Liquidity Commonality During the Financial Crisis: Effects of News Announcements

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Abstract

This paper studies commonality in liquidity across currencies during the period of financial crisis, and examines the variation in liquidity commonality around the release of macroeconomic news. Considering the time-varying dynamics in liquidity, we use the Generalized Dynamic Factor Model (GDFM) to identify the market-wide liquidity. We show that strong commonality in liquidity exists in the foreign exchange market during the periods of subprime mortgage crisis and European sovereign debt crisis. We also find that U.S. macroeconomic announcements have effects on the liquidity commonality. Furthermore, the quantitative easing policies of the U.S. that injects high capital inflows into markets actually improve the financial sector's funding liquidity and induces a decrease in liquidity commonality across currencies. We infer that the significant effect of announcements on the market-wide FX liquidity is attributed to either supply-side forces related to the funding liquidity and to investors' fear or the market volatility involving dealers' inventory cost and announcement surprises.

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1. Introduction

The foreign exchange (FX) market is the world's largest financial market, and trading in the FX market reached a historical high of $5.3 trillion per day in April 2013, a 35% increase relative to 2010 (BIS, 2013). However, as noted in Macini et al. (2013) and Krnaukh et al. (2015), research on FX liquidity is relatively few and limited, compared to the literature focusing on the liquidity in equity and bond markets.

Approximately 60% of FX trading volume is composed by major currencies. Liquidity in the FX market differs by currency and changes over time at both intraday and daily frequencies (Mancini et al, 2013). Inspiring by Mancini et al. (2013), we study commonality in liquidity in the FX market and examine how the monetary policy affects the FX liquidity commonality in the periods of subprime mortgage crisis and European sovereign debt crisis.

Commonality in liquidity refers to the existence of a significant common component that influences the liquidity of individual currency-pair exchange. Chordia et al. (2000) acknowledge that the liquidity commonality in the stock market reflects a spillover effect that a stock's liquidity affects other stocks' liquidity and trading in the same market. The issue of liquidity commonality in the stock market has been studied in the recent literature at different perspectives. One strand of research has addressed the existence of liquidity commonality (Chordia et al., 2000; Huberman and Halka, 2001; Hasbrouck and Seppi, 2001; Brockman et al., 2009). The other strand of research focuses on the impact of financial crisis on the liquidity commonality (Kamara et al., 2008; Andrew et al. 2012, Roach et al., 2013). These studies support that the sudden liquidity dry-up in the market induced by the financial crisis may lead to an increase in liquidity commonality.

In contrast, the liquidity commonality in the FX markets has received much less attention. The co-movement in liquidity of FX markets during the 2007-2008 crisis period has been documented in Melvin and Taylor (2009), Banti et al. (2012), Mancini et al. (2013), and Karnaukh (2015).

We further study the impact of macroeconomic news on the liquidity in FX market. It has been addressed that the liquidity responds to macroeconomic announcements (Andersen et al. (1998, 2003, 2007); Bauwens et al. (2005); Evans and Lyons (2005, 2008); Fleming and Remolona (1999), among others). Fleming and Remolona (1999) show that the spread in the treasury market widens dramatically at announcements, which is evidently driven by the channel of inventory control. The theory of inventory control argues that the increased risk to market makers of high price volatility reflects dealers' reluctance to trade when price changes sharply, hence it leads to a wider bid-ask spread (see Amihud and Mendelson (1980), Ho and Stoll (1983), and O'Hara and Oldfield (1986)). Considering the higher volatility aroused by macroeconomic news announcements, we infer that the extent of liquidity commonality in the FX markets may change around the announcement.

By using the EBS (Electronic Broking Services) intraday data set, we investigate factors that drive the dynamics of FX liquidity commonality. We find the liquidity measures calculated from the EBS data exhibit a significant autocorrelation. We furthermore use the GDFM (Generalized Dynamic Factor Model) approach to extract the commonality in FX liquidity to consider the effect of autocorrelation in liquidity. The traditional PCA (Principal Component Analysis) method ignores the autocorrelation in the data and will lead to a biased measure for the common component in individual currency market’s liquidities.

Our results show that liquidity commonality significantly varies over time and provide the ample evidence of strong commonality in liquidities during periods of financial crisis. Consistent with Mancini et al. (2013) and Roach et al. (2013), we find that an increased systematic market liquidity risk triggers illiquidity spillovers across the market and that liquidity commonality can be a source of financial contagion.

Furthermore, we investigate whether liquidity commonality differs at times of positive and negative macroeconomic announcements. We also examine the reaction of liquidity commonality at Fed's release of quantitative easing (QE) announcements. By including dummy variables indicating announcement release in the model, we can distinguish how liquidity commonality changes at news release. We show that the price volatility raised by news releases affects the extent of FX liquidity commonality. In most cases, liquidity commonality tends to have a greater response to negative announcements than to positive announcements. We also find that QE policies ease the funding constraint and decrease FX liquidity commonality.

The paper contributes to the existing literature on FX market liquidity in several aspects. The use of GDFM method mitigates the bias in measuring the common liquidity factor for FX markets, in light of the significant autocorrelation in the liquidity of individual market. Forin et al. (2000) provide theoretical background on this method and Hallin et al (2011) scrutinize its empirical properties for the equity market. However, previous studies on the common component in FX liquidity consider the PCA method, ignoring the characteristic of autocorrelation in liquidity. Without using the rolling-sample estimation techniques, we directly find the time-varying common liquidity by using the GDFM method. Our finding supports that the common liquidity in FX markets significantly increases during periods of 2007-2008 subprime-mortgage debt crisis and 2011 European sovereign debt crisis. Second, we analyze the effects of macroeconomic announcements on liquidity commonality and FX market-wide liquidity. The consideration of announcement effect on liquidity commonality can enhance our understanding about the link between market liquidity and macroeconomic announcements. Our findings reinforce and significantly extend the result of Mancini et al. (2013) and Karnaukh et al. (2015).

Third, with a longer sample period, our analysis studies the two recent important financial crisis events. The study based on the subprime-mortgage financial crisis and Eurozone sovereign debt crisis enables us to analyze whether the effects of news announcements on liquidity are different between crisis periods and non-crisis periods. Finally, we investigate factors that determine the FX market-wide liquidity. The empirical results reveal that both of funding liquidity factors, including TED and VIX, and global market volatility factor (i.e., inventory risk and news surprise) have a significant influence on market-wide FX liquidity.

The rest of this paper is organized as follows. Section 2 gives a brief review on related literature. Section 3 describes the EBS data and macroeconomic announcements data. Section 4 displays the measure of liquidity we use and the approach to constructing the common liquidity or market-wide liquidity. Section 5 presents and interprets the empirical results. Section 6 concludes.

2. Literature Review

2.1 Liquidity commonality

Commonality in liquidity means the impact of a common or market-wide liquidity factor on the liquidity of an individual asset. It refers to the synchronicity that an individual asset's liquidity varies with aggregate market-wide liquidity. Chordia et al. (2000) firstly point out that the variation in an individual stock’s bid-ask spread and depth is associated with movements in the aggregate market-wide spread and depth.

Hasbrouck and Seppi (2001) use a principal component analysis (PCA) to retrieve the common component in liquidities of 30 stocks in the Dow Jones index. In addition, the canonical correlation analysis shows that the common factor in order flows is highly correlated with the common factor in returns. Korajczyk and Sadka (2008) use a latent factor model to find the common liquidity, and find that shocks to assets' liquidity also have a common component across measures which accounts for most of the explained variation of the individual liquidity. After controlling for the systematic liquidity risk, their empirical results suggest that the aggregate systematic liquidity is still a price factor in the cross section of firms.

The issue of commonality in liquidity has been investigated in other markets as well. Chordia et al. (2005) analyze the liquidity co-movements between the stock and bond markets. Banti et al. (2012) provide the evidence of the presence of a common component in liquidity across currencies, consistent with the literature that identifies FX dealers' inventory control constraints. In other words, dealers' response to incoming orders of different currencies has a common component that is attributed to their inventory position choices. Furthermore, funding liquidity is found to be a major factor that triggers the commonality in liquidity. In this sense, changes in the funding conditions affect an investor’s transaction for the provision of liquidity in all currencies.

Using the high-frequency data, Mancini et al. (2013) indicate that there exists a strong commonality in liquidity across currencies, as well as a comovement among liquidities of FX, bond, and equity markets. In particular, they emphasize that the financial crisis strengthens the liquidity commonality. Furthermore, a more liquid FX market has a lower liquidity sensitivity to the FX liquidity commonality. Exchange rate returns are negatively correlated to the liquidity risk, thus offering insurance against liquidity risk. A negative correlation between exchange rate returns and liquidity appears for currencies with higher interest rates, reflecting a larger exposure to liquidity risk.

Other models are closer in spirit to Chordia et al. (2000) and try to identify the source of commonality on the demand side. Chordia et al. (2001) find that the market-wide liquidity is influenced by inventory factor and information asymmetry factor. The competition among the larger number of informed traders would drive down the cost of asymmetric information dealers facing and result in the higher liquidity. Brokman et al. (2009) also show that within-exchange commonality is present in a cohort of exchanges, and document the “across-exchange” co-movement of liquidity, or the existence of a global liquidity commonality.

2.2 Liquidity around announcements

Macroeconomic surprises announcements and their effect on the volatility of exchange rates are of crucial for the understanding of market behavior. This has become even more apparent in recent years, as the financial market crisis and consecutive global economic recessions have revealed that investors conduct transactions based on major economic news and information.

A number of studies have shown how scheduled macroeconomic news announcements affect FX markets, such as Degennaro and Shrieves (1997), Andersen and Bollerslev (1998), Cai et al. (2001), Bauwens et al. (2005), and Evans and Lyons (2008). Concerned about the impact of US macroeconomic announcements, each study focused on FX market volatility variations for the most active currency markets, which include the Euro/US Dollar (EUR/USD), the British Pound/US Dollar (GBP/USD) and the Japanese Yen/US Dollar (JPY/USD). One common finding among these studies is that US domestic news announcements increase FX volatility between the dollar and other currencies.

More extensive studies have examined the link between macroeconomic news surprises in several countries and increases in FX volatility Andersen et al. (2003), Andersen et al. (2007). Andersen et al. (2003) investigate the responses of more than one currency return and volatility to US and German macroeconomic news concerning foreign exchange rate markets. Any one big surprise, however, increases volatility in other asset or markets as well. Andersen et al. (2007) characterize the response of US, German and British stocks to US macroeconomic announcements and find a strong simultaneous volatility interaction between bond and foreign exchange markets is also affected by US macroeconomic announcements.

Other studies using intraday data show the volatility spillover from one currency market to another, including Cai et al. (2009) and Omrane and Hafner (2015). Cai et al. (2009) is the first study that analyzes how the US and domestic macroeconomic announcements affect exchange rates in emerging markets, and find that most emerging market currencies are growing more sensitive to US news.

Omrane and Hafner (2015) study how macroeconomic news surprises affect the two components of volatility, namely direct volatility and indirect volatility. The latter one is induced from volatility spillover. European news surprises, for example, trigger significant boosts of the British Pound, Japanese Yen and contribute to the volatility of the Euro, with the same results emanating from the British and Japanese News. They conclude that US macroeconomic announcements have the largest impact, as US news surprises, including both scheduled and unscheduled announcements, have a significant effect on the volatility of EUR/USD, GBP/USD, and JPY/USD exchange rates.

Finally, Fleming and Remolona (1999) show that new releases sharply affect the asset volatility. Dealers react to news releases by escalating or withdrawing quotes in response to inventory risks or sharp price changes. As a result, during the announcement period the spread increases are evidently driven by inventory control concerns.

3. Data

3.1 The EBS data

The FX market is by far the largest financial market, with a daily turnover of us dollar

3210 billion, a third of which is in spot transactions (Rime et al., 2010).[1]

Most of electronic spot interdealer trading occurs on two competing platforms: Reuters System and Electronic Brokerage System (EBS). Especially, EBS has a market share of more than 60% and is the leading global marketplace for spot interdealer FX trading. For the two major currency pairs, EUR/USD and USD/JPY, the vast majority of spot trading is represented by the EBS data set. All dealers on the EBS platform are prescreened for credit and bilateral credit lines, which are continuously monitored by the system, so counterparty risk is virtually negligible when analyzing this data set (Mancini et al. (2013)). Moreover, there is also a rapidly growing literature on using EBS data set to analyze the FX markets (e.g., Mancini et al. (2013), Karnaukh et al. (2015), Ito and Hashimoto (2006), among others).

The exchange rate data set used in this paper is from the brokered segment of inter-dealer FX market, especially from the EBS system. We consider 9 currency pairs: USD/GBP, USD/CHF, USD/AUD, USD/JPY, USD/CAD, USD/EUR, EUR/GBP, EUR/JPY, and EUR/CHF. The data period is from January 7, 2008 to December 31, 2013. The dataset contains a quote price and a deal price on a 0.1s time-slice basis. The quote price is a snapshot of the ten best levels of the book at the end of a time-slice (if a price or a volume in the book changed within the time-slice). The deal price lists the highest buying deal price and the lowest selling deal price (with the dealt volumes) during the time-slice.

On the EBS trading platform, foreign currencies are continuously traded 24 hours a day; however, the transaction volume is relatively smallest on the weekend. We exclude weekends from Friday 24:00 to Sunday 24:00 GMT. To avoid extreme

[1] The EBS Partnership was established by several major market making banks to counter the dominant role of Reuters, and EBS acquired Minex in December 1995 and thereby gained a significant market share in Asia. For a detailed description of the structure of the FX market and electronic trading platforms, see Rime(2003).

high-frequency noise and no-activity periods in very small time windows, we focus on the 1-min frequency. We choose a one-minute sampling frequency, i.e., at the end of each minute of our sample we record the last transaction price in the each exchange rate. Each trade contains the volume of buyer-initiated trades in each minute, the volume of seller-initiated trades in each minute, and the transaction price. The volume of buyer- initiated trades means the total volume transacted where a quote to buy euros for dollars, or dollars for yen, who is then regarded as the initiator of the transaction. The volume of seller-initiated trades is defined similarly.

3.2 Macroeconomic announcements data

Andersen et al. (2003, 2007), Ehrmann and Fratzscher (2005), and Evans and Lyons (2005, 2008) have verified that US macroeconomic information might well move other foreign exchange rates if it has information content for the state of other economies, perhaps because the U.S. economic performance indicates the well-being of the "global economy."

We collect three U.S. macroeconomic news announcements (e.g. CPI, GDP, and unemployment rate) that seem the most relevant. For each macroeconomic news announcement we report the release date, time-stamped to the minute in GMT, the announced series value and the median market survey expectation in Table 1.[2]

Following Balduzzi, Elton and Green (2001), we construct the standardized news surprise as follows:

$$S_{k,t} = \frac{|Actual_{k,t} - Expected_{k,t}|}{\sigma(\mathrm{Actual}_{k,t} - Expected_{k,t})Act} \quad (1)$$

where $Actual_{k,t}$ is the announced actual value of indicator k at time t,

[2] The median market survey expectation is the median value of the survey conducted by the Econoday and is collected weekly and processed on the Friday prior to the announcement week. It can be considered as the market consensus value. Several studies such as Scholtus et al. (2014) and Opschoor et al. (2014) have verified that the Econoday expectations contain valuable information about the expected value.

$Expected_{k,t}$ is the median forecast value of indicator k from the survey conducted by the Econoday, and $\sigma(Actual_{k,t} - Actual_{k,t})$ denotes the standard error of the difference between actual and expected value of indicator k.

We further identify news surprises as favorable or adverse ones by considering whether it will lead to the appreciation of the U.S. dollar when the actual announced value is greater than the expected value. For example, a favorable surprise of the U.S. GDP is identified when its actual announced value is higher than the expected value, that is, $S_{GDP} > 0$, as it is considered as “good” news or leading to the appreciation of the U.S. dollar; while an adverse surprise is defined when the actual value is lower than the expected value, $S_{GDP} < 0$, as it shows “bad” news and leads to the depreciation of the U.S. dollar. For unemployment rate and CPI, an adverse surprise is associated with a positive surprise ($S_{UR} > 0$ or $S_{CPI} > 0$) as it is considered “bad” news and leads to the depreciation of the U.S. dollar; whereas a favorable surprise involves with a negative surprise ($S_{UR} < 0$ or $S_{CPI} < 0$), as it is cosidered “good” news and leads to the appreciation of the U.S. dollar.

Moreover, we define a dummy variable with a value of one for the day with a quantitative easing (QE) policy announcements. These events are documented in Fawley and Neely (2013) that described in detail the timeline of the economic events that led to Fed responses. Therefore, the U.S. announcement data we consider include three macroecnomic surprise variables and one announcement dummy variable related to QE. Table 1 provides a summary of the announcements, including the number observations, the source reporting the news, and the date of release.

4. Liquidity Commonality

This section explores the global common liquidity in FX markets. We first calculate several different measurements of FX market liquidity. In the next step, we then rely on the GDFM approach to extract the global-wide systematic liquidity. Finally, we explore to which extent the co-movements in FX liquidity can be explained.

4.1 Liquidity measures

We calculate the liquidity measures based on Mancini et al. (2013). The first liquidity measure is the proportional quoted spread calculated as follows:

$$L^{(ba)} = (P_A - P_B)/P_M \tag{2}$$

where P_A, P_B and P_M indicate the ask, bid, and mid quotes, respectively. The latter is defined as $P_M = (P_A + P_B)/2$. A market can be regarded as liquid if the proportional quoted spread is low. The second liquidity measure is effective cost or effective spread. Because some traders in the electronic market may post hidden limit orders that are not reflected in quoted spreads, trades are not always executed at the posted bid or ask quotes. On the other hand, effective cost can be used to compare transaction prices with the quotes prevailing at the time of execution. The effective cost is calculate as follows:

$$L^{(ec)} = \begin{cases} (P - P_M)/P_M & for\ buyer - initiated\ trades \\ (P_M - P)/P_M & for\ seller - initiated\ trades \end{cases} \tag{3}$$

where P denotes the transaction price. Daily average proportional quote spread and effective cost are calculated by for each FX rate.

The last two liquidity proxies are price impact and return reversal. According to Kyle (1985), the price impact of a trade measures how much the exchange rate moves in response to a given order flow imbalance. In this opinion, when price impact incurs large fluctuations by a trade, the liquidity of the currency market would be relatively poor. Moreover, under a lower liquid currency market, the price impact is temporary and return reversal departed from the fundamental value would be expanded. The price impact and return reversal are calculated as follows:

$$r_{t_i} = \vartheta_t + \varphi_t\left(v_{b,t_i} - v_{s,t_i}\right) + \sum_{k=1}^{k} \gamma_{t,k}\left(v_{b,t_i} - v_{s,t_i}\right) + \varepsilon_{t_i} \tag{4}$$

where r_{t_i}, v_{b,t_i}, and v_{s,t_i} denote the log exchange rate return between $t_i - 1$ and

t_i, the volume of buyer-initiated trades, and the volume of seller-initiated trades at time t_i during day t, respectively. The lag length would be regarded as $k = 5$ inspired by Mancini et al. (2013). We expect that the return reversal of a trade $L^{(rr)} = \gamma_t = \sum_{k=1}^{5} \gamma_{t,k}$ is negative due to a reversal to the fundamental value. The price impact is measure by $L^{pi} = \varphi_t$, which is expected to be positive.

Summary statistics for the liquidity measures (price impact, return reversal, bid-ask spread, effective cost) are reported in Table 2. The data cover the period from January 7, 2008 through December 31, 2013 for each exchange rate. In line with the results of Evans and Lyons (2002) as well as Berger et al. (2008), more liquid assets should exhibit the lower price impact. Table 2 shows all the average of the trade impact coefficient is positive and the range is from 0.00001 to 0.00007. Our result also shows that EUR/USD has the smallest price impact but EUR/GBP has the largest ones.

The average return reversal, i.e., the temporary price change accompanying order flow, is negative. Therefore, it captures delayed price adjustments due to lower illiquidity. As we can see from Table 2, one-minute returns are on average reduced by -0.00001 to -0.00003 points if there was a lagged order flow in the previous minute. This slight reduction is economically significant given the fact that if the market is resilient, price recovers quickly from overshooting following a market order flow. For the average percentage bid-ask spread, it exhibits a strong variability, with a relatively high standard deviation over the mean.

In most cases, the market illiquidity variables of USD/CAD and AUD/USD have a significantly higher variability than those of the other currency pairs. EUR/USD has a lower mean and lower standard deviation than the other currencies. It seems to be the most liquid exchange rate, which corresponds to the perception of market participants and the fact that it has by far the largest market share in terms of turnover (Bank for International Settlements, 2013). However, the trading of GBP/USD is one of the largest market share in the world, and it displays as the less illiquid currency. The exact cause of this results can be explained that GBP/USD is mostly traded on the Reuters rather than the EBS trading platform (Chaboud, Chernenko, and Wright, 2007). In the last two columns of Table 2, we report the autocorrelation and the Ljung-Box *Q*-test for serial correlation. For most of the currencies, the liquidity measures exhibit strong autocorrelation.

4.2 Common liquidity across exchange rates

We apply a generalized dynamic factor model (hereafter calls as GDFM) to assess market-wide liquidity based on Forin et al. (2000). This models offer a parsimonious and realistic representation of the data, and have proven successful in construction of macroeconomic index Forni et al. (2000, 2003), in forecasting (Stock and Watson (2002a, 2002b),[3] Forni et al. (2005)), as well as in the analysis of financial markets (Corielli and Macrellion (2006), Ludvigson and Ng (2007, 2009), Hallin et al. (2011), Luciani and Veredas (2015)).

There are three reasons why the GDFM model has been a common tool used in many research fields such as the financial market dynamics and macroeconomic forecasts. First, the GDFM model could handle the time series nature of the data. As addressed in Hallin et al. (2011), liquidity might be significantly autocorrelated. If we

[3] Stock Watson (1998) is one of the first paper forecasting using principal components from a large number of predictors. By comparison, there are three principal distinctions between the Stock Watson factor model (hereafter calls as SW) and GDFM model. First, the common factor calculation is different. The SW factor model uses the least squares regression. The GDFM model, in turn, employs a non-parametric regression accounting for the differences between dynamic factors and their lagged values, imposing rank reduction to the spectral frequency matrix. Second, the weights differ when common factors are calculated. The SW factor model employs the standard principal component model for the purpose of acquiring common factors, while GDFM model estimation is based on the method of generalized principal components. This weighting scheme is a more efficient estimation method. Third, the methods differ in the way they are used to forecast the idiosyncratic component. The SW model utilized lagged values in the forecast calculation, however, the GDFM model forecasts the idiosyncratic component on the basic of the assumption about orthogonality of common and idiosyncratic components.

overlook the leading-lagging phenomenon may cause inefficient estimation, whereas the GDFM model exploits the potentially crucial information contained in the leading-lagging relations between the observations of variables to solve the problem.

Moreover, information inherent in a large number of variables can be more broad and improve the estimation efficiency. Both Stock and Watson (1998) and Forni et al. (2000) demonstrate that GDFM analysis can be estimated on a large database without suffering the decrease of dimensionality. Finally, the GDFM approach allows for a moderate correlation between idiosyncratic components, while the classical factor model has to presume that variables are mutually orthogonal.

To avoid overweighting some measures that are much more volatile than other measures simply because of their scale of measurement, we first choose to standardize our liquidity measures. For each exchange rate, a given liquidity measure is standardized by the time-series mean and standard deviation of the average of liquidity measure obtained from the cross section of exchange rates.

Let L^i be the $n \times T$ matrix of observations on the ith standardized liquidity measure (i = 1, 2, 3, 4). We assume that the data generating process for L^i is a dynamic factor model:

$$L^i = X^i + Z^i = B^i(L)u^i + Z^i \tag{5}$$

where u^i is a $k \times T$ matrix of common factors to liquidity measure i that is common across the set of n exchange rates, B^i is an $n \times k$ vector of factor sensitivities to the common factors to liquidity measure i, and Z^i is the $n \times T$ matrix of exchange rate-specific shocks to liquidity measure i.

The estimation of the common component X^i and the idiosyncratic component Z^i is executed in two steps. First, we decompose the cross-covariance matrices $\mathbf{\Gamma}_{L^i;n,k} := E[L_{n,t}L'_{n,t-k}]$ of L^i:

$$\mathbf{\Gamma}_{L^i;n,k} = \mathbf{\Gamma}_{X^i;n,k} + \mathbf{\Gamma}_{Z^i;n,k} \tag{6}$$

Then, to obtain the estimation of common and idiosyncratic variance-covariance matrices at all leads and lags, we use inverse Fourier transforms of the corresponding estimated spectral density matrices. At a given frequency, there exists

$$\hat{\mathbf{\Gamma}}_k^{X^i} = \frac{2\pi}{2M+1} \Sigma_{j=-M}^{M} \hat{\Sigma}_{X^i}(\theta_h) e^{ik\theta_k} \tag{7}$$

$$\hat{\mathbf{\Gamma}}_k^{Z^i} = \frac{2\pi}{2M+1} \Sigma_{j=-M}^{M} \hat{\Sigma}_{Z^i}(\theta_h) e^{ik\theta_k} \tag{8}$$

According to the central idea of principal component analysis (PCA) which requires that the first few q largest dynamic factors will contain the most of the variation in the original variables, the spectral density matrix of the common component has the following relationship with the first q largest eigenvalues and their corresponding eigenvectors:

$$V_q(\theta) \sum\nolimits_{X^i} (\theta) = D_q(\theta) V_q(\theta) \tag{9}$$

where $D(\theta)$ is a diagonal matrix having the eigenvalues of $\sum (\theta)$ on the diagonal and $V(\theta)$ is the $n \times n$ matrix whose columns are the corresponding row eigenvectors.

The spectral density matrix of the idiosyncratic component can be the estimated as:

$$\sum\nolimits_{Z^i;n} (\theta) = \sum\nolimits_{L^i;n} (\theta) - \sum\nolimits_{X^i;n} (\theta) \tag{10}$$

The second step is to use these covariance matrices to calculate the minimized ratio of the common variance and idiosyncratic variance. The resulting aggregates can be obtained as the solution to a generalized principal component problem:

$$\mathbf{V}_G \hat{\mathbf{\Gamma}}_0^{X^i} = \mathbf{A}_G \mathbf{V}_G \hat{\mathbf{\Gamma}}_0^{Z^i} \tag{11}$$

where A_G is a diagonal matrix having the generalized eigenvalues of the pair

$(\hat{\boldsymbol{\Gamma}}_0^{X^i}, \hat{\boldsymbol{\Gamma}}_0^{Z^i})$ on the diagonal and V_G is the $n \times n$ matrix whose columns are the corresponding row eigenvectors. The definition of the i^{th} generalized principal components is expressed as :

$$\widehat{\mathbf{P}}_{t,i} = \mathbf{V}_{G,i}\mathbf{X}_{nt}^{i} \tag{12}$$

where $V_{G,i}$ is the i^{th} generalized row eigenvector corresponding to the i^{th} largest generalized eigenvalues. According to the generalized principal component theory, the r aggregates $\widehat{\mathbf{P}}_{t,i}$, $j = 1,\cdots,r$ keep the most of the information of $\mathbf{X}_{\mathbf{n}}^{\mathbf{i}}$. We thus employ the first factor as a proxy for market-wide liquidity, $L_{M,t}$, combining the most of the infromation across exchange rates for each measure of liquidity.

We use the above process to estimate the common factor for each measure of liquidity individually. We also assess common factors across all measures of liquidity. Following Mancini et al. (2013), we stack all four liquidity measures into $\tilde{L}_t = [\tilde{L}_t^{(ba)}, \tilde{L}_t^{(ec)}, \tilde{L}_t^{(pi)}, \tilde{L}_t^{(rr)}]'$ and extract the eigenvector. We refer to systematic factors extracted across the liquidity measures as “across-measure factor” or “global-wide liquidity index,” $L_{M,t}$.

5. Empirical Result

We divide our empirical funding into four main parts: we first investigate the pervasiveness of co-movements of the individual FX liquidity and global-wide FX liquidity, following Mancini et al. (2013)’s commonality methodology for FX markets. Then we examine the commonality in FX liquidity around macroeconomic announcements and QE announcements. Finally, we study potential determinants of the FX liquidity commonality.

5.1 Liquidity commonality for FX markets

We begin our empirical analysis by characterizing the effects that financial crisis have on liquidity commonality. As outlined in the Introduction, while, given previous research, we would expect that financial crisis significantly and substantially affects the FX liquidity commonality. We first extend the analysis of Mancini et al. (2013) to include the financial crisis factor, focusing our attention on subprime-mortgage financial crisis and Eurozone Sovereign Debt Crisis periods. This hypothesis can scrutinize whether the financial turmoil of the financial crisis had any impact on the commonality in liquidity.

First of all, we determine the crisis length based on official timeline provided by Federal Reserve Board of St. Louis (2009) and BIS (2010).[4] We separately add two dummy variables to capture the impact of financial crisis: $I_{crisis1,t}$ correspons with the subprime-mortgage financial crisis, and equals 1 for *t* during Septmber 2008 - March 2009; $I_{crisis2,t}$ correspons with the Eurozone Sovereign Debt Crisis and equals 1 for *t* during October 2009 - July 2011. For each currency j, we test for commonality in liquidity using the following time-series regression:

$$L_{j,t}^{EC} = \alpha_{0,j} + \beta_{0,j} L_{M,t} + I_{crisis1,t}(\alpha_{1,j} + \beta_{1,j} L_{M,t}) + I_{crisis2,t}(\alpha_{2,j} + \beta_{2,j} L_{M,t}) + \varepsilon_{j,t} \tag{13}$$

where $I_{crisis1,t} = 1$ if *t* occurs during the subprime-mortgage financial crisis period, and 0 otherwise; $I_{crisis2,t} = 1$ if *t* occurs during during the Eurozone sovereign debt crisis period, and 0 otherwise; the terms of $\beta_{0,j} + \beta_{1,j}$ and $\beta_{0,j} + \beta_{2,j}$ in Eq. (13) measure the effect of liquidity commonality during the subprime-mortgage financial crisis period and Eurozone sovereign debt crisis period, respectively. The parameter of $\beta_{0,j}$ indicates the effect of liquidity commonality in the non-crisis period, which

[4] According to official the Federal Reserve Board of St. Louis (2009) and the Bank for International Settlements (BIS 2010), the timeline of subprime-mortgage financial crisis is separated in four phases. Phase 1 spans a period from 1st August 007 until mid-September 2008 and is described as “initial financial turmoil”. Phase 2 (16th September 2008 until 31st December 2008) is defined as “sharp financial market deterioration”, phase 3 (1st January 2009 until 31st March 2009) is a phase of “macroeconomic deterioration” and phase 4 is described as “stabilization and tentative signs of recovery” (post-crisis period) including a financial market rally (from 1st April 2009 onwards).

we label as the liquidity beta. Based on Rösch et al. (2013) that find an increasing impact of financial crisis on the liquidity commonality, we thus expect the coefficient on the crisis dummy variables to be positively significant, indicating that commonality in liquidity enlarges during times of crisis.

Table 3 presents strong evidence for the existence of liquidity commonality. We find a co-movement of individual currency's liquidity with the aggregate FX liquidity, except for EUR/CHF, USD/CHF, and EUR/USD. This finding implies that the liquidity co-movement is a pervasive phenomenon across all currencies and supports our hypothesis. As adressed in Mancini et al. (2013), we confirm that liquidity commonality exists in FX markets. We also observe that the coefficient of crisis dummy variables are significant and positive across almost all currency markets studied during times of crisis. This result indicates that the relation between individual FX liquidity and the aggregate common FX liquidity becomes much stronger in times of crisis. Our finding is consistent with Rösch and Kaserer (2013), Andrew et al. (2012), and Kamara et al. (2008), showing that the commonality in FX liquidity is strengthening during crisis periods.

Consequently, based on the theoretical study of Brunnermeier and Pedersen (2009), co-movement in liquidity can at least partially belongs to liquidity supply effects. As the market declines or fluctulates, the fall or fluctuation in the asset value affects a trader's portfolio value, thereby increasing the probability of margin calls. This might force a trader to partially liquidate her portfolio, which is putting additional price pressure on the asset. A self-enforcing liquidity spiral is likely to occur and has an adverse effect on the liquidity in most markets. Therefore, during the financial crisis the demand of and supply for liquidity across many assets are affected commonly and it leads to an increase in the liquidity commonality.

Meanwhile, we find that the coefficients on crisis dummy variables for the

USD/CHF and EUR/CHF markets are significantly negative, which implies a declined liquidity commonality in the USD/CHF and EUR/CHF market instead. As noted in Mancini et al. (2013) and Ranaldo and Söderlind (2010), the weaker liquidity commonality in the CHF markets may imply that the Swiss franc offers insurance against the liquidity risk during the financial crisis. Furthermore, we also observe that the EUR/USD appears an inverse phenomenon. The negative effect of the financial crisis on the liquidity commonality of the EUR/USD market is partially explained by the depreciation of the USD caused by the subprime-mortgage financial crisis, as the depreciation in USD would leads to an increase in the demand for the liquidity of EUR. As a result, an increase in the demand for euro liquidity is negatively correlated with a decrease in the common compnenet of FX liquidities. This further supports that the level of liquidity commonality would be affected by events of market declines or financial crisis.

The results support our hypothesis that the liquidity commonality exists and it is time-varying. Almost all currencies we study are strongly related to the global-wide common liquidity component. Overall, the results corroborate the view that the relation between the liquidity in individual currency market and the common componenet of liquidity turns out to be stronger during the crisis periods.

5.2 Liquidity commonality around macroeconomic announcements

We now move on to see how the FX liquidity responds to the arrival of the news. Based on the inventory-control model of Amihud and Mendelson (1980), Ho and Stoll (1983), O'Hara and Oldfield (1986), and Fleming and Remolona (1999), the wide bid-ask spread at announcement reflects dealer's reluctance to make markets at a time of high price volatility. As Andrew et al. (2012) show, a higher market volatility either affects the liquidity demand (i.e. panic selling, risk aversion) or the supply for liquidity (capital constraint) across many assets, leading to the declined market-wide liquidity or common component of liquidity. The resulting decrease in an individual market's liquidity causes further asset price pressures, creating an illiquidity spiral that further strengthens the co-movement of liquidity. Our analysis aims to test whether a news announcement that invokes a higher market uncertainly or volatility would reinforce the commonality in liquidity and whether the market liquidity reacts asymmetrically to positive and negative news surprises, with a more pronounced reaction to negative than to positive news.

U.S. macroeconomic information might well move exchange rates if it has information content for the state of other economies, because it indicates the well-being of the "global economy." Therefore, we expect that, small changes in underlying U.S. news announcements might cause sharp price volatility during times of crisis, leading to increase commonality liquidity.

Eq. (13) is then further extended by considering good and bad news macroeconomic announcements separately. The revised regression for the positive news is as follows:

$$L_{j,t}^{(.)} = \alpha_{0,j} + \beta_{0,j} L_{M,t} + I_{News,t}^{(+)} \times I_{crisis1,t}(\alpha_{1,j} + \beta_{1,j} L_{M,t}) + I_{News,t}^{(+)} \times I_{crisis2,t}(\alpha_{2,j} + \beta_{2,j} L_{M,t}) + \varepsilon_{j,t} \qquad (14)$$

A similar approach can be used to examine whether it is a similar the effect of negative news on the liquidity commonality. We estimate an equation analogous to Eq. (13) for the negative news:

$$L_{j,t}^{(.)} = \alpha_{0,j} + \beta_{0,j} L_{M,t} + I_{News,t}^{(-)} \times I_{crisis1,t}(\alpha_{1,j} + \beta_{1,j} L_{M,t}) + I_{News,t}^{(-)} \times I_{crisis2,t}(\alpha_{2,j} + \beta_{2,j} L_{M,t}) + \varepsilon_{j,t} \qquad (15)$$

where $I_{News,t}^{(+)} = 1$ if there is a positive U.S. macroeconomic announcement during day t, and 0 otherwise; $I_{crisis1,t} = 1$ if day t is during the subprime-mortgage financial crisis period, and 0 otherwise; $I_{crisis2,t} = 1$ if day t is during the Eurozone sovereign debt crisis period, and 0 otherwise. The parameter of $\beta_{0,j}$ represents the extent of commonality in liquidity during the non-crisis period. $\beta_{0,j} + \beta_{1,j}$ and $\beta_{0,j} + \beta_{2,j}$ in Eq. (14) measure the extent of liquidity commonality during the subprime-mortgage financial crisis period and Eurozone sovereign debt crisis period, respectively. A similar notation for negative news, which sign is from positive $(+)$ to negative $(-)$. $I_{News,t}^{(-)} = 1$ if there is a negative U.S. macroeconomic announcement during day t, and 0 otherwise.

Tables 4 and 5 report the results for the change in liquidity commonality in responses to U.S. positive and negative announcement surprises, respectively. During periods of financial crisis, we observe that the coefficient on the U.S. positive announcement is significant at the 10% level and two are significant at the 5% level, for five out of the nine FX markets studied. We also find that liquidity commonality increases in response to U.S. positive positive news only for the EUR/JPY market, while the liquidity commonality declines for other currency-pairs. This phenomenon suggests that, overall, the liquidity commonality decreases as there is good news about the US economy. With the arrival of positive news about the US economy, the liquidity commonality for the USD against other currency becomes much smaller. As shown in Table 4, the lowest of liquidity commonality occurs in the USD/CHF market, while the highest of liquidity commonality occurs in the EUR/JPY market. As "good" news about the U.S. economy would strengthen the dollar immediately, and hence it lears to a positive return expectation for dollar exchange rates. For example, a positive return of USD/CHF induces a higher demand for the US dollar but a higher supply of CHF, leading to a higher liquidity in the USD/CHF market. Therefore, an increase in USD/CHF return is associated with an increase in liquidity demand for USD/CHF.

The increases in USD/CHF liquidity then corresponds to a lower extent of liquidity commonality of the USD/CHF market.

Moreover, a negative U.S. announcement generally induces dollar depreciation and the market stress may cause a higher volatility in the market, resulting in a higher level of liquidity commonality. As shown in Ehrmann and Fratzscher (2005), exchange rates respond more strongly to negative or large shocks or when the market is more uncertaint. In Table 5, we find that only in the EUR/USD market the negative news has a significantly positive effect on the liquidity commonality, while negative news has a negative impact on the liquidity commonality in other FX markets. These results are opposite to our expectation. One possible explanation for this outcome stems from shorter-lived effects of market volatility on the liquidity. Consistent with Andersen and Bollerslev (1998), news announcements have a significanty positive impact on volatility, but for a very short period of time. The uncertainty associated with the announcement may reduce quickly and disappear over the horizon of one day.

Overall, the results show that FX liquidity commonality reponds asymmetrically to positive and negative news. We find that macroeconomic announcements significantly affect the FX liquidity co-movements as measured in efficient spread, consistent with the prediction of Brockman et al. (2009). Our findings also suggest that the FX dealers seems to trade more actively and faster in response to good news than to bad news, as positive news exerts a larger impact on the liquidity commonality during the crisis period.[5]

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[5] In the analysis of announcement effect, we report the result based on only three major announcements, following the analysis of Brockman et al. (2009). Actually we have also considered announcements of other macroeconomic indicator, including nonfarm production, consumer confidence index (CCI), durable orders, housing starts, industrial production, jobless claims, producer price index (PPI), personal spending, retail sales, and trade balance, but only the three announcements,

5.3 Liquidity commonality around monetary policy announcements

Given the strong variation in liquidity commonality during the crisis periods, we further explore the impact of certain monetary policies on the liquidity commonality over time. According to Brunnermeier and Pedersen (2009), when the funding liquidity is tight, traders become risk averse by shifting their portfolio from high risk asset to insurance asset. This leads to declined market liquidity and higher volatility. Further, under certain conditions, lower expected liquidity increases the risk of financing a trade across assets, thus increasing the co-movements in liquidity among markets.

During the recent financial crisis, the Federal Reserve (Fed) adopts quantitative easing (QE) policies to inject high capital inflows into the economy to improve the liquidity in the asset markets. Based on the links between funding and market liquidity, we especially want to understand whether quantitative easing policy can enhance the FX liquidity and affect the extent of liquidity commonality in FX markets.

Following the framework of Mancini et al. (2013), we estimate the liquidity betas by adding the dummy variables indicating the announcement of a certain monetary policy and explore the impact of the unconventional monetary policy on the liquidity commonality. We rewrite the regression model as follows:

$$L_{j,t}^{(.)} = \alpha_{0,j} + \beta_{0,j} L_{M,t} + I_{QE,t} \times I_{crisis1,t}(\alpha_{1,j} + \beta_{1,j} L_{M,t}) + I_{QE,t} \times I_{crisis2,t}(\alpha_{2,j} + \beta_{3,j} L_{M,t}) + \varepsilon_{j,t} \quad (16)$$

where $I_{QE,t} = 1$ if the quantitative easing policy is announced during day t, and 0 otherwise; β_0 measures the extent of liquidity commonality during the normal period

including GDP, CPI, and unemployment rate have significant influence on liquidity commonality. Therefore, we only report the results based on the three types of announcements.

without quantitative easing policy announcement; $I_{crisis1,t} = 1$ and $I_{crisis2,t} = 1$ refer to the days during the subprime-mortgage financial crisis period and Eurozone sovereign debt crisis period, respectively, and 0 otherwise. The estimated coefficients of $\beta_{0,j} + \beta_{1,j}$ and $\beta_{0,j} + \beta_{2,j}$ represent the impact of quantitative easing policy announcement on the liquidity commonality during the period of subprime-mortgage financial crisis and the period of Eurozone sovereign debt crisis, respectively.

Table 6 displays the results for the responses of liquidity commonality to QE announcement. We observe that for most markets, the coefficient on the dummy variable of QE announcement is significantly negative, except for EUR/GBP, EUR/JPY, GBP/USD, and USD/CHF. This result implies that QE announcement improves investors' funding restrictions and stimulates more trading activities. As mentioned by Neely (2015), the unconventional monetary policy has large international spillover effects and leads to dollar depreciation during recent financial crisis period. As the depreciation of USD resulted from Fed's QE policy might lead risk-averse traders to shift the potfolio allocation from dollar-denominated assets to foreign currency-denominated assets. In other words, investors would demand for a higher risk premium to compensate the loss from holding USD that is more likely to depreciate sharply than to appreciate sharply, and thus traders decrease the demand for USD but increase the demand for non-dollar currencies. As a result, when the market liquidity increases due to the announcement of expansionary monetary policy, the liquidity commonality is reduced. Consistent with Coughenour and Saad (2004), Brunnermeier and Pedersen (2009), Hameed et al. (2010), and Rösch et al. (2013), the significant effect of QE announcement on the FX liquidity commonality suggests an important role the funding liquidity channel plays on the market liquidity.

In summary, our results show that FX liquidity commonality varies over time, increases during periods with higher market volatility and uncertainty, increases at major crisis events, and becomes weaker at the announcement of QE policy.

5.4 Determinants of FX global-wide systematic liquidity

After detecting a stronger liquidity commonality during recent financial crisis periods, we in turn investigate potential determinants that affect the systematic liquidity, that is, L_M. We begin by estimating the time-series regression model of the systematic liquidity as follows:

$$L_{M,t} = \alpha + \beta^{M} L_{M,t-1} + \beta^{other} f_{t-1}^{other} + \varepsilon_t \qquad (17)$$

where $L_{M,t-1}$ is lagged global-wide FX liquidity index, and f_{t-1}^{other} is the set of lagged control variables which include global FX volatility (VXY), Chicago Board Options Exchange Volatility Index (VIX), and TED spread (TED). Furthermore, let S_i = 1, 2, and 3 denote CPI, GDP, and unemployment rate news announcements, respectively. $S_{i,t}^{(+)}$ and $S_{i,t}^{(-)}$ reflect positive and negative news surprises, respectively.

Table 7 presents the OLS estimation results with robust standard errors calculated from the approach of Newey and West (1987). In Model (5) of Table 7, we regress the systematic liquidity on lagged *VIX*, lagged *VXY*, and lagged *TED*. Our results corroborate the theoretical predictions proposed by Brunnermeier and Pedersen (2009). In fact, by using different measures of funding liquidity tightness, we observe that there is a clearly negative relationship between the systematic liquidity and proxy variables of funding liquidity (e.g. *VIX* and *TED*). For instance, a one-unit increase in the *TED* on day $t-1$ would yield a 0.0091-unit decrease in the FX systematic liquidity on day t. This implies that, when traders face a more restrictive funding situation, it would trigger an increase in liquidity commonality, which then leads the systematic liquidity to dry up.

On the other hand, *VXY* is a proxy for perceived FX inventory risk. We find that the estimated coefficient on *VXY* has a largely significant associatio with the systematic liquidity, compared to other explanatory variables. In Model (5) of Table 7, *VXY* has the largest coefficient, -0.2179 (in absolute value), and *TED* has the smallest coefficient, -0.0909 (in absolute value). This result is in line with earlier insights of Stoll (1978) and Fleming and Remolona (1999), supporting that an increase in volatility leads to a wider bid-ask spread and lower liquidity. Dealers usually widen the spread or withdraw their quotes in response to the inventory risks resulted from the sharp shift in price volatility.

Moreover, in Models (6) and (7) of Table 7, we include the absolute value of positive and negative news surprises to study potentially asymmetric reactions of the systematic liquidity to news shocks. We observe that the FX systematic liquidity is more sensitive to economic fundamentals when positive news shocks occur. This is somewhat different from the finding of Riordan et al. (2013) in which the liquidity increases with news that is associated with positive or neutral sentiment, whereas news with negative sentiment is associated with a decrease in liquidity. In Model (6) of Table 7, we observe that two of our three U.S. macroeconomic announcements, that is, CPI and unemployment rate, have a significant impact on the global-wide systematic liquidity. In particular, the estimated coefficient of CPI is larger than that of unemployment rate in scale. The lagged news surprise effect is studied in Model (7) of Table 7. Similarly, the coefficient of lagged CPI surprise is larger than those of other macroeconomic indicators.

Additionally, we consider whether this result be different during financial crisis periods in comparison with tranquil periods. We incorporate the crisis dummy variable into the regression model as follows:

$$L_{M,t} = \alpha_0 + \beta_0^M L_{M,t-1} + \beta_0^{other} f_{t-1}^{other} + I_{crisis1,t}(\alpha_1 + \beta_1^M L_{M,t-1} + \beta_1^{other} f_{t-1}^{other}) +$$

$$I_{crisis2,t}(\alpha_2 + \beta_2^M L_{M,t-1} + \beta_2^{other} f_{t-1}^{other}) + \varepsilon_t \qquad (18)$$

where $I_{crisis1,t} = 1$ if day t occurs during the subprime-mortgage financial crisis period, and 0 otherwise; $I_{crisis2,t} = 1$ if day t is during the period of Eurozone sovereign debt crisis, and 0 otherwise. Compared with the non-crisis periods, the sensitivity of control variables during the financial crisis period is different. During times of crisis, we observe that control variables have no significant influence on the systematic FX liquidity, except for news surprises. The coefficients of the lagged *VIX*, *VXY*, and TED are not significantly different from zero in times of crisis. This funding is inconsistent with liquidity spiral effects that is stronger during crisis periods, as predicted by Brunnermeier and Pedersen (2009). However, news surprises still impact the global-wide systematic liquidity in the FX markets during the period of financial crisis period, particularly the GDP announcements has a significant effect on the systematic liquidity.

6. Conclusions

Using the high-frequecy EBS data over six years and nine major currency pairs, covering the period from January 5, 2008 through December 31, 2013, we study the FX liquidity in depths. Extending the analysis of Mancini et al. (2013) we consider the financial crisis factor, by focusing our attention on the subprime-mortgage financial crisis and Eurozone Sovereign Debt Crisis periods. This study contributes to provide the understanding about the dynamics of the FX systematic liquidity in times of crisis.

We apply a generalized factor model, the GDFM approach, to extract the sytematic liquidity (or the commonn componenet in liquidity) among FX markets. The use of this method allows us to resolve the problem caused by the salient autocorrelation in liquidity.

Our main results can be summarized as follows. First, we provide the evidence of stronger liquidity commonality in times of crisis, indicating a stronger comovement between the liquidity in individual currency-pair and the aggregte systematic liquidity among many currecy-pairs during times of crisis. On the other hand, the liquidity commonality of the USD/CHF and the EUR/CHF are significantly weaker during crisis periods. As addressed in Mancini et al. (2013) and Ranaldo and Söderlind (2010), this finding implies that the Swiss franc offers insurance against liquidity risk during the financial crisis.

Second, we show that the increased uncertainly or price volatility invoked by news releases may induce the liquidity commonality to vary around the announcement. Separating news surprises into positive and negative news, we can better understand the variation in the FX liquidity commonality around the announcement. We find that the good news has a larger impact on the FX liquidity commonality than does the negative news during the crisis periods.

Furthermore, the announcement of expanionary QE policy also affects the FX liquidity commonality. As the QE policy may improve investor's funding restrictions and stimulate trading activities, the liquidity commonality is reduced during the financial crisis. This empirical evidence corroborates the influence of funding constraint on the liquidity, which is theoretically proposed by Brunnermeier and Pedersen (2009). Although the QE policy might improve the entire systematic liquidity and lower the adverse effect of liquidity spiral on individual liquidity, but the weaker comovement between the systematic liquidity and individual liquidity in response to the QE announcemnet may reflect that the recovery speeds in the systematic liquidity and in the liquidity of an individual currency-pair are different.

Finally, we examine factors that affects the systematic liquidity over time. Our results show that the systematic liquidity is affected either by supply-side forces related to the funding liquidity (i.e. VIX and TED) or by the increased price volatility related to dealers' inventory cost or news surprises. Overall, the results are in line with the perception that news releases have played an important role in times of financial crisis.

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Table 1: U.S. Macroeconomics Announcements

Announcements	Obs number	Sources	Dates	Favorable News if
U.S.				
1. GDP	24	BEA	01/2008 – 12/2013	Actual value higher than expected value
2. CPI	72	BLS	01/2008 – 12/2013	Actual value lower than expected value
3. Unemployment rate	72	BLS	01/2008 – 12/2013	Actual value lower than expected value

Table 1 illustrates the U.S. macroecnomic announcement category, source, observations, and dates. The announenements considered include GDP, CPI, and unemployment rate. The sources are Bureau of Labor Statistics (BLS) and Bureau of Economic Analysis (BEA).

Table 2: Descriptive Statistics for Daily Liquidity Measures

	GBP/ USD	USD/ CHF	EUR/ CHF	EUR/ GBP	EUR/ JPY	AUD/ USD	USD/ CAD	USD/ JPY	EUR/ USD
Price impact									
Mean	0.00003	0.00002	0.00004	0.00007	0.00005	0.00006	0.00005	0.00002	0.00001
Std.dev.	0.00018	0.00009	0.00007	0.00027	0.00009	0.00023	0.00022	0.00004	0.00003
Skewness	0.10627	-0.00450	4.48208	-0.36279	2.31167	0.19708	-3.79171	1.29612	1.35704
Kurtosis	35.49537	107.2549	71.16350	21.58791	25.66543	20.51877	61.17666	12.04614	10.15909
ρ_{20}	0.0327	0.0415	0.0496	0.0151	0.0762	0.0925	0.0763	0.1336	0.1822
$Q(20)$	78.625***	194.56**	149.71**	68.367***	375.54***	440.98**	184.8***	911.06**	2419.7***
Return									
Mean	-0.00001	-0.00001	-0.00002	-0.00002	-0.00003	-0.00003	-0.00002	-0.00001	-0.00001
Std.dev.	0.00019	0.00009	0.00007	0.00031	0.00011	0.00024	0.00022	0.00004	0.00002
Skewness	2.76867	-0.66639	-3.77403	6.15266	-7.90214	0.32338	-0.51799	-1.16282	-1.30987
Kurtosis	90.79783	103.8367	60.63043	124.39027	150.76438	39.93582	40.76378	13.37111	14.66110
ρ_{20}	0.0025	-0.0193	0.0536	0.0244	0.0378	0.0271	0.0339	0.0225	0.0228
$Q(20)$	16.429	33.551	77.964**	19.204	165.59***	36.801	44.828**	97.862**	151.91***
Bid-ask spread									
Mean	0.00051	0.00054	0.00044	0.00045	0.00057	0.00067	0.00059	0.00024	0.00017
Std.dev.	0.00099	0.00095	0.00098	0.00039	0.00115	0.00216	0.00072	0.00032	0.00027
Skewness	11.54239	5.85526	13.34012	7.88772	6.36560	20.24357	6.81580	6.99097	12.30278
Kurtosis	204.82773	52.86486	263.1542	94.58296	56.10461	525.9314	83.23321	83.26849	257.95691
ρ_{20}	0.1458	-0.0498	0.0014	0.1550	-0.0642	0.0043	0.3048	-0.0879	-0.0608
$Q(20)$	1582.7***	2095.7**	508.58**	1281.7***	2337***	456***	3618.7**	2385.9**	1335.2***
Effective cost									
Mean	0.00268	0.00281	0.00167	0.00250	0.00349	0.00357	0.00289	0.00239	0.00230
Std.dev.	0.00222	0.00214	0.00228	0.00201	0.00260	0.00344	0.00269	0.00167	0.00149
Skewness	3.45906	3.57380	11.98414	3.93773	2.65287	4.94980	3.93208	2.25953	1.47410
Kurtosis	26.73532	32.63595	284.1989	39.21771	16.22018	48.59023	28.60488	12.90021	6.17838
ρ_{20}	0.3212	0.0816	0.2400	0.2007	0.1271	0.2124	0.2790	0.0989	0.1006

Table 2 (continued)

	GBP/ USD	USD/ CHF	EUR/ CHF	EUR/ GBP	EUR/ JPY	AUD/ USD	USD/ CAD	USD/ JPY	EUR/ USD
Q(20)	3827.7***	886.42***	3180.9***	1801.5***	2038.7***	3169.5***	4437.5***	1264.7***	1720.4***

This table shows summary statistics about mean, standard deviation, skewness, and kurtosis for various daily measure of liquidity of each currency. Bid-ask spread is the average bid-ask spread computed intrday data for each trading day (Eq.(2)). Effective cost is the average relative difference between the transaction price and the bid/ask quote prevailing at the time of trade (Eq.(3)). Price impact is the estimated coefficient of contemporaneous of order flow φ_t, in a regression of one-minute returns on contemporaneous and lagged of order flow. Return reversal denotes the sum of the coefficients of lagged order flow, as shownn in Eq. (4). ρ_{20} is the sample autocorrelation at lag 20 for each currency. The Ljung-Box Q is testing for autocorrelation in time series data. $Q(20)$ is the critical value for rejection of the null hypothesis of randomness up to lag 20. The data cover the period from January 7, 2008 through December 31, 2013. $***$, $**$, and $*$ denote the significance at the levels of 1%, 5%, and 10%, respectively.

Table 3: Commonality in FX Liquidity during the Crisis and Non-Crisis Periods

	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	AUD/USD	USD/CHF	USD/CAD	USD/JPY
$\alpha_{0,j}$	0.0784	-0.0911**	-0.0272	-0.1198***	-0.1303***	-0.0454	0.2089***	-0.0555	-0.0416
	(0.0989)	(0.0330)	(0.0372)	(0.0297)	(0.0291)	(0.0346)	(0.0375)	(0.0352)	(0.0399)
$\beta_{0,j}$	0.2346**	0.1124**	0.1681***	0.1807***	0.1185***	0.1304***	0.3007***	0.1208***	0.1250***
	(0.0744)	(0.0162)	(0.0227)	(0.0146)	(0.0162)	(0.0211)	(0.0236)	(0.0207)	(0.0194)
$\alpha_{1,j}$	-0.2133*	0.1196	-0.1136	0.4526***	0.1902*	0.1195	-0.3774***	0.0383	0.2635**
	(0.1082)	(0.1198)	(0.0862)	(0.0773)	(0.0838)	(0.1178)	(0.0818)	(0.1420)	(0.0906)
$\beta_{1,j}$	-0.1479*	0.0664	0.0672*	-0.0583*	0.1360***	0.1060*	-0.1485***	0.1059*	0.0056
	(0.0754)	(0.0428)	(0.0329)	(0.0241)	(0.0306)	(0.0431)	(0.0331)	(0.0496)	(0.0279)
$\alpha_{2,j}$	0.1369	0.1263**	0.0124	-0.3488***	0.0802*	-0.1253**	-0.2528***	-0.0501	0.0164
	(0.1037)	(0.0462)	(0.0460)	(0.0438)	(0.0384)	(0.0396)	(0.0452)	(0.0406)	(0.0553)
$\beta_{2,j}$	-0.0954	0.0159	0.0839**	0.1114***	-0.0035	-0.0012	-0.1161***	-0.0116	0.1118*
	(0.0757)	(0.0243)	(0.0320)	(0.0283)	(0.0191)	(0.0236)	(0.0304)	(0.0226)	(0.0444)
$H_0 : \beta_{1,j} = \beta_{2,j}$	0.004***	0.247	0.612	0.000***	0.000***	0.006**	0.281	0.010*	0.017
Adj. R^2	0.366	0.315	0.571	0.525	0.544	0.502	0.629	0.423	0.333

Table 3 reports the estimation results of the following model:

$$L_{j,t}^{(.)} = \alpha_{0,j} + \beta_{0,j} L_{M,t} + \alpha_{1,j} I_{crisis1,t} + \beta_{1,j} I_{crisis1,t} L_{M,t} + \alpha_{2,j} I_{crisis2,t} + \beta_{2,j} I_{crisis2,t} L_{M,t} + \varepsilon_{j,t}$$

$I_{crisis1,t} = 1$ if t is during the subprime-mortgage financial crisis period; $I_{crisis2,t} = 1$ if t is during the Eurozone sovereign debt crisis period, and 0 otherwise. $\beta_{0,j}$ indicates the individual liquidity sensitivity to market-wide FX liquidity. $\beta_{0,j} + \beta_{1,j}$ measured the change in the liquidity commonality during the subprime-mortgage financial crisis period. $\beta_{1,j} + \beta_{3,j}$ refers to the change in the liquidity commonality during the Eurozone sovereign dDebt crisis period. The heteroscedasticity-and-autocorrelation-consistent standard errors (Newey and West, 1987) are reported in parentheses. The data cover the period from January 7, 2008 through December 31, 2013.

$***$, $**$, and $*$ denote the significance at the levels of 1%, 5%, and 10%, respectively.

Table 4: Impacts of U.S. Positive Macroeconomic Anouncements on Lquidity Cmmonality

	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	AUD/USD	USD/CHF	USD/CAD	USD/JPY
$\alpha_{0,j}$	-0.0035	-0.0069	0.0027	0.0053	-0.0014	0.0011	0.0023	-0.0029	-0.0020
	(0.0223)	(0.0215)	(0.0172)	(0.0188)	(0.0188)	(0.0193)	(0.0174)	(0.0201)	(0.0214)
$\beta_{0,j}$	0.1467***	0.1461***	0.2030***	0.1911***	0.1873***	0.1843***	0.2053***	0.1668***	0.1500***
	(0.0327)	(0.0165)	(0.0141)	(0.0112)	(0.0150)	(0.0181)	(0.0170)	(0.0184)	(0.0125)
$\alpha_{1,j}$	-0.2009	0.0313	0.0093	0.1537	-0.0355	0.2893	-0.2399	-0.1959	0.4603
	(0.1070)	(0.3140)	(0.1647)	(0.1659)	(0.1450)	(0.1802)	(0.1518)	(0.1859)	(0.2623)
$\beta_{1,j}$	-0.0478	0.0997	0.0769**	-0.1603***	0.0947	-0.0178	-0.1895***	0.2445	0.0891
	(0.0539)	(0.0987)	(0.0256)	(0.0361)	(0.0734)	(0.0541)	(0.1444)	(0.0791)	(0.0809)
$\alpha_{2,j}$	0.1624	0.2571	-0.0711	-0.0135	-0.0970	-0.2559***	0.1600	-0.1944*	-0.0208
	(0.1123)	(0.1639)	(0.1617)	(0.1597)	(0.1141)	(0.0726)	(0.0949)	(0.0862)	(0.1340)
$\beta_{2,j}$	0.0498	-0.0297	0.0632	-0.0291	-0.1516**	-0.0858**	0.0691	-0.0856***	0.1060
	(0.0661)	(0.0789)	(0.0965)	(0.0964)	(0.0467)	(0.0292)	(0.0502)	(0.0256)	(0.0729)
H_0: $\beta_{1,j}=\beta_{2,j}$	0.419	0.100*	0.873	0.000***	0.317	0.623	0.29	0.000***	0.001***
Adj. R^2	0.282	0.298	0.560	0.476	0.476	0.451	0.553	0.402	0.317

Table 4 reports the estimation results of the following model:

$$L_{j,t}^{(\cdot)} = \alpha_{0,j} + \beta_{0,j}L_{M,t} + I_{News,t}^{(+)} \times I_{crisis1,t}(\alpha_{1,j} + \beta_{1,j}L_{M,t}) + I_{News,t}^{(+)} \times I_{crisis2,t}(\alpha_{2,j} + \beta_{2,j}L_{M,t}) + \varepsilon_{j,t}$$

$I_{News,t}^{(+)} = 1$ if a U.S. positive macroeconomic news announcement is released during day t, and 0 otherwise. $I_{crisis1,t} = 1$ if t is during the subprime-mortgage financial crisis period; $I_{crisis2,t} = 1$ if t is during the Eurozone sovereign debt crisis period, and 0 otherwise. $\beta_{0,j}$ indicates the individual liquidity sensitivity to the systematic liquidity during days without announcement. $\beta_{0,j} + \beta_{1,j}$ and $\beta_{0,j} + \beta_{2,j}$ refer the change in liquidity commonality related to a U.S. positive announcement during the subprime-mortgage financial crisis period and Eurozone sovereign debt crisis period, respectively. The heteroscedasticity-and-autocorrelation-consistent (Newey and West, 1987) standard errors are reported in parentheses. The data cover the period from January 7, 2008 through December 31, 2013.

$***$, $**$, and $*$ denote the significance at the levels of 1%, 5%, and 10%, respectively.

Table 5: Impacts of U.S. Negative Macroeconomic Announcements on Liquidity Commonality

	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	AUD/USD	USD/CHF	USD/CAD	USD/JPY
$\alpha_{0,j}$	0.0022	-0.0094	0.0079	-0.0054	-0.0062	-0.0031	0.0017	0.0052	0.0001
	(0.0238)	(0.0205)	(0.0173)	(0.0187)	(0.0192)	(0.0192)	(0.0181)	(0.0206)	(0.0218)
$\beta_{0,j}$	0.1495***	0.1397***	0.2063***	0.1898***	0.1831***	0.1756***	0.2046***	0.1798***	0.1510***
	(0.0345)	(0.0131)	(0.0138)	(0.0104)	(0.0150)	(0.0158)	(0.0172)	(0.0184)	(0.0131)
$\alpha_{1,j}$	-0.4701**	-0.4417	-0.5372	0.8620**	-0.3564	-0.1151	0.0396	1.1803	0.0483
	(0.1505)	(0.6627)	(0.4861)	(0.3127)	(0.3187)	(0.5731)	(0.4449)	(0.6178)	(0.2026)
$\beta_{1,j}$	-0.0171	0.1457	0.0085	-0.1060	0.0943	0.1379	-0.0435	-0.1963***	0.0347
	(0.0386)	(0.1835)	(0.1058)	(0.0579)	(0.0546)	(0.1266)	(0.0917)	(0.0479)	(0.0382)
$\alpha_{2,j}$	-0.0496	0.1699	-0.0768	0.3330*	0.1912	-0.2524***	-0.0585	-0.1713	0.0305
	(0.0972)	(0.1470)	(0.1458)	(0.1364)	(0.1370)	(0.0677)	(0.0841)	(0.0890)	(0.1777)
$\beta_{2,j}$	-0.0462	-0.0235	0.0800	0.2222***	0.0120	-0.0918**	-0.0249	-0.0524	-0.0923
	(0.0597)	(0.0569)	(0.0468)	(0.0603)	(0.0651)	(0.0299)	(0.0447)	(0.0332)	(0.0619)
H_0: $\beta_{1,j}$=$\beta_{2,j}$	0.0251**	0.1572	0.1159	0.143	0.478	0.8273	0.9925	0.8178	0.0592*
Adj. R^2	0.482	0.540	0.280	0.308	0.559	0.454	0.380	0.315	0.479

This table reports the estimation results of the following model:

$$L_{j,t}^{(.)} = \alpha_{0,j} + \beta_{0,j} L_{M,t} + I_{News,t}^{(-)} \times I_{crisis1,t}(\alpha_{1,j} + \beta_{1,j} L_{M,t}) + I_{News,t}^{(-)} \times I_{crisis2,t}(\alpha_{2,j} + \beta_{2,j} L_{M,t}) + \varepsilon_{j,t}$$

$I_{News,t}^{(-)} = 1$ if a U.S. negative macroeconomic news announcement is released during day *t*, and 0 otherwise. $I_{crisis1,t} = 1$ if t is during the subprime-mortgage financial crisis period; $I_{crisis2,t} = 1$ if *t* is during the Eurozone sovereign debt crisis period, and 0 otherwise. $\beta_{0,j}$ indicates the individual liquidity sensitivity to the FX systematic liquidity during the non-country announcement and normal period. $\beta_{0,j} + \beta_{1,j}$ and $\beta_{0,j} + \beta_{2,j}$ refer to the change in the liquidity commonality related to a negative U.S. news announcement during the subprime-mortgage financial crisis period and the Eurozone sovereign debt crisis period, respectively. The null hypothesis reports the F tests for the coefficient restrictions. The heteroscedasticity-and-autocorrelation-consistent (Newey and West, 1987) standard errors are reported in parentheses. The data cover the period from January 7, 2008 through December 31, 2013.

$***$, $**$, and $*$ denote the significance at the levels of 1%, 5%, and 10%, respectively.

Table 6: Effect of Quantitative Easing Policy Announcements on Liquidity Commonality

	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	AUD/USD	USD/CHF	USD/CAD	USD/JPY
$\alpha_{0,j}$	0.0015	-0.0048	0.0011	0.0007	-0.0045	0.0008	0.0020	0.0004	-0.0005
	(0.0221)	(0.0210)	(0.0171)	(0.0186)	(0.0183)	(0.0191)	(0.0174)	(0.0202)	(0.0213)
$\beta_{0,j}$	0.1465***	0.1457***	0.2042***	0.1901***	0.1846***	0.1844***	0.2034***	0.1701***	0.1536***
	(0.0319)	(0.0156)	(0.0138)	(0.0110)	(0.0143)	(0.0177)	(0.0167)	(0.0184)	(0.0124)
$\alpha_{1,j}$	-0.1477	-4.1330*	-1.5400**	1.2139***	-2.3688***	-0.5236	1.7818**	2.4043**	1.5379***
	(0.4269)	(2.0029)	(0.4793)	(0.1437)	(0.0324)	(0.3341)	(0.6639)	(0.8217)	(0.0381)
$\beta_{1,j}$	-0.0910	0.7832***	0.1480***	-0.3059***	0.5940***	0.0419	-0.3382***	-0.2653***	-0.1722***
	(0.0495)	(0.1782)	(0.0446)	(0.0167)	(0.0145)	(0.0344)	(0.0611)	(0.0751)	(0.0127)
$\alpha_{2,j}$	0.0378	0.1206	-0.0812	0.3255	-0.0276	-0.0930	-0.0313	-0.1822	0.0344
	(0.0708)	(0.1625)	(0.1275)	(0.2050)	(0.1769)	(0.1061)	(0.0806)	(0.1091)	(0.1534)
$\beta_{2,j}$	-0.3743***	-0.5160**	0.2965**	0.2450	-0.2153	-0.0804	0.1689*	-0.1966	0.2607
	(0.0856)	(0.1928)	(0.0934)	(0.1624)	(0.2373)	(0.1032)	(0.0744)	(0.1407)	(0.1386)
H_0 :									
$\beta_{1,j} = \beta_{2,j}$	0.002***	0.036**	0.055*	0.577	0.148	0.294	0.100*	0.649	0.183
Adj. R^2	0.282	0.330	0.559	0.478	0.498	0.453	0.548	0.386	0.314

This table reports the estimation results of the following model:

$$L_{j,t}^{(.)} = \alpha_{0,j} + \beta_{0,j} L_{M,t} + I_{QE,t} \times I_{crisis1,t}(\alpha_{1,j} + \beta_{1,j} L_{M,t}) + I_{QE,t} \times I_{crisis2,t}(\alpha_{2,j} + \beta_{2,j} L_{M,t}) + \varepsilon_{j,t}$$

$I_{QE,t} = 1$ if a quantitative easing policy announcement is announced during day *t*, and 0 otherwise. $I_{crisis1,t} = 1$ if *t* is during the subprime-mortgage financial crisis period, and 0 otherwise; $I_{crisis2,t} = 1$ if *t* is during the Eurozone sovereign debt crisis period, and 0 otherwise. The parameter $\beta_{0,j}$ indicates the individual liquidity sensitivity to the FX systematic liquidity during days without quantitative easing policy announcement. The parameters of $\beta_{0,j} + \beta_{1,j}$ and $\beta_{0,j} + \beta_{2,j}$ indicate the change in the liquidity commonality related with a quantitative easing policy announcement during the subprime-mortgage financial crisis period and the Eurozone sovereign debt crisis period, respectively. The heteroscedasticity-and-autocorrelation-consistent (Newey and West, 1987) standard errors are reported in parentheses. The data cover the period from January 7, 2008 through December 31, 2013.

$***$, $**$, and $*$ denote the significance at the levels of 1%, 5%, and 10%, respectively.

Table 7: Determinants of the Systematic Liquidity in FX Markets

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
$L_{M,t-1}$	0.9308***				0.5702***	0.5660***	0.5693***
	(0.0283)				(0.0558)	(0.0560)	(0.0557)
VXY_{t-1}		-1.3653***			-0.3497***	-0.3501***	-0.3464***
		(0.0448)			(0.0634)	(0.0635)	(0.0618)
VIX_{t-1}			-0.3634***		-0.0526**	-0.0540**	-0.0522**
			(0.0111)		(0.0182)	(0.0184)	(0.0183)
TED_{t-1}				-0.0683***	-0.0091***	-0.0092***	-0.0092***
				(0.0039)	(0.0024)	(0.0024)	(0.0024)
$S_{1,t}^{(-)}$						0.1412	0.1181
						(0.2584)	(0.2607)
$S_{2,t}^{(-)}$						-0.4694	-0.4977
						(0.2876)	(0.2913)
$S_{3,t}^{(-)}$						-0.7011	-0.7327
						(0.4001)	(0.4015)
$S_{1,t-1}^{(-)}$							-0.2279
							(0.2911)
$S_{2,t-1}^{(-)}$							0.0482
							(0.1595)
$S_{3,t-1}^{(-)}$							-0.1912
							(0.2744)
$S_{1,t}^{(+)}$						0.3173*	0.2822
						(0.1504)	(0.1501)
$S_{2,t}^{(+)}$						-0.4724	-0.5042
						(0.4456)	(0.4460)
$S_{3,t}^{(+)}$						-0.5323*	-0.5526*
						(0.2555)	(0.2553)

Table 7 (continued)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
$S_{1,t-1}^{(+)}$							-1.3101*
							(0.5344)
$S_{2,t-1}^{(+)}$							-1.9760
							(1.3516)
$S_{3,t-1}^{(+)}$							0.4299
							(1.0226)
Adj. R^2	0.820	0.711	0.703	0.450	0.852	0.854	0.856

Table 7 reports the estimation results of the following model:

$$L_{M,t} = \alpha + \beta L_{M,t-1} + \beta^{other} f_{t-1}^{other} + \varepsilon_t$$

where $L_{M,t-1}$ is the lagged FX systematic liquidity, f_{t-1}^{other} is the set of lagged control variables, including global FX volatility (VXY), Chicago Board Options Exchange Volatility Index (VIX), TED spread (TED), positive news surprise ($S_{i,t}^{(+)}$), and negative news surprises ($S_{i,t}^{(-)}$). The heteroscedasticity-and-autocorrelation-consistent (Newey and West, 1987) standard errors are reported in parentheses. The data cover the period from January 7, 2008 through December 31, 2013.

$***$, $**$, and $*$ denote the significance at the levels of 1%, 5%, and 10%, respectively.

Table 8: Determinants of the Systematic Liquidity in the FX Markets during Crisis Periods

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
$I_{crisis1,t}$	-0.7759*	1.6531	6.8351***	-3.5751***	0.8038	1.2585	0.443
	(0.3581)	(1.135)	(2.470)	(0.796)	(2.292)	(2.330)	(2.155)
$I_{crisis2,t}$	-0.4081**	-4.7721***	-3.7721***	-1.6137***	-2.6150*	-2.5035	-2.394
	(0.1522)	(0.487)	(1.096)	(0.272)	(1.482)	(1.519)	(1.508)
$L_{M,t-1}$	0.7410***				0.3564***	0.3535***	0.3533***
	(0.0512)				(0.0632)	(0.0634)	(0.0639)
$I_{crisis1,t}L_{M,t-1}$	0.2400**				0.3379**	0.3288**	0.3191**
	(0.0752)				(0.1090)	(0.1088)	(0.1079)
$I_{crisis2,t}L_{M,t-1}$	-0.0673				0.1904*	0.1779*	0.1680*
	(0.0688)				(0.0803)	(0.0822)	(0.0800)
VXY_{t-1}		-0.3105***			-0.0746***	-0.0761***	-0.0774***
						(0.0171)	(0.0170)
$I_{crisis1,t}VXY_{t-1}$		(0.0102)			(0.0169)	0.0331	0.0279
		-0.0891**			0.0337	(0.0524)	(0.0522)
$I_{crisis2,t}VXY_{t-1}$		(0.0290)			(0.0514)	0.0635*	0.0668*
		0.1706***			0.0589*	(0.0284)	(0.0282)
VIY_{t-1}		(0.0231)	-1.1351***		(0.0283)	-0.4419***	-0.4411***
			(0.0374)		-0.4404***	(0.0633)	(0.0634)
$I_{crisis1,t}VIY_{t-1}$		0.1126	0.0279	0.0949		-0.0349	0.0285
			-0.5235***		(0.0636)	(0.1935)	(0.1769)
$I_{crisis2,t}VIY_{t-1}$			(0.1520)		-0.0124	0.0402	0.0252
			0.3535***		(0.1915)	(0.1408)	(0.1394)
TED_{t-1}			(0.0939)		0.0554	-0.0105***	-0.0105***
					(0.1381)	(0.0020)	(0.0020)
$I_{crisis1,t}TED_{t-1}$				-0.0366***	-0.0104***	-0.0019	-0.0017
				(0.0025)	(0.0020)	(0.0063)	(0.0063)
$I_{crisis2,t}TED_{t-1}$				-0.0200*	0.0101	0.0093	0.0095
				(0.0100)	(0.0084)	(0.0084)	(0.0084)
$S_{1,t}^{(-)}$						0.1469	0.1349
						(0.2190)	(0.2212)

Table 8 (continued)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
$I_{crisis1,t}S_{1,t}^{(-)}$						-0.3470	-0.5159
						(2.5428)	(2.5459)
$I_{crisis2,t}S_{1,t}^{(-)}$						-0.9934	-1.0259
						(1.2275)	(1.2344)
$S_{2,t}^{(-)}$						-0.2802	-0.3053
						(0.4923)	(0.4980)
$I_{crisis1,t}S_{2,t}^{(-)}$						-0.5818	-0.5350
						(0.5159)	(0.5202)
$I_{crisis2,t}S_{2,t}^{(-)}$						-1.3006	-1.3698
						(1.3322)	(1.3274)
$S_{3,t}^{(-)}$						-0.6248	-0.6504
						(0.3341)	(0.3413)
$I_{crisis1,t}S_{3,t}^{(-)}$						-0.6658	-0.7105
						(0.8765)	(0.8968)
$I_{crisis2,t}S_{3,t}^{(-)}$						0.0833	0.0757
						(0.6221)	(0.6328)
$S_{1,t}^{(+)}$						0.3208	0.2952
						(0.2209)	(0.2201)
$I_{crisis1,t}S_{1,t}^{(+)}$						0.1236	0.0636
						(0.3744)	(0.3652)
$I_{crisis2,t}S_{1,t}^{(+)}$						-0.5856	-0.5901
						(0.6318)	(0.6361)
$S_{2,t}^{(+)}$						-1.6310***	-1.6645***
						(0.3882)	(0.3883)
$I_{crisis1,t}S_{2,t}^{(+)}$						1.8968***	1.7861***
						(0.4752)	(0.4553)
$I_{crisis2,t}S_{2,t}^{(+)}$						1.5032***	1.5238***
						(0.3979)	(0.3983)

Table 8 (continued)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
$S_{3,t}^{(+)}$						-0.8504*	-0.8735*
						(0.3692)	(0.3725)
$I_{crisis1,t}S_{3,t}^{(+)}$						1.3980	0.8967
						(1.0772)	(1.0641)
$I_{crisis2,t}S_{3,t}^{(+)}$						0.6243	0.6295
						(0.4589)	(0.4607)
$S_{1,t-1}^{(-)}$							-0.2331
							(0.3478)
$I_{crisis1,t}S_{1,t-1}^{(-)}$							1.8282**
							(0.6656)
$I_{crisis2,t}S_{1,t-1}^{(-)}$							-1.2057
							(1.3681)
$S_{2,t-1}^{(-)}$							-0.0169
							(0.1445)
$I_{crisis1,t}S_{2,t-1}^{(-)}$							0.1352
							(0.2235)
$I_{crisis2,t}S_{2,t-1}^{(-)}$							3.5268***
							(0.4688)
$S_{3,t-1}^{(-)}$							-0.4910*
							(0.2277)
$I_{crisis1,t}S_{3,t-1}^{(-)}$							0.0000
							(.)
$I_{crisis2,t}S_{3,t-1}^{(-)}$							0.0000
							(.)
$S_{1,t-1}^{(+)}$							1.0069
							(0.5957)

Table 8 (continued)

	Model (1)	Model (2)	Model (3)	Model (4)	Model (5)	Model (6)	Model (7)
$I_{crisis1,t}S_{1,t-1}^{(+)}$							0.7511
							(0.8829)
$I_{crisis2,t}S_{1,t-1}^{(+)}$							-0.5291
							(0.7901)
$S_{2,t-1}^{(+)}$							-1.2242**
							(0.4337)
$I_{crisis1,t}S_{2,t-1}^{(+)}$							-27.9350***
							(3.5719)
$I_{crisis2,t}S_{2,t-1}^{(+)}$							0.000
							(.)
$S_{3,t-1}^{(+)}$							0.0679
							(0.7869)
$I_{crisis1,t}S_{3,t-1}^{(+)}$							0.000
							(.)
$I_{crisis2,t}S_{3,t-1}^{(+)}$							0.000
							(.)
Adjusted R^2	0.833	0.742	0.727	0.597	0.862	0.863	0.867

Table 8 reports the estimation results of the following model:

$$L_{M,t} = \alpha_0 + \beta_0 L_{M,t-1} + \theta_0^{other} f_{t-1}^{other} + I_{crisis1,t}(\alpha_1 + \beta_1 L_{m,t-1} + \theta_1^{other} f_{t-1}^{other}) + I_{crisis2,t}(\alpha_2 + \beta_2 L_{M,t-1} + \theta_2^{other} f_{t-1}^{other}) + \varepsilon_t.$$

where $L_{m,t-1}$ is lagged FX systematic liquidity, f_{t-1}^{other} is the set of lagged explanatory variables, including the global FX volatility (VXY), Chicago Board Options Exchange Volatility Index (VIX), TED spread (TED), positive news surprise ($S_{i,t}^{(+)}$), and negative news surprises ($S_{i,t}^{(-)}$). For dummmy variables, $I_{crisis1,t} = 1$ if day *t* is during the subprime-mortgage financial crisis period , and 0 otherwise; $I_{crisis2,t} = 1$ if *t* is during the Eurozone sovereign debt crisis period, and 0 otherwise. The heteroscedasticity-and-autocorrelation-consistent (Newey and West, 1987) standard errors are reported in parentheses. The data cover the period from January 7, 2008 through December 31, 2013.

$***$, $**$, and $*$ denote the significance at the levels of 1%, 5%, and 10%, respectively.