Market Uncertainty and Liquidity Connectedness in Foreign Exchange Markets

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Abstract

We study the role of market uncertainty in the time variation of connectedness in liquidity across foreign exchange (FX) markets. Using the spillover measure based on generalized variance decomposition within a VAR system, proposed by Diebold and Yilmaz (2012), we find the FX liquidity connectedness is stronger when global financial market uncertainty is higher. The time-varying dynamics in liquidity transmission across nine FX markets is also associated with the inventory risk, information asymmetry, and U.S. economic policy uncertainty.

Keywords: Liquidity connectedness; Market uncertainty, Foreign exchange market.

JEL Classification**:** F31, G15, C22.

1. Introduction

Liquidity dry-ups in recent global financial crises alert people about the importance of the systemic liquidity risk in in financial markets (Brunnermeier and Pedersen, 2009; Melvin and Taylor, 2009). Even though the foreign exchange (FX) market is the most liquid asset market in the world in terms of trading volume, there is evidence of a strong systematic component of liquidity in global FX markets (Banti and Phylaktis, 2015; Banti, Phylaktis, and Sarno, 2012; Melvin and Taylor, 2009, Mancini et al., 2013, Karnaukh et al., 2015, Ranaldo et al., 2019). In this paper, we study the transmission of liquidity across markets using the connectedness measures of Diebold and Yilmaz (2009, 2012, 2014) and account for the time variation in liquidity connectedness in nine FX markets: USD/GBP, USD/CHF, USD/AUD, USD/JPY, USD/CAD, USD/EUR, EUR/GBP, EUR/JPY, and EUR/CHF.

Menkhoff et al. (2012) highlight the association between FX volatility risk and carry trade activities and argue that FX volatility and liquidity are positively correlated. Brunnermeier et al. (2009) link funding constraints and the unwinding of carry trades in FX markets to explain currency crashes. The liquidity spirals attributed to funding constraints cause severe liquidity dry-ups during crisis periods. Brunnermeier et al. (2009) point out funding constraints are likely to be particularly important when global uncertainty or risk aversion increases, inducing capital redemptions by speculators, losses, higher volatility, and higher margins. They show that, with the higher VIX, the implied volatility of the S&P 500, which is derived from prices of S&P 500 options traded at the Chicago Board Options Exchange (CBOE), more unwinding of speculators' carry trade position incurs, and the higher crash risk induces liquidity spirals across currency markets. Based on the mechanism of liquidity spirals, we argue that when the uncertainty is higher or when the market is more stressful, the liquidity spillover across currency markets is stronger.

Cespa and Focault (2014) argue that liquidity comovements and liquidity dry-ups are important for asset pricing and market volatility. Most of previous studies of liquidity spillovers in FX markets focus on the liquidity commonality (Mancini et al., 2013; Banti et al., 2012; Banti and Phylaktis, 2015; Karnaukh et al., 2015, Chang et al., 2017; Sensoy et al., 2020). Recently, Chang et al. (2021) examine the liquidity spillovers in FX market. We argue the time variation in liquidity spillover varies with the magnitude of market uncertainty, and the connectedness in liquidity is stronger when the uncertainty is above some threshold level. In particular, there exists a positive and nonlinear impact of market uncertainty on liquidity connectedness, the effect of which depends on the level of uncertainty. High uncertainty excites the liquidity spillover more than low uncertainty.

Studying liquidity spillover allows us to determine how liquidity transmission across FX markets in response to uncertainty shocks. In this paper, we consider how market uncertainty exacerbates the liquidity risk in the FX market. To capture the nonlinearity in the dynamic effect of uncertainty on liquidity, we estimate a nonlinear, logistic smooth transition regression (LSTR) model to capture the dependence between liquidity transmission and market risk.

We use a two-stage procedure to examine the association of liquidity spillover and uncertainty. We first use the connectedness index of Diebold and Yilmaz (2012) to evaluate daily connectedness in liquidity among nine FX markets. With measures of liquidity connectedness, we then estimate the LSTR model to determine how liquidity transmission varies with market uncertainty.

Our paper highlights the time-varying dynamics in liquidity spillovers depends on the level of market uncertainty. Our contribution is two-fold. First, we study the linkage of liquidity and uncertainty through the evolution of liquidity transmission among FX markets. Second, we provide evidence of a nonlinear relationship between liquidity and global financial market uncertainty.

Our empirical results show the liquidity connectedness among FX markets increases with a tightening of funding constraints, uncertainty about economic and monetary policies, and volatilities in stock, bond, and FX markets. As noted by Ranaldo and Santucci de Magistris (2019), shocks in international stock and bond markets prompt international portfolio rebalancing, and thus affect the liquidity and trading activities in FX markets. Our evidence of the linkage across bond, stock, and FX markets is consistent with Mancini et al. (2013) and Karnaukh et al. (2015).

Moreover, when the uncertainty is higher than a certain threshold level, the impact of uncertainty on liquidity connectedness is more profound. The asymmetric effects of TED spread, global bond implied volatility (MOVE), and global FX implied volatility (VXY) on the liquidity connectedness can be explained with the flight-to-quality hypothesis and hot-potato phenomenon. Currency dealers tend to dispose of undesired inventory positions at a low-cost way and typically pass positions among each other quickly. Such hot-potato phenomenon will be more pervasive when the market uncertainty is higher (Melvin and Taylor, 2009; Banti, 2016).

The events of global financial crises may explain the appearance of structural change in the relation of liquidity and uncertainty. When we use discrete threshold regression model to estimate the liquidity connectedness, those identified break dates are close to the global financial crisis period in 2008. Our paper complements the literature that documents volatility connectedness and liquidity connectedness are intensified during the crisis periods (Greenwood-Nimmo et al., 2016; Baruník et al., 2017, Kočenda and Moravcová, 2019; Chang et al., 2021).

The remainder of this paper is organized as follows. Section 2 describes the data and measures of liquidity. Section 3 outlines our measure of liquidity connectedness. Section 4 introduces the LSTR model. Section 5 presents the empirical results. Section 6 concludes.

2. Data and Liquidity Measures

Our data provided by EBS (Electronic Broking Services) include all spot deals and quotes at second-basis over the trading days from January 2, 2008 to December 31, 2015. We focus on the nine most liquid currency pairs: USD/GBP, USD/CHF, USD/AUD, USD/JPY, USD/CAD, USD/EUR, EUR/GBP, EUR/JPY, and EUR/CHF (BIS, 2019). The EBS data reveals best ask quote, best bid quote, transaction price, trade direction, trading volume, date and time to the second. The information of trade initiator in EBS data allows us to avoid the mistakes of trade classification (Odders-White, 2000) or the need to extract spreads indirectly from trading prices (Hasbrouck, 2009). Following Ito and Hashimoto (2006), we exclude the data on national (or bank) holidays and over the period from 22:00 GMT Friday to 22:00 GMT Sunday.

We measure order flow as the difference between the trading volumes initiated by buyers and the trading volumes initiated by sellers within a five-minute interval. To obtain the spread at the 5-min frequency, we use the bid and ask quotes prevailing at the end of a 5-min interval.

We consider three measures of liquidity, including the proportional quoted bid-ask spread, effective spread, and price impact, as suggested in Mancini et al. (2013). The proportional quoted spread at the *i*-th interval of day *t* is defined as

$$L_{t_i}^{BA} = \frac{Q_{t_i}^{A} - Q_{t_i}^{B}}{Q_{t_i}^{M}} \tag{1}$$

where $Q_{t_i}^A$, $Q_{t_i}^B$, and $Q_{t_i}^M$ denote the ask-quote, bid-quote, and mid-quote, respectively. $L_{t_i}^{BA}$ is the cost of a round-trip trade and is a usual proxy of market illiquidity. We calculate daily quoted spread as the average of all 5-min proportional quoted spreads in day t.

The other cost-based measure of liquidity is the effective spread that can measure the actual cost of executing a trade. Since trades are not always executed at the bid or ask quotes in practice, a better measure of transaction cost is the effective spread. We define the effective spread, *ES*, as follows:[1]

$$L_{t_i}^{ES} = \begin{cases} \dfrac{P_{t_i} - Q_{t_i}^M}{Q_{t_i}^M}, & \text{for buyer-initiated trades} \\ \dfrac{Q_{t_i}^M - P_{t_i}}{Q_{t_i}^M}, & \text{for seller-initiated trades} \end{cases} \tag{2}$$

where P_{t_i} denotes the transaction price at the end of interval i on day t. The effective spread reflects the effective trading cost incurred. A market can be regarded as liquid if L^{ES} is low. We use the average of all 5-minute effective spreads on day t as daily effective spread.

Similar to Banti et al. (2012) and Mancini et al. (2013), we also consider the price impact of a trade to measure the liquidity. As proposed by Kyle (1985), the price impact of a trade can measure how much the exchange rate changes in response to the contemporaneous order flow. r_{t_i} is the log exchange rate return between interval i-1 and interval i on day t; v_{s,t_i}, and v_{b,t_i} denote the trading volumes of buyer-initiated trades and seller-initiated traders at interval i on day t, respectively. We estimate the

[1] Compared with the quoted spread, the effective spread can better reflect the actual trading cost incurred. In the electronic limit-order market, some market participants may post hidden limit orders that are not reflected in quoted spreads immediately. Therefore, the transactions are not always executed at the posted bid or ask quotes. However, effective spreads can capture the costs that arise when the volume of an incoming order exceeds the posted size at the best price.

following model:

$$r_{t_i} = \theta_t + \phi_t(v_{b,t_i} - v_{s,t_i}) + \sum_{j=1}^{J} \gamma_{t,j} (v_{b,t_{i-j}} - v_{s,t_{i-j}}) + \varepsilon_{t_i} \tag{3}$$

We estimate the coefficients ϕ_t and $\gamma_{t,j}$ ($j = 1, \cdots, J$) on each day. In this way, we obtain daily measures of price impact and return reversal. The price impact ϕ_t captures the pressure of net demand on the price and is expected to be positive. The price impact is a measure of transaction cost based on the extent to which an order generates a reaction in the market price. The reciprocal of ϕ_t is a measure of market depth, by which a lower value of ϕ_t means prices are less sensitive to order imbalance. Therefore, when a market is more liquid, the price impact is smaller. Similarly, if the price is less sensitive to lagged order imbalances, the market is deeper or more liquid.

Denote $L_{k,t}$ as the liquidity of currency-pair k on day *t*. Considering the seasonality of liquidity, we use the approach of Chordia et al. (2005) to remove the weekday and monthly periodicity as follows.

$$L_{k,t} = \sum_{j=1}^{4} d_{k,j} DAY_{j,t} + \sum_{j=1}^{11} e_{k,j} \ MONTH_{j,t} + f_k TIME_t + L_{k,t}^* \tag{4}$$

where $DAY_{j,t}$ (j =1, 2, 3, 4) denote day-of-the-week dummy variables for Monday through Thursday, $MONTH_{j,t}$ (*j* =1, …, 12) denote month dummies for January through November; $TIME_t$ is the time-trend variable. The sum of regression residual and the intercept gives the adjusted liquidity, $L_{k,t}^*$, for currency-pair *k* on day *t*.

3. Liquidity Connectedness

Following Diebold and Yilmaz (2012), we measure the connectedness in liquidity across currencies markets. The magnitude of liquidity connectedness or spillover is measured by the spillover index which is defined by the generalized variance decomposition (GVD) within a framework of vector autoregresssion (VAR) (Koop et al., 1996; Pesaran and Shin, 1998).

We construct a VAR model for K exchange rates. Define y_t as a $K \times 1$ vector in a VAR(p) system:

$$y_t = \sum_{j=1}^{p} \mathrm{B}_j \, y_{t-j} + u_t \tag{5}$$

where $y_t = (y_{1t}, \dots, y_{Kt})'$, B_j is a $K \times K$ matrix of coefficients, and $u_t \sim (0, \Omega)$ is a vector of iid errors. Given the covariance stationarity, we can rewrite Equation (5) into a VMA presentation:

$$y_t = \sum_{j=0}^{\infty} A_j \, u_{t-j} \tag{6}$$

where the $K \times K$ coefficient matrices A_j are defined by $A_j = \sum_{h=1}^{p} \mathrm{B}_h A_{j-h} = \mathrm{B}_1 A_{j-1} + \mathrm{B}_2 A_{j-2} + \cdots + \mathrm{B}_p A_{j-p}$, $A_0 = I_K$, and $A_j = 0$ for $j < 0$.

For $y_{i,t}$, the H-step-ahead forecast error is $y_{i,t+H} - y_{i,t+H|t}$. We can decompose the respective forecast error variance into parts attributable to shocks $u_{k,t}$, $k = 1, 2, \cdots, K$. Since the variance decomposition relied on Cholesky factorization is dependent on the ordering of variables in the VAR(p) model, Diebold and Yilmaz (2012) suggest to use the generalized VAR framework (Koop et al., 1996; Pesaran and Shin, 1998) to conduct forecast-error variance decompositions that are invariant to variable ordering.

Define the generalized variance decompositions by $\theta_{ij}(H)$, for $H = 1, 2, \dots$,

$$\theta_{ij}(H) = \frac{\sigma_{ii}^{-1} \sum_{h=0}^{H-1} (e_i' A_h \Sigma e_j)^2}{\sum_{h=0}^{H-1} (e_i' A_h \Sigma A_h' e_i)} \times 100 \tag{7}$$

where Ω is the variance matrix for u_t, σ_{ii} is the variance of u_{it}, and e_i denotes the selection vector with one for the ith element and zero otherwise. Because the shocks to each variable $(y_i, \ i = 1, \dots, K)$ are not necessarily orthogonalized, the sum of contributions to the variance of forecast error of a specific variable is not necessarily equal to one. That is, $\sum_{j=1}^{K} \theta_{ij}(H) \neq 1$. Consequently, we use the normalization to recalculate the variance decompositions as

$$\tilde{\theta}_{ij}(H) = \frac{\theta_{ij}(\mathrm{H})}{\sum_{j=1}^{K} \theta_{ij}(\mathrm{H})} \times 100 \quad (8)$$

and obtain $\sum_{j=1}^{K} \tilde{\theta}_{ij}(\mathrm{H}) = 1$ and $\sum_{i=1}^{K} \sum_{j=1}^{K} \tilde{\theta}_{ij}(H) = K$.

Using the normalized forecast error variance decomposition, the cross market connectedness is given by the off-diagonal elements (the fractions of the H-step-ahead error variances in forecasting y_i attributed to the shock to y_j), and the own market shares are given by the diagonal elements.

We can use the directional connectedness to capture the shocks received by y_i from all other variables (y_i), as well as shocks from y_i to all other variables. There are $2K$ total directional connectedness measures, K "to others" and K "from others" connectedness measures for a set of K endogenous variables. Under the GVD framework, the total directional connectedness (of y_i from all other variables y_j) is defined as follows:

$$S_{i\leftarrow\cdot}(H) = \frac{\sum_{j=1,\, j\neq i}^{K} \tilde{\theta}_{ij}(H)}{\sum_{j=1}^{K} \tilde{\theta}_{ij}(H)} \times 100 \quad (9)$$

$$S_{\cdot\leftarrow i}(H) = \frac{\sum_{j=1,\, j\neq i}^{K} \tilde{\theta}_{ji}(H)}{\sum_{j=1}^{K} \tilde{\theta}_{ji}(H)} \times 100 \quad (10)$$

$S_{i\leftarrow\cdot}(H)$ denotes directional spillovers received by y_i from all other variables y_j. Alternatively, $S_{\cdot\leftarrow i}(H)$ measures directional spillovers transmitted from y_i to all other variables y_j. Finally, the net spillover from y_i to all other variables y_j is defined as

$$S_i(H) = S_{\cdot\leftarrow i}(H) - S_{i\leftarrow\cdot}(H) \quad (11)$$

There are K net total directional connectedness measures for a set of K variables.

The total spillover index is calculated as the sum of the off-diagonal elements in the GVD framework:

$$S(H) = \frac{\sum_{i=1}^{K}\sum_{j=1,j\neq i}^{K}\tilde{\theta}_{ij}(H)}{\sum_{i=1}^{K}\sum_{j=1}^{K}\tilde{\theta}_{ij}(H)} \times 100 = \frac{\sum_{i=1}^{K}\sum_{j=1,j\neq i}^{K}\tilde{\theta}_{ij}(H)}{K} \times 100 \tag{12}$$

4. Determinants of Liquidity Connectedness

4.1 Factors affecting liquidity connectedness

To decide the possible determinants of liquidity connectedness, we follow Chordia et al. (2005) to consider inventory costs and adverse selection costs.[2] From the aspect of inventory cost, we can consider the inventory risk as the determinant of liquidity (Stoll, 1978; Ho and Stoll, 1981). The TED spreads, the difference between the three-month Treasury bill and the three-month LIBOR based on the U.S. dollar, is a usual proxy for the risk of holding inventory. Higher financing costs may result in increased costs for currency dealers to hold inventory positions. The smaller TED spread indicates reduced cost of inventory, thus stimulating trading activities and increasing the liquidity (Brunnermeier and Pedersen, 2008; Chordia et al. 2005). To dispose of undesired inventory positions at a low-cost way, currency dealers typically pass positions among each other quickly, and this "hot-potatoes" phenomenon is also prevalent among non-dealer financial institutions in recent years (Melvin and Taylor, 2009; Banti, 2016). Instead, the higher TED spread deteriorates the liquidity of risky currencies even more and propagates the illiquidity to other currency markets.

The other determinant of liquidity is the adverse selection cost and we use the events of macro news announcements to quantify the effect of adverse selection cost on the liquidity spillover.[3] We acknowledge that the Federal Open Market Committee

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[2] In theories of market microstructure, the spread can be decomposed into three components: order processing costs, inventory costs, and adverse selection cost (Glosten and Harris, 1988; Madhavan and Smidt, 1997). Since order processing costs are associated with the operation costs and can be ignored, studies of FX market microstructure mainly focus on the inventory cost and adverse selection cost components (Lyons, 2001).

[3] Market-wide private information exits in FX markets Evans and Lyons (2008). Their evidences indicate that some FX dealers own superior information than others.

(FOMC) announcements are critical for the global economy, arguably more critical than other central banks announcements (Fischer and Ranaldo, 2011). As a key channel of the transmission of policy uncertainty to financial markets, FOMC announcements deliver systematic risk about current and future interest rate policies. Here, we use a news-based index of monetary policy uncertainty (MPU) constructed by Husted et al. (2020) as a proxy for the adverse selection. Specifically, the MPU index is to tract the frequency of newspaper articles related to Federal Reserve policy actions and their consequences on FOMC meeting days.

Their approach follows the news-based search approach in Baker et al. (2016).[4]

A higher MPU index implies the media sentiment about the monetary policy uncertainty is increasing and the public is more uncertain about Fed's actions. Therefore, traders' interpretations and opinions about FOMC announcements are more heterogeneous, in turn stimulating an increase in information asymmetry. In response to the increase in information asymmetry, the spread increases in markets of currencies against USD, thus inducing more spillover in illiquidity.

Moreover, financial stress can adversely affect the liquidity because traders face stronger funding constraints and have to unwind their trading positions (Brunnermeier and Pedersen, 2009). Therefore, the rising financial market uncertainty potentially affects the structure of liquidity connectedness in FX markets.

Baruník et al. (2017) argue that FX volatility connectedness is stronger when the financial stress is higher. Similarly, Diebold and Yilmaz (2009, 2012) find the

[4] Compared with the related indicator constructed by Baker et al. (2016), MPU indicator proposed by Husted et al. (2020) is U.S. centric and goes around uncertainty related to Fed monetary policy. They construct the U.S. MPU index by searching for keywords related to monetary policy uncertainty in the New York Times, Wall Street Journal and Washington Post based on the FOMC calendar.

magnitude of the volatility spillover increases significantly during periods of higher market uncertainty. Mancini et al. (2013), Karnaukh et al. (2015) and others also show that FX liquidity commonality increases with higher volatilities in global stock and bond markets. Shocks in international stock and bond markets prompt international portfolio rebalancing, and thus affect the liquidity and trading activities in FX markets. Additionally, the FX market acts as a channel that propagates shocks across countries' stock and bond markets (Hau et al., 2010, Pavlova and Rigobon 2007). It suggests cross market linkages may exist between FX illiquidity and the global risk in stock and bond markets (Fleming, Kirby, and Ostdiek 1998).

In addition, we use the time-varying effects of U.S. economic policy uncertainty index (USEPU)[5] measured by Baker et al. (2016) and the St. Louis Fed Financial Stress Index (FSI)[6] constructed by Kliesen and Smith as a proxy for financial market conditions. These indicators convey information about the health of the economy. Several empirical studies use a FSI index to be the mirror image of the financial stability index (Morales and Estrada, 2010). Phan et al. (2021), and Segal et al. (2015), empirically has confirmed the positive relationship between economic policy uncertainty (EPU) and financial stress. Previous research also documents that the connectedness measure can serve as an indicator of systematic risk (Diebold and Yilmaz, 2014; Hu and Gong, 2019; Hsu et al., 2020).

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[5] The data of daily U.S. EPU are available at http://www.policyuncertainty.com. The U.S. EPU index is constructed based on the relative frequency of keywords on economic policy uncertainty in in major newspapers.

[6] The St. Louis Fed's FSI index data comes from the Federal Reserve Bank of St. Louis (http://research.stlouisfed.org/fred2/). The FSI is constructed from the principal component analysis (PCA) on 7 interest rates, 6 yield spreads, and 5 other indicators. For details see the online appendix at http://research.stlouisfed.org. In addition, the FSI index is weekly frequency data and is released on every Friday. In order to correspond to daily frequency, we apply the frequency-conversion method provided by EViews to change the data from weekly frequency to daily frequency.

When economic policy uncertainty is higher, traders tend to have more revisions to the expectations of the economic fundamentals that determine the value of the exchange rate, leading to greater exchange rate fluctuations (Krol, 2014; Bartsch, 2019). We expect that adverse financial conditions may exacerbate exchange rate fluctuations, resulting in a decline in trading activities, liquidity and even economic vitality. Therefore, a larger USEPU or FSI is associated with the simultaneous improvement or deterioration in liquidity in the exchange of foreign currencies against USD. We expect US economic policy uncertainty and financial stress are positively related to FX liquidity connectedness.

Consequently, we consider USEPU, FSI, global FX volatility (JP Morgan launches implied volatility index, VXY), equity volatility (Chicago Board Options Exchange creates volatility index, VIX), and bond volatility (Merrill establishes the average implied volatility across a wide range of outstanding options of the U.S. Treasury securities, MOVE index) as determinants of liquidity connectedness.

Hence, the current determinant model can be used not only as the benchmark model, but also as the benchmark model for applied to the time-varying linear and threshold regression model in this study.

Henceforth, the current determinant model can be used not only as the benchmark model, but also as the benchmark model for applied to the time-varying linear and threshold regression model in this study.

$$\Delta LC_t = \alpha_0 + \beta_1 \Delta LC_t + \beta_2 \Delta TED_{t-1} + \beta_3 \Delta VIX_{t-1} + \beta_4 \Delta MOVE_{t-1} + \beta_5 \Delta VXY_{t-1} + \beta_6 USEPU_t + \beta_7 USMPU_t + \varepsilon_t, \qquad (13)$$

where LC_t is the aggregate liquidity connectedness of nine FX markets, TED_t is the TED spread; VIX_t denotes the CBOE Implied Volatility Index; $MOVE_t$ is the Merril's implied volatility index for Treasury bonds, VXY_t is the JP Morgan's global

FX volatility, USEPU is the U.S. economic policy uncertainty (Baker et al., 2016), and USMPU denotes the U.S. monetary policy uncertainty focused on the FOMC meetings. We use the heteroscedasticity-and-autocorrelation-consistent (Newey and West, 1987) standard errors to adjust for the heteroscedasticity and autocorrelation in error terms.

4.2 Structural change in liquidity connectedness

Considering the structural change in liquidity connectedness in FX markets, we first apply the test of multiple breaks developed by Bai and Perron (1998, 2003) to identify the number of breaks. Compared to other structural break tests, the Bai-Perron test allows for the autocorrelation and heteroscedasticity in the error term.

One straightforward specification for structural break is the discrete threshold regression model. If m breaks occur, we can specify the model with $m + 1$ regimes as

$$\Delta LC_t = \sum_{j=1}^{J+1} Regime_{j,t} \times [\beta_{j0} + \beta_{j1}\Delta LC_{t-1} + \beta_{j2}\Delta TED_{t-1} + \beta_{j3}\Delta VIX_{t-1} + \beta_{j4}\Delta MOVE_{t-1} + \beta_{j5}\Delta VXY_{t-1} + \beta_{j6}USEPU_t + \beta_{j7}USMPU_t] + \varepsilon_t, \quad (14)$$

where J is the number of breaks. With T as the total sample size, $T_1, \cdots, T_J$ as unknown breakpoints, $T_0 = 0$ and $T_{m+1} = T$, we define $Regime_{j,t}$ as the indicator variable for regime j, $Regime_{j,t} = 1$ if $T_{j-1} < t \leq T_j$, 0 otherwise. The $SupF(L+1|L)$ test statistic allows us sequentially to test for null of L breaks against the null of L+1 breaks and decide the optimal number of breaks.

4.3 Logistic smooth transition regression (LSTR) model

To assess the potential nonlinear relationship between the liquidity connectedness and uncertainty, we consider the LSTR model, which can capture smooth transitions between regimes. In each regime, the dynamics of the focal variable can be described properly by a linear regression model. More detailed discussions of the LSTR model specification and estimation techniques can be found in Teräsvirta (1994, 1998, 2004) and van Dijk et al. (2002). Here, we specify a two-regime LSTR model as follows:

$$\Delta LC_t = \beta_0 + \beta_1 \Delta LC_{t-1} + \beta_2 \Delta TED_{t-1} + \beta_3 \Delta VIX_{t-1} + \beta_4 \Delta MOVE_{t-1} + \beta_5 \Delta VXY_{t-1} + \beta_6 \Delta USEPU_t + \beta_7 \Delta USMPU_t + [\theta_0 + \theta_1 \Delta LC_{t-1} + \theta_2 \Delta TED_{t-1} + \theta_3 \Delta VIX_{t-1} + \theta_4 \Delta MOVE_{t-1} + \theta_5 \Delta VXY_{t-1} + \theta_6 USEPU_t + \theta_7 USMPU_t] G(\gamma, c, s_t) + \varepsilon_t, \quad (15)$$

where β's and θ's denote the regression coefficients for the linear and nonlinear parts of the model, respectively. The effect of explanatory variables can differ across regimes, according to the coefficients θ's. s_t is the transition variable that governs smooth switches between regimes. $G(\gamma, c, s_t)$ is the transition function, bound in the interval [0, 1], where γ is the slope parameter which indicates how fast the transition of $G(\cdot)$ from 0 to 1 is; c is the vector of location parameters that determines where the transition occurs. We specify the transition function as the logistic function, $G(\gamma, c, s_t) = \left(1 + \exp\left\{-\frac{\gamma}{\hat{\sigma}_{s_t}}(s_t - c)\right\}\right)^{-1}$, $\gamma > 0$. $\hat{\sigma}_{s_t}$, the estimated standard deviation of s_t, here makes γ approximately scale-free and facilitates the convergence of the nonlinear least squares estimation.

The transition function determines how regimes switch and is governed by the transition variable (s_t) and the speed of transition (γ). By definition, $G(\gamma, c, s_t) \to 0$ as $s_t \to -\infty$, $G(\gamma, c, s_t) = 0.5$ as $s_t = c$, and $G(\gamma, c, s_t) \to 1$ as $s_t \to +\infty$. In the case of two regimes, two regimes are associated with small ($s_t < c \Rightarrow G(\gamma, c, s_t) < 0.5$) and large ($s_t > c \Rightarrow G(\gamma, c, s_t) > 0.5$) values of the transition variable, relative to the threshold value (c). In this way, the regression coefficient monotonically changes with s_t, from β_j (when $G(\gamma, c, s_t) = 0$) to $\beta_j + \theta_j$ (when $G(\gamma, c, s_t) = 1$).

The parameter γ determines the smoothness (or speed) of the transition from one regime to another. A smaller γ indicates the transition between regimes is slower; as $\gamma \to 0$, the logistic function approaches a constant, $G(\gamma, c, s_t) = 0.5$ for all s_t, and the LSTR model reduces to a linear regression model. As γ increases, the transition between regimes becomes faster. As $\gamma \to \infty$, the transition is abrupt and jumpy, and $G(\gamma, c, s_t)$ turns out to be a step function, with a discrete transition between regimes at $s_t = c$. In this case, the LSTR model becomes a discrete threshold regression model.

As we are concerned mainly on the threshold effects of financial stress on FX liquidity connectedness, the benchmark threshold variable in our analysis is the U.S. economic policy uncertainty index (USEPU) from Baker et al. (2016). Because the U.S. has a relatively strong influence on the global economy, while the performance of other countries' economic indicators impacted on global economy system is relatively weak. Nevertheless, we also consider four more market-specific uncertainty measures: (1) Chicago Board Options Exchange Volatility Index (VIX), (2) global FX volatility (VXY), (3) Merrill's bond implied volatility (MOVE), and (4) St. Louis fed financial stress index (FSI), since all of them also represent uncertainty measure that are widely used in the literature.

5. Empirical Results

5.1 Descriptive statistics

We construct the total liquidity connectedness based on 10-stap ahead error variance in forecasting liquidity with a VAR(2) model. To obtain a series of connectedness index we estimate the VAR(2) models with 100-day rolling samples.[7] This approach allows us to assess the evolution of the FX liquidity connectedness of nine currency-pairs over time.

Table 1 reports the summary statistics of the total liquidity connectedness and

[7] In previous studies, there is not a conclusive length of the rolling samples. For examples, Diebold and Yilmaz (2014) use 100-day rolling samples; Diebold and Yilmaz (2012) and Baruník et al. (2017) adopt 200-day rolling samples; Greenwood-Nimmo et al. (2016) use 250-day rolling samples. We also use 90-day, 120-day, and 200-day rolling samples to obtain the connectedness measures, and find results are similar to those based on 100-day rolling samples. The results of 90-, 120-, and 200-day rolling samples are available from the authors upon request.

uncertainty proxies. Panel A shows that, for the four liquidity measures, the average values of the total connectedness range from 25.96 (Price Impact) to 61.33 (Bid-Ask Spread), suggesting bid-ask spreads across markets are more connected than the other liquidity measures. The ADF unit root tests show that all the four measures of total liquidity are stationary.

Panel B of Table 1 displays the proxies of the uncertainty of financial markets, TED Spread, VIX, VXY, MOVE, FSI, USEPU, and USMPU. The average values of uncertainty measures range from 0.25 (FSI) to 118.72 (USEPU). The patterns of dispersion are similar for these uncertainty indicators. In terms of standard deviation, USEPU fluctuates most than other proxies. The skewness shows all uncertainty measures are positively skewed. value and right-biased. This is also reflected in the kurtosis, which are highly leptokurtic and in the range of 4.9 and 23.94. The finding shows that the presence of extreme fluctuations as well as over-dispersion in these markets.

5.2 Liquidity connectedness and financial uncertainty indicators

Figure 1 plots the evolution of FX liquidity connectedness index against the financial uncertainty proxies, including the TED spread, VIX, VXY, MOVE, USEPU, and USMPU.[8]

The blue area in Figure 1 reports the evolution of the total liquidity connectedness

[8] 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 FX Volatility Index, which tracks the implied volatility of three-month at-the-money forward options for major currencies and development currencies. The bond market 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. 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 U.S. dollars.

for the effective spread over sample period.[9] Several major events are evident in the time-varying total FX liquidity 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 spillover intensifies climbed to reach its maximum at about 80%.

In addition, as Figure 1 reveals, we find the liquidity spillover levels rises slowly and experiences 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 status, market uncertainty is high and the liquidity spillover magnitude becomes stronger. As noted in Bubák et al. (2011) and Kočenda and Moravcová (2019), the FX liquidity spillovers seem stronger when the market is experiencing high level of financial stress.

We also find that the fluctuated patterns of the FX liquidity connectedness seem to increase in the post-crisis period. As mentioned by Baruník et al. (2017), the liquidity spillover extent begins to be stronger in 2013 due to the different monetary policies of the world major countries' central banks. 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 policies 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

[9] 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 et al. (2013). For the sake of simplicity of illustration, we only list the efficiency spread estimation as our representative empirical results.

substantial rebalance in global portfolios and exerted substantially larger effects on asset prices.

The upper panel of Figure 1 plots the rolling connectedness along with the USEPU index, FSI index, and TED spread, respectively. USEPU and FSI are commonly-used proxies to the financial uncertainty in the U.S. As Huynh et al. (2020) argue, a higher degree of global EPU could raise instabilities in the FX market, leading to intensified spillovers in liquidity. This result is consistent with our finding. In most cases, we observe that the patterns of the FX liquidity connectedness are similar to the trend of USEPU and FIS. As described by Greenwood-Nimmo (2016), risk-averse investors may become more sensitive to changes in the risk environment during market turbulence, leading to increased FX spillovers.

Moreover, we compare total connectedness and TED spread.[10] As predicted by Mancini et al., (2013), 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), tighten funding constraint could cause the FX market to lose coordination and collapse. This is completely shown in Figure 1. We observe that the relation between FX spillover activity and the TED spread is likely to be positive, and strongly so during the recent crisis events.

Finally, in the bottom of Figure 1, we plot the total FX connectedness and the global volatility indices such as VIX, MOVE, and VXY.[11] The figure shows that the

[10] 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 U.S. dollars.

[11] 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. The MOVE is the

FX connectedness and the global volatility indices spiked to a peak during the recent crisis. Karnaukh et al. (2015) show that the FX liquidity tends to deteriorate with the volatility of both global stocks and bonds. This finding is consistent with our results. In an uncertain environment, risk-averse investors may rebalance their investment portfolios and adjust hedging strategies more frequently (Greenwood-Nimmo et al., 2016). Consequently, the international portfolio reallocations create a cross-market transmission channel. The pattern of movements from these measurements indicates that the FX liquidity spillover seems to increase with global risk. There exist cross-market linkages between the FX liquidity risk and stock-bond volatilities (Banti, 2016).

5.3 Network diagram of FX liquidity connectedness

We further rely on the graphical display to comprehend the structure of connectedness, and the direction and strength of spillover reception and transmission between currencies. We develop the network topology of all market connectedness following Diebold and Yilmaz (2014) and Diebold et al. (2015). Figure 2 (a)-(c) present the network diagram of the static liquidity connectedness among all possible pairs formed by the nine currency pairs estimated from the full-sample period (May 9, 2008 to Dec 31, 2015), and two subsample periods: the financial crisis period (May 29, 2008 to July 25, 2012) and the post-crisis period (July 26, 2012 to Dec. 31, 2015).

The size of the node shows the magnitude of transmission/reception of liquidity connectedness for each currency pair. Node colors specify whether a market is a net transmitter (light blue) or receiver (gray) of the liquidity connectedness. The bigger

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. VXY is JP Morgan global FX Volatility Index, which tracks the implied volatility of three-month at-the-money forward options for major currencies and development currencies.

node size (node size is based on the weighted out-degree) implies higher transmission/reception of spillover effects. Arrow width implies the strength of the pairwise directional connectedness. The wider arrow reflects stronger pairwise liquidity connectedness. From Figure 2, we find that EUR/CHF is the dominant transmitters of liquidity spillovers to the other markets. We also observe that the pairwise directional liquidity connectedness is particularly strong between EUR/CHF and USD/CHF in the two possible directions. Our result shows the FX liquidity connectedness varies across currency-pairs.

During the financial-crisis period, the strongest spillover transmitters are EUR/CHF and EUR/JPY, and to a lesser degree the EUR/GBP and USD/AUD. The wider dark gray arrows are pairwise connectedness for the EUR/CHF to USD/CHF, EUR/JPY to USD/EUR, and EUR/CHF to USD/CHF, suggesting that the connectedness in liquidity increases during the period of financial crisis. Since risk-averse investors prefer to hold less risky currencies, such as the Swiss franc (CHF) and the Japanese yen (JPY) during the crisis period, the liquidity connectedness is higher for riskless currencies. Consistent with Chang et al. (2021), with various measures of liquidity, we observe that liquidity spillover is stronger during the crisis periods than in tranquil periods.

For the post-crisis period, EUR/JPY and EUR/GBP become the primary spillover receivers. On the other hand, the highest pairwise connectedness measure is observed from EUR/CHF to USD/CHF. The pairwise connectedness from USD/CHF to USD/EUR is ranked the second. One factor behind the high pairwise directional connectedness between these currencies could be due to the fact that there is a strong tie between their financial and economic sectors, and European currencies are closely integrated (Greenwood-Nimmo et al. 2016).

5.4 Estimation results of the structural change

As the FX market evolves over time, the dynamic interrelation between markets may undergo structural changes along with changes in policies, economic environment, and political regime. We use Bai-Perron tests of multiple breaks (Bai and Perron, 1998, 2003) to detect structural changes in total liquidity connectedness. The results of Bai-Perron tests are reported in Table 2.

All *UD-max* and *WD-max* statistics are statistically significant at the 1% level for the total connectedness built on various measures of liquidity; they reject the null hypothesis of no structural break in the liquidity connectedness. It implies at least one break exists in the liquidity connectedness series. Then, we use the sequential $SupF(L+1|L)$ test statistics to determine the appropriate number of breaks in the liquidity connectedness. Specifically, the numbers of break points in liquidity connectedness detected are 4 based on effective spread, 3 based on bid-ask spread, 1 based on price impact, and 1 based on return reversal.

During the period of the U.S. subprime mortgage crisis and the period of Greek sovereign debt collateral crisis, economies in the world had suffered extremely high uncertainty. Baruník et al. (2017) document the FX volatility spillover is stronger during the global turmoil period. Our finding that FX liquidity spillover is stronger during the global crisis period conceptually supports that the liquidity spiral during the crisis period in that funding constraints and the unwinding of currency carry trade activities intensify the liquidity commonality in FX markets.

We find that FX liquidity connectedness increases with TED spread, VIX, MOVE, and VXY. As currencies act as a medium of international payment, FX markets are linked to global asset markets (Hau et al., 2010, Pavlova and Rigobon 2007, Fleming et al., 1998). The volatility of global stock markets is affecting the liquidity and trading activities in FX markets (Karnaukh et al., 2015 and Fleming et al., 1998). Therefore, we analyze the connection between VIX and the FX liquidity connectedness. However, our results show no significant relation between VIX and liquidity connectedness during the period from May 11, 2010 to March 18, 2011. In periods of March 21, 2011—Dec. 30, 2014 and Dec. 31, 2014—Dec. 31, 2015, we observe a significantly positive relationship between liquidity connectedness and USEPU (U.S. economic policy uncertainty index). This implies that investors tend to have more revisions to the expectations of the economic fundamentals when the U.S. economic policy uncertainty is much higher (as documented by Bartsch, 2019). It may exacerbate the fluctuations in exchange rates, resulting in simultaneous improvement or deterioration in the liquidity of foreign currencies against USD. Consequently, this dynamic mechanism further strengthens the extent of the FX illiquid connectedness. Moreover, we observe that the lagged FX illiquid connectedness have significant autocorrelation post-crisis period. However, other estimated parameters have no statistically significant on liquidity connectedness in this time period.

These results support that there is clear indication of multiple structural breaks in FX liquidity connectedness of effective spread. Also, market pressure sources play an important role in the impact of FX liquidity connectedness. Overall, our results show that the liquidity connectedness depends on funding liquidity (i.e., TED), global volatility (i.e., VIX, VXY, and bond volatility), and U.S. economic policy uncertainty index (USEPU).

5.5 Estimation results of the threshold regression model

To the investigation of whether liquidity connectedness behavior changes when market uncertainty increases beyond a certain level, we estimate the threshold model given in Equation (15). Table 4 presents the threshold regression results, where the dependent variable is the effective spread of liquidity connectivity, and the threshold variable is market uncertainty, including the U.S. EPU, VIX, VXY, MOVE, and FIS indices, respectively.

The first column reports the results of estimation a linear regression, which does not consider the threshold effect. The results corroborate the view that liquidity connectedness exists and is time varying by inventory risk and information factors. These results support our hypothesis that the FX connectedness increase with a tightening of financial constraints and U.S. economic policy uncertainty. Our findings also suggest that the liquidity connectedness increases with market volatility. Ranaldo et al. (2019) argue that shocks in international stock and bond markets prompt international portfolio rebalancing, and thus affect the liquidity and trading activities in FX markets. There exist cross-market linkages between the FX liquidity risk and stock-bond volatilities (Karnaukh et al., 2015)

Next, when the results divide the regression sample into high and low uncertainty regimes, we obtain the following results. There is evidence of a strong threshold effect (significant at the one percent level) when using U.S. EPU proxy of market uncertainty. As revealed by the regression (2) in Table 4, the regression parameters estimate in each regime are significantly from each other. In the low uncertainty regime, the estimate of the coefficients is statistically significant for the lagged FX liquid connectedness, USEPU, and VIX. In contrast, in the high uncertainty regime, the estimate of the coefficients is positive (except for the lagged FX liquid connectedness and VIX). In the regression (2) of Table 4, we find statistically significant asymmetric effects of TED and MOVE as well as VXY on the liquidity connectedness under high and low uncertainty regimes. This finding confirms our a priori belief that currency dealers prefer to dispose of undesired inventory positions at a low-cost way and typically pass positions among each other quickly in more uncertain regimes (Melvin and Taylor, 2009; Banti, 2016). However, the evidence is weaker when using the FSI proxy, whereby the asymmetric effect is significant at the 5% level only for USMPU under low and high market uncertainty.

Moreover, we observe that the asymmetry effects are much weaker when using VIX, VXY, and MOVE as threshold variable. In the regressions (4)-(6) of Table 4, we only find that the lagging MOVE and VXY parameter estimates are significant under high uncertainty regime at the 1% level. The results suggest that uncertainty in the market-specific nature of VIX, VXY or MOVE does not seem as important as U.S. economic policy uncertainty. This finding consistent with Jurado et al. (2015). This occurs because these market-specific uncertainty proxy variables have specific fluctuations when measuring market uncertainty. And because U.S. economic policy uncertainty be observed in many economic indicators at the same time, market-specific uncertainty may not reflect the true aggregate uncertainty state of the economy.

The penultimate row of Table 4 reports the results of testing the null hypothesis of no break against the alternative of at least one break. As the row shows, all $SupF(1|0)$ statistics are statistically significant at the 5% level in all cases. More specifically, the $SupF(1|0)$ statistics for a single threshold are 351.0, 57.2, 136.0, 162.5, and 60.1, respectively. These evidences indicate that the test for a market uncertainty threshold is highly significant regardless of the market uncertainty proxy. Therefore, the evidence supports that market uncertainty affects the liquidity connectedness by dividing the regression sample into two regimes. Moreover, we also test the existence of two or more threshold effects, which means that the sample should be divided into three or more uncertainty regimes. However, apart from one regime we reported, there is no more evidence to find additional uncertainty regimes. Thus, we did not report these tests in

Table 4.

5.6 Robustness checks

To assess the robustness of our main findings, we use an alternative definition of market-wide liquidity proxy. In more detail, we use three different liquidity connectedness proxies to measure the daily average bid-ask spread, price impact, and return reversal. This approach helps to identify which aspects of liquidity connectedness may be more susceptible to funding constraints, information asymmetry, and market volatility.

As note by Banti and Phylaktis (2015), dealers quote prices by balancing the expected total revenues after receiving orders from customers and other dealers. When we use quote spread proxy as another measure of liquidity spillover, we find evidence that the null hypothesis of no threshold effect against multiple thresholds can be rejected in all cases at the five percent significance level. In Table A.1, we also find statistically significant asymmetric effects of market volatility on the connectedness series under low and high market uncertainty (specifications (3) and (4)) at the one percent significance level, similar to our benchmark estimates reported in Table 4. This suggests that market volatility affects the liquidity connectedness mainly through its effect as an uncertainty threshold variable.

Another measure of liquidity variables related to price changes with net order flow is the price impact and return reversal. According to Pástor and Stambaugh (2003) and Banti (2012), transitory price changes tend to be associated with the behavior of risk-averse market makers. To examine whether different liquidity measures have significant asymmetry effects, we use price impact and return reversal as alternative independent variables to explore this possibility. In Table A.2 and A.3, we conduct a similar analysis in Table 4.

Here, we find weaker or asymmetric effects of control variables on the connectedness series under low and high market uncertainty. Furthermore, we observe that the coefficients of lagged FX liquidity connectedness are significantly negative different from zero in times of highly volatile market. This result is line with insights by Brunnermeier et al. (2009), supporting that traders become risk-averse and cause a self-enforcing liquidity spiral, thus weakening trading intentions. Moreover, the change in TED is significantly and negatively associated with the change in liquidity connectedness under the high market uncertainty. As a possible explanation, during high global risks periods, traders become risk-averse and cause a self-enforcing liquidity spiral, thus leading to diminished market-wide liquidity and trading activity (e.g., Ranaldo and Soderlind, 2010; Karnaukh et al., 2015). Thus, on average, changes in funding cost lead to less trading activity in the FX market, and the FX connectedness accordingly grows weaker.

6. Conclusions

In light of recent market turmoil, the liquidity across FX markets commove and spillover significantly. We use intraday trading data of FX markets to explore the evolution of spillovers in liquidity of nine major FX markets. With the connectedness index (Diebold and Yilmaz, 2012) built on the generalized variance decomposition of a VAR model of liquidities of the nine markets, we find the uncertainty of global financial markets and economic policy uncertainty significantly affect the liquidity spillover in FX markets, and their impacts differ under states of low and high uncertainty.

We also study the effects of monetary policy uncertainty focusing on FOMC meetings but find its effect is no as significant as the effect of the broader economic policy uncertainty index on the FX liquidity spillover. Out finding contributes to provide useful insights on practical international investment portfolio formation for investors and policy implications for regulators.

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Figure 1
Liquidity connectedness and selected market uncertainty indicators
This figure shows the liquidity connectedness index against the U.S. economic policy uncertainty (USEPU), St. Louis Fed financial stress index (FSI), the TED spread, Chicago Board Options Exchange (CBOE) Implied Volatility Index (VIX), Merrill's bond implied volatility (MOVE), and the global FX volatility (VXY), respectively. The aggregate liquidity connectedness is calculated by the rolling-samples of 100 trading days with the 10-step-ahead forecast error variances. In each panel, the left-hand scale is aggregate liquidity connectedness (LC) and the right-hand scale is the selected market uncertainty indicators. (Sample period: January 2008 - December 2015)

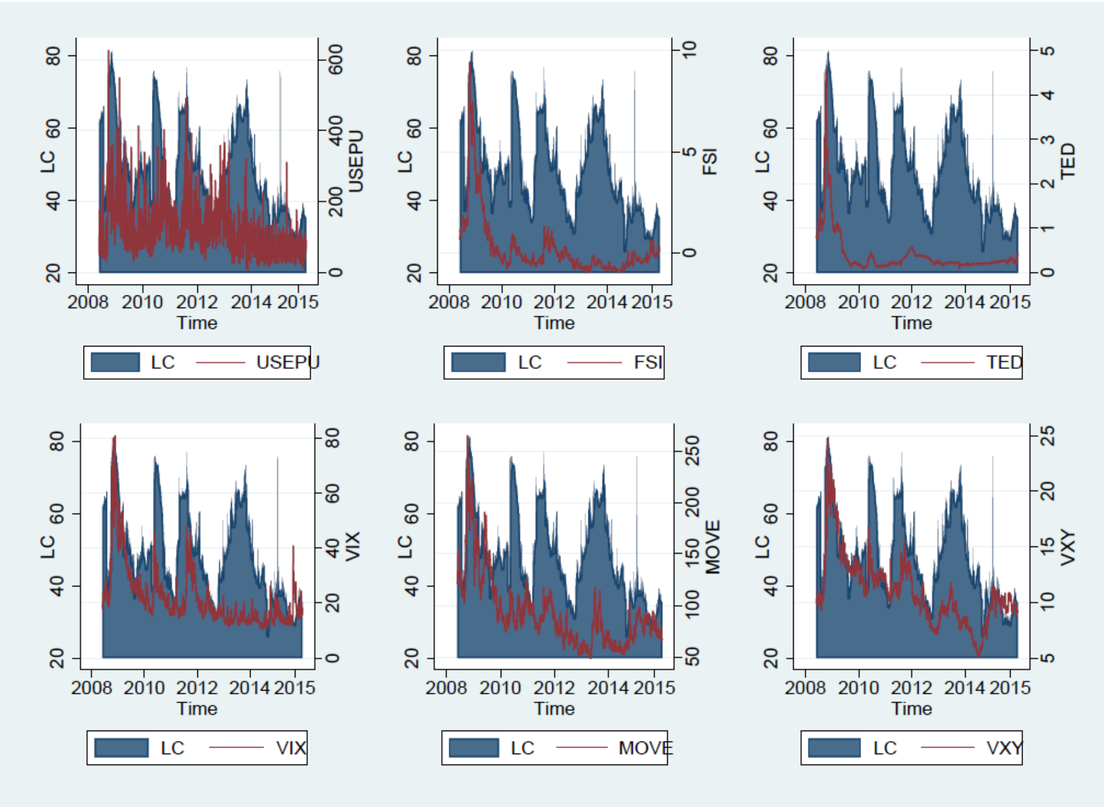
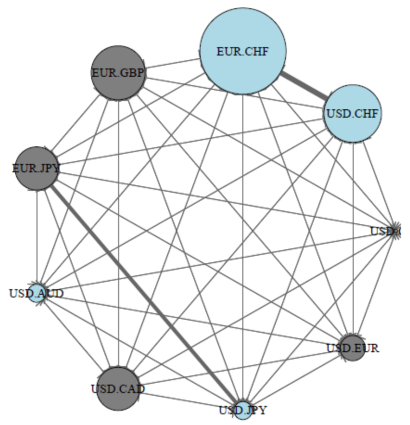


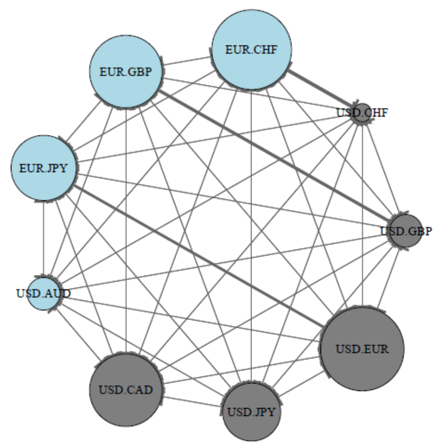
Figure 2

Network plot of directional spillovers of liquidity

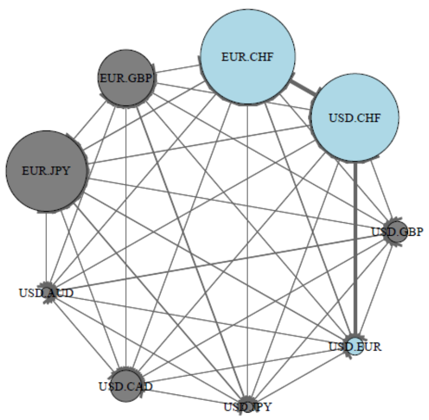
This figure shows the network plot of the net-pairwise directional liquidity connectedness among nine currency pairs or the three following sub-sample periods: full-sample period (May 9, 2008 – Dec. 31, 2015), the crisis period (May 9, 2008 – July 25, 2012), and the post-crisis period (July 26, 2012 – Dec. 31, 2015). Net transmitters are in light blue color and net receivers are in gray color. The size of the node shows the magnitude of the net-pairwise directional connectedness for each currency pair. Arrow width implies the strength of the pairwise directional connectedness. The wider arrow reflects stronger pairwise liquidity connectedness, from light gray (weakest) to dark gray (strongest).



(a) Full sample



(b) Financial crisis



(c) Post-crisis

Table 1
Summary statistics of liquidity connectedness and market uncertainty
This table reports summary statistics for four daily measures of liquidity connectedness and proxies of market uncertainty. Daily liquidity connectedness is constructed following Diebold and Yilmaz (2012) based on 10-step ahead forecast error variances from VAR(2) estimated from the rolling-samples of 100 days. Proxies of market uncertainty include the CBOE Implied Volatility Index (VIX), JP Morgan's global FX implied volatility (FXY), Merril's implied volatility index for Treasury bonds (MOVE), financial stress index constructed by the Federal Reserve Bank of St. Louis (FSI), U.S. economic policy uncertainty constructed by Baker, Bloom, and Davis (USEPU), and meetingly Husted-Rogers-Sun monetary policy uncertainty index for the U.S. (MPU). Sample period: May 27, 2008 - December 31, 2015. AC(1) refers to the first order autocorrelation of the series. The p-value of the ADF test of unit root is reported in parentheses.

	Mean	Std. dev.	Min	Max	Skewness	Kurtosis	AC(1)	ADF
Panel A: Liquidity connectedness								
Effective Spread	50.17	12.53	25.96	81.60	0.41	2.21	0.93	-3.84 (0.00)
Bid-Ask Spread	61.33	13.51	33.13	85.93	0.00	2.01	0.94	-3.52 (0.01)
Price Impact	25.96	3.54	19.35	44.61	0.09	3.89	0.92	-4.83 (0.00)
Return Reversal	26.51	3.50	19.13	44.63	1.03	6.04	0.91	-3.96 (0.00)
Panel B: Uncertainty proxies								
TED	0.40	0.49	0.09	4.58	4.13	23.94	0.89	0.94 (0.99)
VIX	21.56	10.46	10.32	80.86	2.19	8.80	0.90	-3.56 (0.00)
VXY	10.96	3.07	5.11	24.78	1.09	4.91	0.92	-3.07 (0.03)
MOVE	91.75	33.45	48.90	239.40	1.71	6.46	0.91	-2.78 (0.06)
FSI	0.25	1.50	-0.96	9.41	3.09	13.84	0.90	-0.85 (0.80)
USEPU	118.72	68.94	7.71	490.89	1.57	7.08	-0.33	-7.35 (0.00)
USMPU	95.53	40.14	37.50	251.81	1.41	6.19	0.50	-4.42 (0.00)

Table 2
Structural breaks in liquidity connectedness of FX markets
This table reports the estimation result of the following regression: $\Delta LC_t = \beta_0 + \beta_1 \Delta LC_{t-1} + \beta_2 \Delta TED_{t-1} + \beta_3 \Delta VIX_{t-1} + \beta_4 \Delta MOVE_{t-1} + \beta_5 \Delta VXY_{t-1} + \beta_6 USMPU_t + \beta_7 USEPU_t + \varepsilon_t$, where ΔLC_t is the first difference of the logarithm of total liquidity connectedness of nine FX markets, where the liquidity is measured by the effective spread, bid-ask spread, price impact, and price reversal. TED_t is the TED spread; VIX_t denotes the CBOE implied volatility index; $MOVE_t$ is the Merril's implied volatility index for Treasury bonds; VXY_t is the JP Morgan's global FX implied volatility; USMPU denotes Husted-Rogers-Sun monetary policy uncertainty focused on the FOMC meetings; USEPU is Baker-Bloom-Davis economic policy uncertainty for the U.S. *SupF*(L+1|L) refers to Bai-Perron multiple-break test (Bai and Perron, 2003) which sequentially tests the null of L breaks against the alternative of L + 1 breaks. The identification of number of breaks and break dates are based on *SupF*(L+1|L) tests. We report the t-value adjusted with heteroscedasticity-and-autocorrelation-consistent standard error in parentheses (Newey and West, 1987). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Effective Spread		**Bid-ask spread**		**Price impact**		**Price reversal**	
ΔLC_{t-1}	0.0895***	(3.7960)	-0.0339	(-0.8370)	0.0153	(0.3950)	-0.1473***	(-3.0116)
ΔTED_{t-1}	1.4988*	(1.8404)	0.8007	(0.8369)	-0.4117	(-0.3931)	-1.4956	(-1.4346)
ΔVIX_{t-1}	0.0172	(0.7303)	0.0242	(0.3902)	0.0211	(1.6335)	0.0226	(1.6161)
$\Delta MOVE_{t-1}$	0.0247**	(2.4814)	0.0096	(0.6998)	0.0025	(0.4889)	0.0157**	(1.9986)
ΔVXY_{t-1}	0.3324**	(2.4956)	0.1362	(0.4924)	0.1756*	(1.6797)	0.0633	(0.3143)
$USEPU_t$	0.0009	(1.5673)	0.0002	(0.2283)	-0.0000	(-0.1266)	0.0007**	(2.2609)
$USMPU_t$	0.0050**	(2.2827)	0.0040	(1.5336)	0.0018	(0.8303)	-0.0002	(-0.2903)
Constant	-0.1894**	(-2.2920)	-0.1376	(-1.3659)	-0.0025	(-0.0649)	-0.0761**	(-2.0844)
Adjusted R^2	0.0261		0.0031		0.0138		0.0359	
SupF(1|0)	55.8852***		9.8050		17.0716		11.8558	
SupF(2|1)	72.4979***							
SupF(3|2)	15.4240							
Number of breaks	2		0		0		0	
Break dates	7/24/2009 10/8/2010							

Table 3
Estimation results of the discrete threshold regression model for connectedness in liquidity measured by effective spread

This table reports the estimation results of the following model: $\Delta LC_t = \sum_{j=1}^{J+1} Regime_{j,t} \times [\beta_{j0} + \beta_{j1}\Delta LC_{t-1} + \beta_{j2}\Delta TED_{t-1} + \beta_{j3}\Delta VIX_{t-1} + \beta_{j4}\Delta MOVE_{t-1} + \beta_{j5}\Delta VXY_{t-1} + \beta_{j6} USEPU_t + \beta_{j7} USMPU_t] + \varepsilon_t$, where LC_t is the total liquidity connectedness of nine FX markets, where liquidity is measured by the effective spread. TED_t is the TED spread; VIX_t denotes the CBOE Implied Volatility Index; $MOVE_t$ is the Merril's implied volatility index for Treasury bonds, VXY_t is the JP Morgan's global FX implied volatility, USMPU denotes Husted-Rogers-Sun monetary policy uncertainty focused on the FOMC meetings, and USEPU is Baker-Bloom-Davis economic policy uncertainty for the U.S. J is the number of breaks, and $Regime_{j,t}$ is the dummy variable for regime j which is dated according to the Bai-Perron test result reported in Table 2. The sample period is May 9, 2008 – December 31, 2015. The t-values adjusted with heteroscedasticity-and-autocorrelation-consistent standard errors are reported in parentheses (Newey and West, 1987). ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Regime	5/29/2008 - 7/23/2009		7/24/2011 - 10/7/2010		10/8/2014 - 12/31/2015	
ΔLC_{t-1}	0.0709	(1.7022)	0.201589	(4.0610)	0.1101	(3.2765)
ΔTED_{t-1}	0.5888	(0.7121)	47.09785	(5.8157)	-2.0872	(-0.4972)
ΔVIX_{t-1}	-0.0459	(-1.3163)	0.325410	(5.1519)	-0.0034	(-0.0965)
$\Delta MOVE_{t-1}$	0.0311	(2.2599)	0.069495	(2.2181)	-0.0039	(-0.2506)
ΔVXY_{t-1}	0.5319	(2.8606)	-0.356932	(-1.0546)	0.1611	(0.7407)
$USEPU_t$	0.0022	(1.8385)	0.000771	(0.4325)	0.0005	(0.7356)
$USMPU_t$	0.0469	(6.0057)	0.001330	(0.2203)	0.0018	(0.7681)
Constant	-0.5956	(-2.7813)	-0.059322	(-0.2452)	-0.1268	(-1.3323)
Number of Observations	249		266		1126	
Adjusted R^2	0.0900					
SIC	3.9269					

Table 4

Estimation Results of The threshold model of liquidity connectedness based on effective spreads

This table reports the estimation results of the logistic smooth threshold regression (LSTR) model for liquidity connectedness: $\Delta LC_t = \beta_0 + \beta_1 \Delta LC_{t-1} + \beta_2 \Delta TED_t + \beta_3 \Delta VIX_t + \beta_4 \Delta MOVE_t + \beta_5 \Delta VXY_t + \beta_6 \Delta USEPU_t + \beta_7 \Delta USMPU_t + [\theta_0 + \theta_1 \Delta LC_{t-1} + \theta_2 \Delta TED_t + \theta_3 \Delta VIX_t + \theta_4 \Delta MOVE_t + \theta_5 \Delta VXY_t + \theta_6 USEPU_t + \theta_7 USMPU_t] G(\gamma, c, s_t) + \varepsilon_t$, where $G(\gamma, c, s_t) = \left(1 + \exp\left\{-\frac{\gamma}{\hat{\sigma}_{s_t}}(s_t - c)\right\}\right)^{-1}$, $\gamma > 0$. $G(\gamma, c, s_t)$ is a bounded function in the interval [0, 1], where γ is the slope parameter which indicates how fast the transition of $G(\cdot)$ from 0 to 1 is; c is the vector of location parameters that determines where the transition occurs; s_t is the transition variable. $\hat{\sigma}_{s_t}$, the estimated standard deviation of s_t, here makes γ approximately scale-free and facilitates the convergence of the nonlinear least squares estimation. LC_t is the total liquidity connectedness of nine FX markets; TED_t is the TED spread. We consider proxies of uncertainty as the transition variable (s_t), including the CBOE Implied Volatility Index (VIX_t), the Merril implied volatility index for Treasury bonds ($MOVE_t$), the JP Morgan global FX implied volatility (VXY_t), the St. Louis Fed Financial Stress Index (FSI_t), U.S. economic policy uncertainty ($USEPU_t$), and U.S. monetary policy uncertainty focused on the FOMC meetings ($USMPU_t$); ε_t is the error term. We report the robust *t* adjusted with the heteroscedasticity-and-autocorrelation-consistent standard errors (Newey and West, 1987) in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Transition variable	USEPU		FSI		VIX		VXY		ΔMOVE	
	β_j	θ_j	β_j	θ_j	β_j	θ_j	β_j	θ_j	θ_j	β_j
ΔLC_{t-1}	0.0924***	-0.2446***	0.1140***	-0.1347***	0.0824***	0.0295	0.0373	0.0718**	0.1078***	-0.3338***
	(3.5534)	(-4.5810)	(7.6719)	(-2.9765)	(3.2669)	(0.3049)	(1.2666)	(2.009)	(3.5981)	(-10.1674)
ΔTED_{t-1}	0.1178	7.3867***	3.8739	-3.6615	-2.8599	4.4099	-14.7768	16.7557*	0.2805	2.3831
	(0.2193)	(2.9788)	(0.9108)	(-0.8700)	(-1.0309)	(1.5084)	(-1.6639)	(1.8812)	(0.3812)	(1.6365)
ΔVIX_{t-1}	0.0634**	-0.3092	0.0789**	-0.1229	0.0051	0.0002	-0.0440	0.0651	0.0253	-0.0355
	(3.6234)	(-1.5466)	(2.5113)	(-0.8863)	(0.1707)	(0.0022)	(-0.8475)	(0.7843)	(0.5113)	(-0.6004)
$\Delta MOVE_{t-1}$	0.0143	0.0111	0.0107	0.0158	0.0078	0.0285	-0.0185	0.0530*	0.0074	0.0893**
	(1.4678)	(0.2096)	(0.5878)	(0.8984)	(0.5706)	(1.2009)	(-0.6813)	(1.8270)	(0.7583)	(2.5032)
ΔVXY_{t-1}	0.1163	2.0551**	0.1805	0.3096	-0.1728	0.7701*	-0.0586	0.4342	0.2931**	0.1609
	(1.3548)	(2.5519)	(0.8660)	(1.4184)	(-0.7535)	(1.9206)	(-0.2354)	(1.4061)	(2.1590)	(0.8252)
$USEPU_t$	0.0003	-0.0050	0.0004	0.0032***	0.0005	0.0002	0.0016*	-0.0011	0.072***	-0.0009
	(0.5401)	(-1.1162)	(0.6263)	(5.8094)	(0.9912)	(0.1907)	(1.9094)	(-1.0598)	(1.7835)	(-0.7712)
$USMPU_t$	0.0012	0.0361**	-0.0003	0.0735***	0.0016	0.0224***	-0.0041	0.0143***	0.0014	0.0633**

	(0.7552)	(2.4794)	(-0.0732)	(6.4694)	(1.1523)	(2.2518)	(-1.1164)	(2.6781)	(1.2338)	(4.1831)
Constant	-0.1203	1.5763	-0.1040	-0.8305***	-0.1518**	0.0004	-0.2861*	0.1635	-0.1611*	-01069
	(-1.6399)	(1.2387)	(-0.7053)	(-6.2913)	(-2.2741)	(0.0018)	(-1.8657)	(0.8035)	(-1.7264)	(-0.4303)
γ	0.2004* (1.6753)		1.6796* (1.6780)		36.5381 (0.1360)		0.1721* (1.9468)		5.6866 (0.4547)	
c	276.1047*** (46.8485)		2.3187* (1.9577)		26.1093*** (622.9196)		7.5517*** (26.8560)		6.4635 (35.2003)	
Parameter Constancy test	3.1507***		2.8732***		4.2841***		2.9456***		2.4342***	
Adjusted R^2	0.0616		0.0562		0.0393		0.0317		0.0651	