 Volatility | 0.025%| (0.0046)       |

Liquidity transmission between different pairwise is described as percentage, and the corresponding standard errors are in bracket. The transmission percentage is indicated by the matrix \( G = (g_{ij}) \) in Eq. (2). For instance, the liquidity transmit from OIS to S&P500 volatility is 0.84% because the \( g_{12} \) value is 0.0084 and \( g_{21} \) value is 0.0638 which gives the liquidity transmission percentage from S&P500 volatility to TED.
indicates that as the overall perceived credit risk rose in the interbank market, the willingness of banks to lend to each other is significantly diminished.

The Ted spread was the most significant of the shock transmitting forces, while the APCB spread was the least influential amongst all sample lending channels. Furthermore, there was an amplifying effect of the liquidity shock transmission through the TED spread channel. The market-wide study provides an insight into the sources of liquidity shock transmission within the banking system during the time of financial distress. Interbank lending channels can turn into channels which transmit liquidity shocks. Further research should focus on analysing other, not so profound, crises. Moreover, the parameters considered have to be adapted to various types of crisis, for instance, in specific industries and regions.

Compliance with ethical standards

Conflict of interest
The authors declare that they have no conflict of interest.

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