Liquidity Spillover in the Foreign Exchange Market

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Abstract

We use an index of spillover based on the generalized variance decomposition developed by Diebold and Yilmaz (2009, 2012, 2014) to measure the connectedness in liquidity in nine currency markets during 2008 and 2013. The results of spillover tables and indices demonstrate how the liquidity of one market spillovers to and from other currency markets. We find that the market of Euro against the US dollar is the main net transmitter in liquidity to the other foreign exchange markets.

Keywords: Liquidity; Spillover; Foreign exchange market.
JEL Classification: F31, G15, C22.

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Abstract

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1. Introduction

The liquidity risk arises when the transaction cannot be executed immediately at the current market price or is delayed for a considerable amount of time due to the absence of a counterparty (Mancini, Ranaldo, and Wrampelmeier, 2013). It is important to understand to what extent the liquidity across different currency markets are connected and spillover. Liquidity in foreign exchange (FX) market is a major concern for currency carry traders when they decide asset allocations conditional on the risk tolerance of a basket of currencies.

Typically, any change of currency risk and returns usually results in portfolio rebalancing. While rebalancing the portfolio, an investor may either reduce the allocation to an asset class that has performed strongly in recent times and increase the allocation to an asset class that has underperformed and vice versa. This kind of feedback trading pattern will induce complex interactions and correlations, both in terms of within and between currency markets.

Most prior research on liquidity focused on the commonality in liquidity (Chordia, Roll, and Subrahmanyam, 2000; Huberman and Halka, 2001; Hasbrouck and Seppi, 2001; Brockman, Chung, and Pérignon, 2009; Banti, Phylaktis, and Sarno, 2012; Mancini, Ranaldo, and Wrampelmeier, 2013; Karnaukh, Ranaldo, and Söderlind, 2015) but the dynamic correlation of liquidity across assets has recently attracted researchers' attention (Chordia, Sarkar, and Subrahmanyam, 2005; Diebold and Yilmaz 2015, Chapter 6; McMillan and Speight, 2010; Buábk, Kočenda, and žikeš, 2011; Baruník, Kočenda, and Vácha, 2017; Greenwood-Nimmo, Nguyen, and Rafferty, 2016). The commonality in liquidity emphasizes the impact of a common or market-wide systemic liquidity factor on an individual asset liquidity. Most of related research regards the systemic liquidity as an exogenous factor which only considers the contemporaneous influence but ignores intertemporal effect across assets. One exceptional research is

Chordia, Sarkar, and Subrahmanyam (2005) which investigate the dynamic correlation of liquidity between stock and bond markets within the vector autoregressive framework.

However, there are few studies addressing the issue of intertemporal liquidity transmission in FX markets. It is a reasonable extension of the research to investigate the dynamics of the liquidity across currencies in a time series aspect because it inspires us to observe how and why liquidity transmits across markets. How does liquidity transmit from a certain currency market to others? What is the relation between liquidity transmissions and macroeconomic conditions? In other words, does the global economic environment play a role in the liquidity spillover effect. Whether rebalancing portfolio can in explaining the liquidity spillovers? In this paper, we study these questions and aim to analyze the pattern of currencies liquidity spillovers in that we can effectively reduce the risk of holding assets and may increase gains from international portfolio diversification.

Given the importance of the transfer process in the dynamics of the FX market, the network analysis provides a natural framework for studying this complex dynamic phenomenon. The approach of network analysis has recently been applied to the investigation of the interconnectedness of volatility in foreign exchange markets (i.e., Diebold and Yilmaz, 2015, Chapter 6; Antonakakis, 2012; McMillan and Speight, 2010) and rarely discussed liquidity.[1] Diebold and Yilmaz (2015, Chapter 6) analyze the

[1] In early research contribution, Diebold and Nerlove (1989) use a latent factor model to construct foreign exchange market volatility and find that the volatility of exchange rate return is correlated. Engle et al. (1990) use the GARCH model to classify volatility spillovers as country-specific fluctuations (heat wave effects) and external market fluctuations (meteor shower effects). Inagaki (2007) applies the cross-correlation approach and analyzed intra-day interdependence and volatility spillovers, and provided evidence of unidirectional volatility spillover from the euro to the British pound. Thus, the euro volatility has a single direction impact on the British pound volatility. Similar evidence of volatility spillover, Kitamura (2010) uses an MGARCH model and demonstrates that volatility spillovers from the euro significantly affect the Swiss franc and Japanese yen. These studies generally agree that rapid and efficient information transmission is consistent with the absence of volatility spillover between different

exchange rates of nine major currencies with respect to the U.S. dollar from 1999 to mid-2013 and show that the Euro/US dollar exchange rate has the highest volatility spillover than of other analyzed currencies. From this viewpoint, it can reasonably infer that the US dollar and the euro are dominant currencies in the global foreign exchange markets. Similar, McMillan and Speight (2010) find that the euro-dollar rate dominates spillovers to other euro exchange rates and the strength of these spillovers peaks up in half a day. Moreover, most of the literature finds that volatility connectedness tends to increase during market uncertainty period (i.e. Buábk, Kočenda, and žikeš, 2011; Baruník, Kočenda, and Vácha, 2017; Greenwood-Nimmo et al., 2016).

Our empirical approach is derived from the generalization of the connectedness frame- work developed by Diebold and Yilmaz (2009, 2012, 2014). In the study of the interconnectedness of financial markets, the VAR model provides a natural and insightful framework to measure network connectedness among financial markets (Diebold and Yilmaz, 2014). Diebold and Yilmaz (2009) first develop a volatility spillover index (DY index) based on vector autoregressive (VAR) model along with variance decompositions to quantify the overall magnitude and evolution of volatility spillovers among markets. Subsequently, Diebold and Yilmaz (2012) further improved this approach by using the generalized VAR framework, in which forecast error variance decomposition can be independent of variable ordering. This generalized DY index approach allows us to quantify the extent to which shocks in different variables spillover to one another. Applying the generalized version of the spillover index of Diebold and Yilmaz (2012, 2014), this paper examines the overall magnitude and evolution of liquidity risk spillovers among the nine currencies pairs.

Our findings show that up to 62.3% percent of the forecast error variance comes

assets or market.

from liquidity risk spillover. We find that the euro versus the dollar is the main net transmitters of liquidity risk to other currencies. In addition, we observed a strong spillover effect during the period of market uncertainty. That is, liquidity risk among markets increases obviously at this time highlighting the role of crash risk during the crises. Finally, our research shows that the spillover effect of the foreign exchange market rises in the period of financial pressure and increases with the worsening of the global financial situation. The remainder of this paper is organized as follows. Section 2 reviews the literature. Section 3 describes the model and methodology. Section 4 introduces the dataset. Section 5 contains the empirical results. Section 6 concludes.

2. Literature Review

Liquidity risk arises when the transaction cannot be executed immediately at the current market price or is delayed for a considerable amount of time due to the absence of a counterparty. According to Bangia, et al. (1999), liquidity risk can take two forms: exogenous liquidity risk and endogenous liquidity risk. The former is regarded as a market characteristic, which is the same for all market participants and cannot be avoided through the transaction. It is usually regarded as systemic liquidity risk. The latter is specific to one's position in the market, which differs across different market participants. The exposure of any one participant will be affected by their own trading behavior.

Much of the research related to exogenous liquidity risk provides profound evidence of liquidity commonality in the stock market (Chordia, Roll, and Subrahmanyam, 2000; Huberman and Halka, 2001; Hasbrouck and Seppi, 2001; Brockman, Chung, and Pérignon, 2009; among others) and in the foreign exchange market (Melvin and Taylor, 2009; Banti, Phylaktis, and Sarno, 2012; Mancini, Ranaldo, and Wrampelmeier, 2013; Karnaukh, Ranaldo, and Söderlind, 2015; among others).

Chordia, Roll, and Subrahmanyam (2000) firstly indicate 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. Korajczyk and Sadka (2008) use a latent factor model to measure the common liquidity across varied liquidity measures and suggest that systematic liquidity is a pricing factor. Mancini, Ranaldo, and Wrampelmeier (2013) discover a strong commonality in liquidity across currencies and show that a more liquid FX market has less liquidity sensitivity to the FX liquidity commonality, such that a negative correlation between exchange rate returns and liquidity exists for currencies with higher interest rates, reflecting their greater exposure to liquidity risk. Banti, Phylaktis, and Sarno (2012) document the presence of a global systemic liquidity risk in the FX market and show that there is a strong common component in liquidity across currencies, suggesting that systemic liquidity is a pricing factor in the cross-section of currency returns.

Unlike the commonality in liquidity research, the literature related to endogenous liquidity risk emphasizes the link between trading behaviors among different investors and is applied to liquidity spillover. When investors observe the flow of market information or suffer the impact of cash shock, they will rebalance their portfolio, leading to spillovers between liquid assets. Theoretical economic explanations for liquidity spillover rely on feedback trading and provide different implications on the relations between endogenous liquidity and liquidity spillovers. According to Fernando (2003), liquidity shocks can be divided into idiosyncratic and common (systematic) components. The model emphasizes the role of idiosyncratic shocks in the transmission of liquidity since such shocks as non- informative shocks heterogeneously affect investors' valuations of risky assets (Karpoff, 1986). In fact, idiosyncratic liquidity shocks create liquidity demand and trading volume, and investors can diversify their risk by trading. When two stocks with different levels of liquidity are substitutes for each other, there is a transmission of liquidity across assets after the arrival of non-information shocks.

Contrary to Fernando (2003)'s idiosyncratic shocks, Watanabe (2004) supports that the information process plays a key role in the transmission of liquidity. In his model, information shock affects the liquidity of assets by increasing returns volatility. When the impact of information shocks on "active" and "passive" stocks will yield asymmetric effects on each other, the increase in the volatility of active stock returns leads market makers to increase passive stocks' transaction costs to cope with an expected higher future volatility of passive stocks. The evidence supports unique lead and lag patterns in liquidity spillovers. Since the model does not require the correlation between information or stocks, contrary to the Watanabe (2004) assumptions, liquidity spillover does not necessarily coincide with return spillovers.

In a similar concept of informational learning Cespa and Foucault (2014) show that the relationship between price informativeness and liquidity generates a positive self- reinforcement, causing liquidity risk spillovers. Cross-asset learning markets the liquidity asset pair interconnected. Therefore, if the liquidity of one asset drops, its price becomes less informative for liquidity providers in another asset, and the liquidity of this asset drops as well. For empirical findings on liquidity spillovers, Chordia, Sarkar, and Subrahmanyam (2005) use the joint dynamics of liquidity, trading activity, returns, and volatility to study the interrelationship between the stock market and the US Treasury bond market, and demonstrate that unexpected liquidity and volatility shocks are positively and significantly correlated across stock and bond markets. This means that investors' trading behavior simultaneously impacts both markets. In fact, the asset allocation strategy will transfer wealth between risky assets and safe assets. As a result, the negative impact of stocks will spillover to U.S. bonds, causing price pressures and affecting the liquidity of the stock and bond markets at the same time. For the FX market, Mancini, Ranaldo, and Wrampelmeyer (2013) analyze the liquidity spillover in bond, equity, and FX markets, and document strong contemporaneous comovements in major currency markets, providing the evidence of cross-market linkages in FX market liquidity. Banti (2016) analyzes the dynamics of the liquidity risk transmission between the Nasdaq and the major FX electronic trading platforms (Reuters and EBS) and demonstrates a significant comovement and cross-market spillovers, especially during the recent crisis. After liquidity risk shocks, there is a significant reduction both in correlated trading and funding availability. Thus, a liquidity shock may trigger liquidity risk spirals in times of distress, as institutional investors reduce their trading activity and dealers provide less liquidity. It supports the transmission of liquidity shocks: when an unexpected increase in the transaction costs of one market occurs, the transaction costs of another market will also increase, especially during a crisis.

By using the low-frequency data, Karnaukh, Ranaldo, and Söderlind (2015) suggest that supply-side factors are important drivers of foreign exchange liquidity and address the fact that foreign exchange liquidity tends to decline along with volatility and liquidity risk of global equity and bond markets. These results have a greater impact on the currencies of developed countries and support risk spillovers. This means that FX liquidity can be severely damaged when funding is constrained, volatility is high, and foreign exchange speculators incur losses. However, the daily trading volume of the foreign exchange market is much larger than that of the stock and bond markets. In the literature, the illiquidity spillover effect in the cross-section of currency markets is yet to be analyzed.

3. Methodology and Data

In this section, we first introduce the measure of FX market liquidity. Next, we summarize the spillover or connectedness measure based on a VAR setup that approximates the network system of cross-market liquidities.

3.1 Liquidity measure

We measure foreign exchange market liquidity risk using efficient spread, which is calculated as the difference between the transaction price and the midpoint of the bid and ask quotes at the time of the transaction. In the electronic market, because some market participants may post hidden limit orders that are not reflected in quoted spreads immediately. 6 Therefore, the transactions are not always executed at the posted bid or ask quotes. How- ever, effective costs can capture the costs that arise when the volume of an incoming order exceeds the posted size at the best prices. Compared with the quoted cost, the effective cost can reflect the actual trading cost incurred. A daily efficient spread is calculated by averaging intraday efficient spreads within a given day with equal weights for each FX rate (Mancini, Ranaldo, and Wrampelmeyer, 2013).[2]

The effective cost is defined as:

$$L^{(ec)} = \begin{cases} \frac{P-P_M}{P_M}, \text{ for buyer} - \text{initiated trades} \\ \frac{P_M-P}{P_M}, \text{ for seller} - \text{initiated trades} \end{cases} \tag{1}$$

where P and P_M denotes the transaction price and the midpoint of the quote prevailing at the time of the trade, respectively.

3.2 Measuring the spillover in liquidity

We use the generalized connection framework proposed by Diebold and Yilmaz (2009, 2012, 2014) to measure the degree of connectedness in the foreign exchange market. Previously, the connection is referred to as the spillover index (Diebold and Yilmaz, 2009), measured by the variance decomposition of the framework and used to analyze the spillover effects of asset returns and volatility.[3] Throughout the variance

[2] We have also considered other liquidity measures, such as price impact, return reversal, and quoted spreads. We find that the lowest correlation between different indicators exceeded the 0.6 value, which is similar to Mancini, Ranaldo, and Wrampelmeyer (2013). For the sake of simplicity of illustration, this paper only lists the efficiency spread estimation as our representative empirical results.

[3] In the past, research has used network models as market connectivity to analyze market spillover effects, including single assets in different countries and multiple assets in different

decomposition, it not only provides information about the impact of endogenous variables themselves, but also considers the impact of any other variables in the system. We follow Diebold and Yilmaz (2012) to use an n-variable generalized VAR (Koop, Pesaran, and Potter 1996, Pesaranand Shin 1998). For asset i, the strength of the connection is that its forecast error variance coming from shocks to the liquidity of asset j, for all j, i. Compared to orthogonalization schemes (such as Cholesky decomposition), the advantage of the generalized VAR framework is that it allows the forecast-error variance decompositions to be invariant to the ordering of variables in the VAR.[4] In addition, the generalized approach allows the correlation between shocks, while the simple VAR has the containment of orthogonal shocks.

Let y_t denote an n-dimensional time-series vector in a VAR(p) system as:

$$y_t = \sum_{i=1}^{p} \Phi_i \, y_{t-i} + \varepsilon_t \tag{2}$$

where $y_t = (y_{1t}, \dots, y_{nt})'$ is a vector of n endogenous variables, Φ_i is a $n \times n$ matrix of parameters, and $\varepsilon_t \sim (0, \Sigma)$ is a vector of independently and identically distributed errors.

Assuming covariance stationarity, this specification can be rewritten in the moving average representation form as:

$$y_t = \sum_{i=1}^{\infty} A_i \, \varepsilon_{t-i} \tag{3}$$

where the $n \times n$ coefficient matrices A_i have the property: $A_i = \sum_{j=1}^{p} \Phi_j A_{i-j} = \Phi_1 A_{i-1} + \Phi_2 A_{i-2} + \cdots + \Phi_p A_{i-p}$, with $A_0 = I_n$ and $A_i = 0$ for $i < 0$.

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countries. However, few references have been explored in the FX market. Some studies support the US dollar and the euro as the major volatility spillover rather than other analyzed currencies in the global FX market (Diebold and Yilmaz 2015, Chapter 6; Antonakakis, 2012; McMillan and Speight, 2010;). Others studies find that volatility connectedness tends to increase during periods of market uncertainty and negative spillovers dominate positive spillovers (Buábk, Kočenda, and žikeš, 2011; Baruník, Kočenda, and Vácha, 2017; Greenwood-Nimmo, Nguyen, and Rafferty, 2016).

[4] In measuring the total spillover effect, Diebold and Yilmaz (2014) pointed out that there is no difference between the results using the general VAR or the Cholesky VAR. However, when the analysis direction spillover effect, the result may be significantly different due to the sensitivity of variable orderings.

We rely on variance decompositions to decompose the forecast error variances of each variable into components which are attributable to the various system shocks. Using the variance decompositions we assess the fraction of the H-step-ahead error variance in forecasting y_i that is due to shocks to y_j $\forall j \neq i$, for each *i*.

For contemporaneously correlated error terms, we usually use the Cholesky factorization to obtain orthogonal innovations and then calculate variance decompositions. As the Cholesky factorization is not unique, the variance decompositions depend on the ordering of the variables in the VAR system. To overcome this difficulty of identification, we use the generalized VAR framework of Pesaran and Shin (1998) to obtain variance decompositions that are invariant to the ordering of variables.

Denote the H-step-ahead forecast error variance decompositions by $\theta_{ij}^{g}(\mathrm{H})$,

$$\theta_{ij}^{g}(\mathrm{H}) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}(e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1}(e_i' A_h \Sigma A_h' e_j)} \tag{4}$$

where Σ is the variance matrix for ε_t, σ_{jj} is the standard deviation of the error term for the *j*th equation, and e_i is the selection vector with one as the *i*th element and zeros otherwise.

As the shocks to each variable are not orthogonalized in the generalized VAR framework, the sum of the contributions to the variance of the forecast error (that is, the sum of the elements in each row of the variance decomposition table) is not necessarily equal to one: $\sum_{j=1}^{n}\theta_{ij}^{g}(\mathrm{H}) \neq 1$. Before calculating the spillover index, we normalize each entry of the variance decomposition matrix by the row sum as:

With the generalized VAR(p), the H-step-ahead forecast error variance decomposition can be written as

$$\tilde{\theta}_{ij}^{g}(\mathrm{H}) = \frac{\theta_{ij}^{g}(\mathrm{H})}{\sum_{j=1}^{n}\theta_{ij}^{g}(\mathrm{H})} \tag{5}$$

The normalization gives $\sum_{j=1}^{n}\tilde{\theta}_{ij}^{g}(\mathrm{H}) = 1$ and $\sum_{i,j=1}^{n}\tilde{\theta}_{ij}^{g}(\mathrm{H}) = n$.

Built on the H-step-ahead forecast error variance decompositions we define the total spillover index:

$$S^g(H) = \frac{\sum_{\substack{i,j=1, \\ i\neq j}}^{n} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{i,j=1, \\ i\neq j}}^{n} \tilde{\theta}_{ij}^g(H)}{n} \times 100 \tag{6}$$

The total spillover index gauges the contribution of spillovers of the shocks across variables to the total forecast error variance.

We further define two measures of directional spillovers as follows:.

$$S_{i\cdot}^g(H) = \frac{\sum_{\substack{j=1, \\ j\neq i}}^{n} \tilde{\theta}_{ij}^g(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{j=1, \\ j\neq i}}^{n} \tilde{\theta}_{ij}^g(H)}{n} \times 100 \tag{7}$$

$$S_{\cdot i}^g(H) = \frac{\sum_{\substack{j=1, \\ j\neq i}}^{n} \tilde{\theta}_{ji}^g(H)}{\sum_{i,j=1}^{n} \tilde{\theta}_{ij}^g(H)} \times 100 = \frac{\sum_{\substack{j=1, \\ j\neq i}}^{n} \tilde{\theta}_{ji}^g(H)}{n} \times 100 \tag{8}$$

$S_{i\cdot}(H)$ measures the directional spillovers received by market *i* from all other markets *j*. Alternatively, $S_{\cdot i}(H)$ measures the directional spillovers transmitted from market *i* to all other markets *j*.

Finally, using the directional spillover measures, we can obtain the net spillover from market *i* to all other market *j*, which is defined as the difference between the gross shocks transmitted to and received from all other assets:

$$S_i^g(H) = S_{\cdot i}^g(H) - S_{i\cdot}^g(H) \tag{9}$$

3.3 EBS Data

To calculate the illiquidity spillover index for the 9 currency pairs, we use the data on the Electronic Brokerage Services (EBS), covering the period from January 2008 through December 2013. We use one-minute intraday data to calculate the liquidity and then average all 1-min effective spreads to obtain daily measure of liquidity, following Mancini et al. (2013). We consider 9 currency pairs, including USD/GBP, USD/CHF, USD/AUD, USD/JPY, USD/CAD, USD/EUR, EUR/GBP, EUR/JPY, and EUR/CHF, in the analysis.

The reason we chose these currencies in our studies is that these are the most active currencies in the global foreign exchange trading (BIS 2016; Baruník, Kočenda, and Vácha 2017). The objective of this article is to analyze the connectedness between currencies that account for two- thirds of global foreign exchange turnover (BIS,2013). Here, we do not discuss currency pairs that occupy less market share in the global foreign exchange markets.

EBS can provide more timely information on the screen, including quote price, quote volume, transaction prices, and trading volumes. EBS price history also shows whether the deal is buyer-driven or seller-driven. We can obtain order ow by calculating the difference between the transaction volume of the buyer-initiated trades and the transaction volume of the seller-initiated trades. At the end of each one-minute interval, we use the immediately preceding and following quotes to construct a series of bid and ask prices and use this transaction price to calculate the liquidity index of the forex market for each currency pair.

In the EBS trading platform, foreign currencies are continuously traded 24 hours a day; however, weekend transactions are relatively minimal. We exclude the data during weekends and national (bank) holidays.

4. Empirical Results

4.1 FX market liquidity risk connectedness

Table 1 presents the strength of total liquidity risk connectedness in the forex market. This connection table provides an "input-output" decomposition of liquidity risk connectedness, which is based on the VAR(2) model (according to Schwarz criterion criteria select an optimal number of lags) and the generalized variance decompositions of the 10-day-ahead forecast errors. According to Table1, the (i,j)th element is the estimated contribution to the forecast error variance of asset i coming from innovations to asset j. Thus, the diagonal elements (i = j) capture own-currency liquidity risk connectedness, while the off-diagonal elements ($i \neq j$) gauge cross-market liquidity risk connectedness within two currency pairs.

The total liquidity risk spillover index, given in the lower right corner of Table 1, is the fraction of the grand off-diagonal column sum (or row sum) to the grand column sum including diagonals (or row sum including diagonals) expressed in percentage. By combining all of the various cross currency pair stress spillovers into a single index for our full sample, we find that, on average, 62.3% of the forecast error variance in whole FX markets comes from liquidity risk spillovers. Spillovers among liquidity risk are particularly strong where currencies share an underlying linkage. This is particularly true for sterling currency pairs and commodity currencies (e.g., the USD- AUD and USD-CAD pairs). Within these currencies, many of the bilateral liquidity risk connectedness reaches 10-14% levels. Such strong bilateral liquidity risk connectedness shows that common rebalancing activity has a degree of impact on these currencies, in line with the views of Greenwood-Nimmo (2016). In the case of adverse impact on commodity prices, investors may simultaneously reduce the commodity currency positions. As documented by Fernando (2003), Watanabe (2004), and Cespa and Foucault (2014), when portfolio rebalancing corresponds to changes in information flow or non-information-based shocks, one may expect to see strong connectedness effects in various currencies.

In addition, the summation of each off-diagonal column (labeled "contributions /directional" to others) or row (labeled "contributions/directional from others") represents the total to and from liquidity risk spillovers in each currency pair, respectively. The difference between "contributions to others" and "contributions from others" values for each variable gives the net spillover from market *i* to all other markets *j*. A positive net spillover value means that the liquidity of a dominant currency will transmit to other currencies and this is called this is called "spillover giver". A negative net spillover value represents a situation where a particular currency accepts liquidity spillovers from other currencies. In this case, the currency is referred as a “spillover receiver”.

These total directional spillovers measurements provide further instructions for the results in Table 1. For each currency, the within-market effect of liquidity risk along the main diagonal is estimated from a minimum value of 27% (the dollar against the euro and yen) to a maximum of 55% (the euro against the sterling), with an average of 37%. By contrast, the contributions to others spillovers across currencies are much stronger, ranging from 50% (the dollar against the Canadian dollar) to 82% (the dollar against the euro). The results of other spillover contributions are similar, ranging from 45% (the euro against the sterling) to 73% (the dollar against the euro). This finding supports that currencies are more strongly influenced by the effect of systematic cross-market spillovers than of idiosyncratic currency-specific effects. It turns out that liquidity risk is spreading quickly and forcefully in the forex market. This is in line with the literature on volatility spillover in the forex market, which emphasizes the role of meteor shower effect (Engel, Ito, and Lin, 1990). The within-market effects can be thought of as heatwave effects while the cross-market spillovers are akin to meteor showers. According to our market connectedness matrix, the within-market heatwave effect is less than 55%, while the spillovers effects from other markets has a significantly dominant influence.

These results are supported by the net liquidity spillovers, which measure the net liquidity spillovers from country i to all other countries j, as shown in the last row of Table1. Positive net spillovers are found in USD/CHF, EUR/GBP, EUR/JPY and EUR/USD, of which EUR/USD (9.974%) is the highest. The euro against the dollar is considered to be the largest spillover giver for all other currency pairs. Consistent with McMillan and Speight (2010), the liquidity in the euro-dollar market dominates other markets' liquidity and therefore has a strong spillover effect to other currencies. Contrary to Greenwood-Nimmo (2016), our results show that the net spillover in liquidity of dollar-yen is -7.06, which is considerably smaller than those in other currency markets analyzed in the paper. This means that the market of USD/JPY has less own-variation effect and is vulnerable to other market's liquidity shocks, which suggests JPY may not be an ideal choice as a safe haven currency.

4.2 Total and directional connectedness/spillover

As mentioned in Diebold and Yilmaz (2012), if the spillover is measured through full sample period, it may only obtain the indicator of "average" spillover and likely ignore the significant cyclical fluctuations of spillovers at different points of business cycle. To obtain the time-varying liquidity spillovers, we use a rolling-window analysis to estimate the liquidity spillover. This approach allows us to assess the evolution of the liquidity spillover of nine currency markets over time. In the analysis, we use a 100-day rolling sample to estimate the liquidity spillovers effect.[5]

4.2.1 Total connectedness

Figure 1 exhibits a dynamic image of the spillovers intensity among currencies. Several major events are evident in the time-varying total connectedness plots, as indicated by the presence of peaks, including the recent financial turmoil followed by the collapse of Lehman Brothers, the European sovereign debt crisis, and the central bank quantitative easing policies. The plot shows that after the collapse of Lehman Brothers in September 2008, the spillovers increase and reach its maximum at about 80%. During

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[5] In the present context, several daily studies such as Diebold and Yilmaz (2014) use a 100-days rolling window; Diebold and Yilmaz (2012) and Baruník, Kočenda, and Vácha (2017), adopt 200-days rolling window samples; Greenwood-Nimmo (2016) take 250-days rolling window samples. Due to the lack of specific guides in earlier studies, we forecast future liquidity risk spillovers with a 10-days horizon using three short-term rolling window horizons: 90-days, 120-days, and 200-days. We find similar rolling estimates with alternate-days horizons (90, 100, and 120) in most of the VAR models. Thus, our results are adequately robust to the rolling-window variations. Here, we will use a 100-day (four months) rolling sample to study the magnitude and behavior of the time-varying liquidity risk spillovers throughout this article.

this period, the spillovers fluctuated at an increasingly higher level, ranging from approximately 70% to 80%.

Subsequently, Fed started lending and implemented quantitative easing (QE) policy, which temporarily eased the level of interdependence and spillovers activity fell to around 55% by the end of 2009. After the 2007-2008 global financial crisis period, the liquidity spillovers effects climbed slowly and experienced the second peak at about 78% (October 2010), in response to the intensification of the Greek sovereign debt crisis during this period. In particular, when Moody's downgraded Greece to junk-bond status, market uncertainty is high and liquidity spillover becomes stronger. As mentioned in Baruník, Kočenda, and Vácha (2017), FX market risk spillovers seem to strengthen during a period of financial stress.

In addition, during the turbulent period, we observed that after the Fed QE news announcements the total connectedness of the liquidity risk dropped significantly. These monetary policy measurements aim at the provision of enhanced market liquidity support, strengthen market functioning, QE and large-scale asset purchases. As illustrated in Neely (2012), the US QE announcement has a substantial impact on both international long-term interest rates and the present value of the US dollar. There are indeed global spillovers and externalizes from monetary policy decisions in advanced economies. When the quantitative easing announcements improve market liquidity during market turmoil, the transmission liquidity induced by information shocks will weaken the intensity of illiquid connectedness.

However, we observe that the fluctuated patterns of the FX liquidity spillovers seem to increase in the post-crisis period. From 2012, the difference of monetary policies among the Fed, ECB, and Bank of Japan affected both capital flows and carry trade operations. For example, Fed slowed down the scale of the QE policy and stopped in 2014, while the ECB was already implemented this policy and the Bank of Japan was active amplification this policy. These QE policies have triggered a substantial rebalance in global portfolios and exerted substantially larger effects on asset prices. As mention by Baruník, Kočenda, and Vácha (2017), the FX liquidity spillover began to strength in 2013 due to the different monetary policies of the world's major central banks.

4.2.2 Total connectedness in liquidity and macroeconomic conditions

We further investigate whether the total connectedness om FX liquidity increases with funding constraints and higher volatility, as postulated by the liquidity spirals theories (e.g., Brunnermeier and Pedersen 2009; Vayanos and Gromb 2002) or international portfolio allocation induced by demand shocks (e.g., Hau, Massa, and Peress 2010).

In Figure 2, we combine the total connectedness with economic conditions represented by five risk indicator graphs. We first show the relation between total connectedness and global risk indices (i.e., VIX, VXY, and bond volatility).[6] Karnaukh, Ranaldo, and Söderlind (2015) showed that there exist cross-market linkages between FX liquidity and stock-bond volatilities. We thus anticipate that the relationship between FX liquidity spillovers and global risk may be positive and strong during the recent financial crisis periods. At the top of Figure 2, we observe several instances when total connectedness increases along with spikes of the global risks in 2008, 2009, 2010, and 2011. As described by Chordia, Sarkar, and Subrahmanyam (2005), FX liquidity tends to deteriorate with the volatility of both global stocks and bonds, revealing cross-market linkages between equities, bonds, and FX markets. This finding is consistent

[6] Here, the VIX stands for investor fears and uncertainty, which is constructed using the implied volatilities of a wide range of S&P 500 index options. VXY is JP Morgan global foreign exchange Volatility Index, which tracks the implied volatility of three-month at-the-money forward options for major currencies and development currencies. The bond volatility is the Merrill's MOVE Index, which is defined as the implied volatility of U.S. Treasury markets and measures by the average implied volatility across a wide range of outstanding options on the two-year, five-year, 10-year, and 30-year U.S. Treasury securities.

with our results. Risk-averse investors may rebalance their portfolios and adjust hedging strategies more often in uncertain environments. Consequently, the international portfolio reallocations create a cross-market transmission channel. The pattern of movements from these measurement indicates that FX liquidity spillovers seem to increase with the global risk.

In the lower panel of Figure 2, we relate the total connectedness to the US dollar index.[7] For most of the sample period, both of these measures experience two spikes related to the collapse of Lehman Brothers and the European debt crisis. As a result, the US dollar index and FX liquidity spillover decrease rapidly as the Fed begins to inject market liquidity and implement the QE policies. However, the liquidity spillover gradually rises during the post-crisis period (from early 2010 to early 2011). This may be related to the depreciation of the U.S. dollar and the capital flow into emerging markets (Lavigne, Sarker and Vasishtha, 2014). QE policies can be seen as a commitment of the Fed to maintain low long-term interest rates, which will lead to a sustained fall in bond yield. It can be expected that the difference of interest rate in emerging markets will continue to expand, which in turn prompt capital inflows into emerging markets and increase carry trade activities (Rajan 2014). However, through the trade, financial and commodity-price channels, the impact of QE policy on the economies of emerging market will ultimately reverse to developed economies along with the magnified liquidity spillover in the FX markets.

Lastly, we compare the total connectedness in FX liquidity and TED spread.[8]

[7] The US dollar index reflects the overall strength of the U.S. dollar in the foreign exchange market. The index is a calculation of six currencies that have been averaged against the US dollar which include the euro, Japanese yen, British pound, Canadian dollar, Swedish krona and Swiss franc.

[8] TED spread is a common proxy fund liquidity in the interbank money market. It is measured by the difference between three-month Treasury bill and three-month LIBOR based on the US dollars.

Mancini, Ranaldo, and Wrampelmeyer (2013) show that the FX market liquidity deteriorates with funding cost. When TED spread reaches the spike after the collapse of Lehman Brothers, funding liquidity tends to dry up during conditions of market stress, forcing investors to unwind carry trade positions quickly. As mentioned in Melvin and Taylor (2009), this could cause the FX market to lose coordination and collapse. Therefore, the relationship between the FX liquidity spillover and the TED spreads may be positive, and stronger during the recent crisis events. This is completely shown in Figure 2 in which both indexes spiked to a peak in stress periods.

4.2.3 Directional connectedness of FX liquidity over time

Figure 3 provides an interesting insight based on dynamic patterns, showing the net position of each currency according to the liquidity risk of received or transmitted spillovers. One might assume that the directions of spillover transmission among currencies are consistent, however, the evidence shown in Figure 3 is exactly the opposite. Both commodity currencies, USD/AUD and USD/CAD, transmit heavily negative spillovers to other currencies. Such commodity currencies tend to have high sensitivity to global risk fluctuations and thus are susceptible to external shocks (Karnaukh, Ranaldo, and Söderlind, 2016). The opposite pattern is the liquidity spillover among FX markets, such as EUR/USD and EUR/JPY, that most of the research phases are the spillover givers. This behavior may be related to the crisis events. Bárunk, Kočenda, and Vácha (2017) found that different types of events are dominated by different type of spillover. This finding is consistent with our results. The positive transmission effect of euro-related currency pairs increases sharply during the period of European sovereign debt crisis.

The rest of the currencies in Figure 3 shows a series of ups and downs due to various major events. The USD/JPY exhibits irregular liquidity spillovers. The sterling shows different dynamics: diffusion of positive liquidity spillovers is evident during most of the crisis time period. On the contrary, in the 2011-2013 period negative liquidity spillovers occur and occasionally a slight swelling of positive liquidity spillovers from sterling to other currencies appears. The results about GBP liquidity are different from Bárunk, Kočenda, and Vácha (2017) which consider GBP as a spillover-giving currency in volatility. It can be explained by the fact that USD/GBP is mostly traded on Reuters rather than on EBS. Moreover, the Swiss franc seems to be the calmest currency as the net directional spillovers are quite low. In general, it can be characterized as a safe haven currency. It may be associated with "flight to quality" effects during the crisis period (Ranaldo and Söderlind, 2010).

5. Conclusions

We study the foreign exchange liquidity risk spillover in the forex electronic brokerage interdealer data for the nine currency pairs. Our use of liquidity measurement accords with recent developments in the literature, which stress the impact of liquidity risk on currency returns (Mancini, Ranaldo, and Wrampelmeier, 2013). Our analysis is a single index based on the generalized variance decomposition developed by Diebold and Yilmaz (2012, 2014) to measure the interconnectedness of nine major global currency pairs during the 2008-2013 period. This approach allows us to gauge (total and directional) liquidity spillovers independent of the variable ordering in VAR.

We provide the spillover tables and indices that demonstrate liquidity to and from other indices, as well as spillover plots showing the dynamics of liquidity spillover. Our findings show that up to 62.3% of the forecast error variance in liquidity comes from the spillovers of all FX market liquidities.Consistent with McMillan and Speight (2010), we find that EUR/USD is the main net transmitter of liquidity to the other currency markets.

Moreover, we observe strong spillovers when global uncertainty is high. The results that liquidity spillover among FX markets increases with global risk evidently highlight the role of crash risk during the crisis periods. We also find increasing cross-market liquidity connectedness. Finally, our findings emphasize the interrelationship of liquidity spillover activity and market stability. We demonstrate that the liquidity spillover among FX markets is stronger during periods of high market stress and volatility.

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Table 1 The connectedness matrix for efficient spread

This table presents the liquidity connectedness table of the efficient spread, which provides an input-output decomposition of the spillover index of the FX liquidity following the VAR framework of Diebold and Yilmaz (2012). The outcome of this table is based on the VAR of order 2 (according to Schwarz information criterion), and the 10-step-ahead forecasts are based on generalized variance decompositions. The (i, j)th value is the estimated contribution to the forecast error of market i coming from innovations to market j.

	USD/GBP	USD/CHF	EUR/CHF	EUR/GBP	EUR/JPY	USD/AUD	USD/CAD	USD/JPY	USD/EUR	Directional from others
USD/GBP	41.857	4.575	3.203	11.181	5.975	11.217	9.765	5.375	6.851	58.143
USD/CHF	3.681	33.874	11.875	3.680	14.654	4.518	3.074	9.397	15.247	66.126
EUR/CHF	3.049	12.678	35.204	4.853	13.487	4.166	3.054	10.434	13.075	67.796
EUR/GBP	9.760	3.200	3.196	55.405	4.803	6.517	8.748	3.623	4.749	44.595
EUR/JPY	4.191	14.381	11.910	4.559	34.405	3.484	1.309	12.641	13.119	65.595
USD/AUD	10.477	5.946	4.756	7.451	5.152	38.694	12.352	6.397	8.776	61.306
USD/CAD	11.768	3.230	2.525	10.007	1.333	13.753	45.807	5.395	6.183	54.193
USD/JPY	4.550	10.668	10.713	5.530	14.827	5.698	5.928	27.222	14.864	72.778
USD/EUR	4.814	14.514	44.302	5.245	12.733	6.424	5.401	12.456	27.111	72.889
Directional to others	52.290	69.194	59.427	52.506	72.965	55.777	49.631	65.718	82.862	
Net spillover	-5.853	3.067	-5.317	7.911	7.370	-5.529	-4.563	-7.060	9.974	
										Total index 62.3%

Figure 1 The total liquidity spillover index of all nine currency pairs

We plot moving liquidity spillover index, defined as the sum of all variance decomposition 'contributions to others,' estimated using 100-day rolling windows.

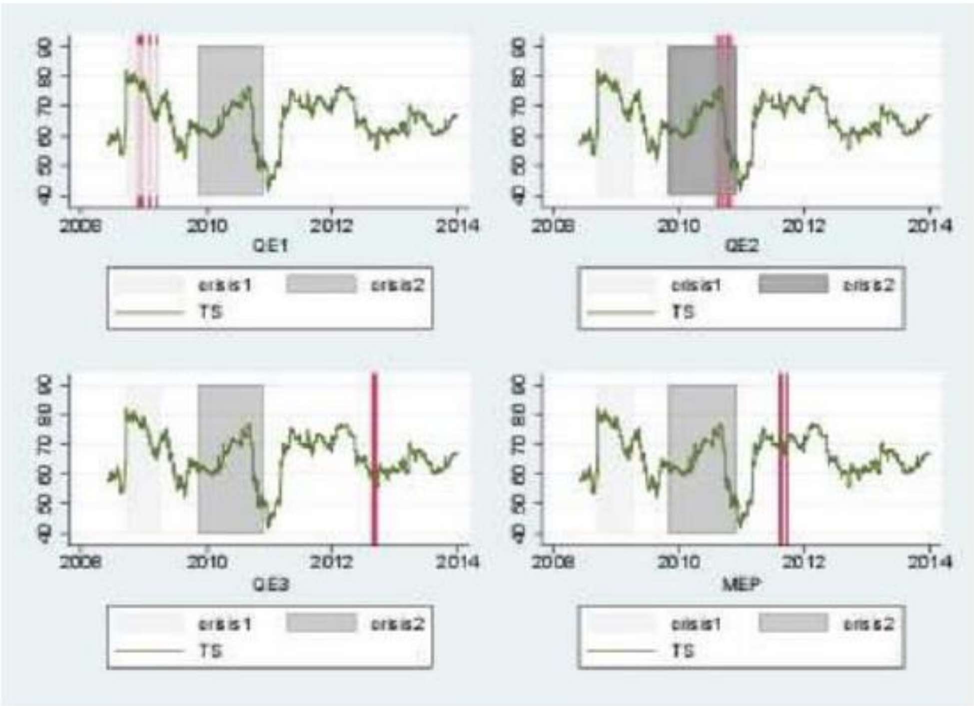

Figure 2 Spillover intensity versus selected macroeconomic indicators

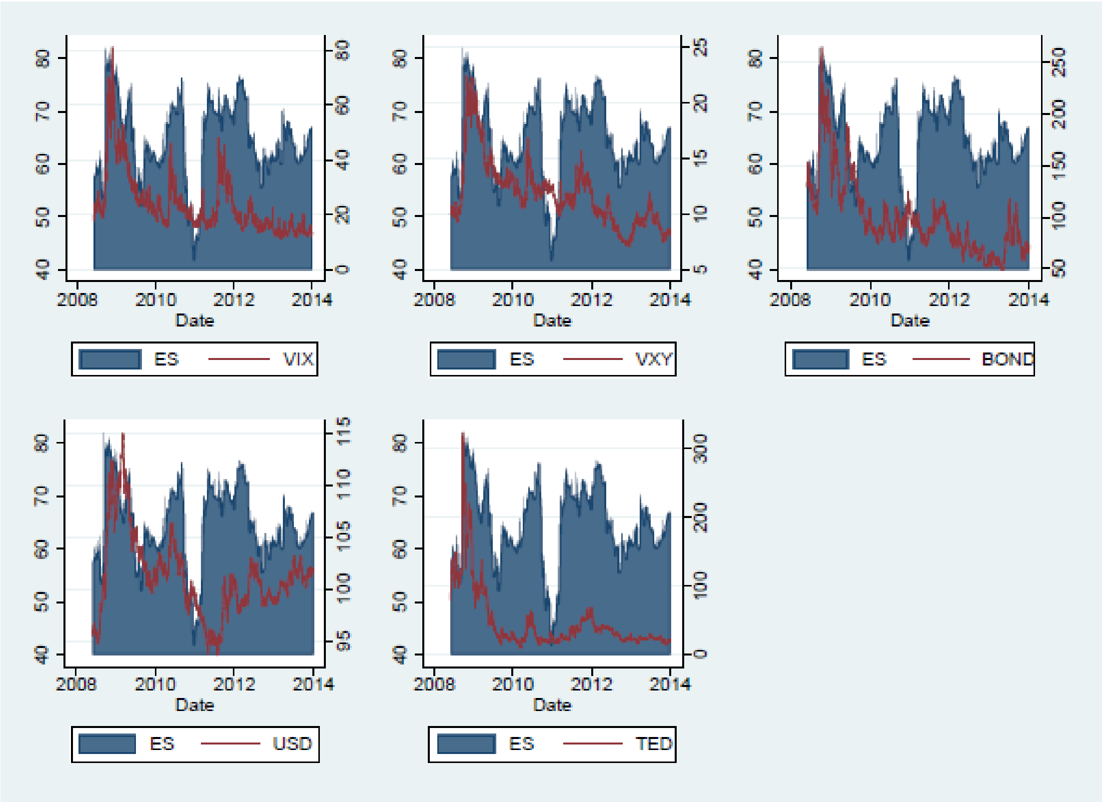

Figure 3 Connectedness of FX liquidity

We plot moving liquidity spillover index for individual currency markets, defined as the sum of the variance decomposition 'contributions to others' estimated using 100-day rolling windows.