Understanding FX Liquidity

Nina Karnaukh, Angelo Ranaldo, Paul Söderlind*

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Abstract

We provide a comprehensive study of liquidity of spot foreign exchange (FX) rates over more than two decades and a large cross-section of currencies. First, we show that FX liquidity can be accurately measured with daily data that are readily available. Second, we demonstrate that FX liquidity declines with funding constraints and volatility supporting the theoretical models relating funding and market liquidity. FX liquidity also deteriorates with volatility and illiquidity of stock and bond markets suggesting cross-market contagion effects. Finally, we show stronger comovements of FX liquidities in distressed markets and for wealthier countries with high-quality institutions. (*JEL* C15, F31, G12, G15)

*University of St. Gallen. *Address:* SBF, University of St. Gallen, Rosenbergstrasse 52, CH-9000 St. Gallen, Switzerland. *E-mail addresses:* Nina.Karnaukh@student.unisg.ch (N. Karnaukh), Angelo.Ranaldo@unisg.ch (A. Ranaldo), Paul.Soderlind@unisg.ch (P. Söderlind). We thank Yakov Amihud, Greg Bauer, Si Cheng, Allaudeen Hameed, Céline Kharma, Loriano Mancini, Michael Melvin, Lukas Menkhoff, Carol Osler, Roberto Renò, Maik Schmeling, Andreas Schrimpf, Avanidhar Subrahmanyam, Adrien Verdelhan, Jan Wrampelmeyer, and Rico von Wyss, as well as participants of the 2013 Arne Ryde Workshop in Lund, 2013 Workshop on "Measuring and Modeling Financial Risk with High Frequency Data" in Florence, 2013 Workshop on "Financial Determinants of Exchange Rates" in Rome, 2014 SGF Conference in Zürich,2014 SNB-UZH Workshop in Zürich, 2014 Annual Central Bank Workshop on "Microstructure of Financial Markets" in Rome, for comments and suggestions. We especially appreciated the detailed comments of the Editor and two anonymous referees, which greatly improved the paper.

Market liquidity is an important feature for all financial markets, yet relatively little is known about liquidity of the foreign exchange (FX) market. A clear understanding of why and how FX illiquidity materializes is still missing. For instance, we do not know what are the fundamental sources driving FX liquidity and co-movements (or so-called "commonality") in liquidity of individual currencies. This paper provides a comprehensive study of FX liquidity and common patterns in FX liquidity over more than two decades and thirty currency pairs. We first identify the most accurate measures for FX liquidity, and then uncover which factors explain the time-series and cross-sectional variation of FX liquidity.

An in-depth understanding of FX liquidity is important for at least three reasons. First, the FX market is the world's largest financial market with a daily average trading volume of more than five trillion U.S. dollars in 2013 (Bank of International Settlements 2013). Second, the FX market is crucial in guaranteeing efficiency and arbitrage conditions in many other markets, including bonds, stocks and derivatives (e.g. Pasquariello 2014). Third, the FX market has unique characteristics, so the characteristics of FX liquidity may differ from those of other asset markets. In particular, the FX market is characterized by limited transparency, heterogeneity of participants, and market fragmentation. In addition, whereas a typical financial transaction entails some maturity transformation (i.e., cash for securities), a spot FX trade converts cash (in one currency) into cash (in another one). Contrary to stocks, an FX rate does not pay any dividend and it is often closely connected to central bank operations. Moreover, a spot FX transaction generally demands little or no margin requirements, allowing FX traders to take highly leveraged positions.

This paper contributes to the international finance literature in three ways. The *first contribution* is to document and explain the significant temporal and cross-sectional variation in currency liquidity. So far, FX liquidity has been analyzed only over short periods (Mancini, Ranaldo, and Wrampelmeyer 2013) or using specific measures, such as the order flow[1] or the bid-ask spread based on indicative quotes.[2] However, none of the previous studies performs a comprehensive analysis of FX liquidity over an extended period of time (in our case, more than twenty years) and a large cross-section of currencies (in

[1]Following the seminal work of Evans and Lyons (2002) on FX order flow, several papers investigate the role of FX order flow, including those by Marsh and O'Rourke (2011), Breedon and Vitale (2010), Breedon and Ranaldo (2012), Berger, Chaboud, Chernenko, Howorka, and Wright (2008) and Banti, Phylaktis, and Sarno (2012).

[2]See Bessembinder (1994), Bollerslev and Melvin (1994), Lee (1994), and Hsieh and Kleidon (1996) and more recently Menkhoff, Sarno, Schmeling, and Schrimpf (2012).

our case, thirty exchange rates). More importantly, no prior research on FX liquidity delves into its fundamental sources and cross-market interactions. We fill this gap in the literature by relating supply-side sources of FX liquidity to funding conditions as postulated by a strand of theoretical models that connect market illiquidity to funding strains and intensified risk (e.g., Brunnermeier and Pedersen 2009; Vayanos and Gromb 2002). We also explore demand-side sources which are broadly related to the traditional portfolio approach to exchange rates (Kouri 1976) and demand shocks inducing portfolio reshuffling (e.g. Hau, Massa, and Peress 2010). Additionally, we propose a research design that explores cross-market linkages between FX liquidity and volatility as well as illiquidity pertaining to other security markets. The rationale for cross-market spillovers is that the FX market is at the crossroads of any international portfolio allocation (e.g. Pavlova and Rigobon 2007) and it is widely used for hedging or speculative strategies, such as carry trade.

The *second contribution* is an analysis of commonality in FX liquidity. By referring to its supply-side and demand-side sources, we proceed in two steps. First, we analyze how commonality in FX liquidity evolves across time. More specifically, we test if commonality in FX liquidity strengthens in distressed markets, such as high FX or stock volatility, and tight funding conditions. Then, we analyze the cross-sectional variation of commonality in FX liquidity. On the demand side, we analyze if stronger FX commonality is positively related to, for instance, common incentives to trade, such as the level of investor protection and transparency in a country (Morck, Yeung, and Wu 2000). On the supply side, we examine if commonality is stronger for currencies characterized by tighter funding and monetary sources.

To comprehensively study FX liquidity, we first need to accurately measure it over a long period and a large and representative panel of currencies. The *third contribution* is therefore methodological: using precise high-frequency data (from Electronic Broking Services) to calculate benchmark measures, we show that it is possible to gauge FX market liquidity using price data that are readily available on a daily frequency (from Thomson Reuters). The possibility to use a low-frequency measure circumvents a number of severe limits related to high-frequency data.[3] Several studies compare low-frequency and high-frequency liquidity measures for stocks and commodities.[4] But, to our knowledge,

[3]These limits are, for instance, a very limited access only to recent data, a restricted and delayed use, and the need of time consuming data handling and filtering techniques.

[4]For stocks, see e.g. (Hasbrouck 2009; Goyenko, Holden, and Trzcinka 2009; Holden 2009; Fong,

there is no such study of FX liquidity.

Some clear results emerge from our study. First, we show that the most accurate and stable low-frequency measures of FX liquidity come from the *Roll's model* (Roll 1984), the *Corwin-Schultz* model (Corwin and Schultz 2012), and the *Gibbs sampler estimate of Roll's model* (Hasbrouck 2009). Combining these measures in the same vein as Korajczyk and Sadka (2008), we can provide monthly estimates of liquidity for individual currencies and of systematic (or market-wide) FX liquidity from January 1991 to May 2012.

Second, we find that FX liquidity systematically worsens with funding strains—pointing to the importance of supply-side factors. We also add to the contagion literature (e.g. Fleming, Kirby, and Ostdiek 1998 and Goyenko and Ukhov 2009) by showing that FX illiquidity is tied to volatility and illiquidity of both stocks and bonds. Another novel result is the identification of currencies that are more exposed to liquidity drops: those of richer countries and those that have larger exposure to systematic risk factors, such as "carry trade risk" (Lustig, Roussanov, and Verdelhan 2011) and "volatility risk" (Menkhoff, Sarno, Schmeling, and Schrimpf 2012) tends to dry up more when FX volatility intensifies.

Third, we provide new findings about commonality in FX liquidity. First, we show that comovements of FX liquidity have been strong throughout the last two decades and systematically stronger than that found in the stock market literature. Second, we find that commonality increases in distressed markets, similarly to what Hameed, Kang, and Viswanathan (2010) and Karolyi, Lee, and Dijk (2012) find for the stock market. Commonality is stronger when volatility in stock and FX markets is particularly high and short-term funding is severely tight, consistent with the supply-side theories. Commonality is also strong when FX carry trade strategies incur large losses evoking the adverse effects of FX liquidity squeezes when traders "rush to exit " from carry trade positions (e.g. Brunnermeier, Nagel, and Pedersen 2009 and Ranaldo and Söderlind 2010). Finally, we find that the liquidity of a currency co-moves more strongly with the market-wide FX liquidity when the degree of institution's quality and investor protection in that country is higher (Morck, Yeung, and Wu 2000) suggesting that common incentive to trade can strengthen the demand for liquidity. Another result arising from the cross-sectional analysis is that richer countries are characterized by stronger commonality consistently with the literature on capital market integration (e.g., Bekaert and Harvey 1997) and global

Holden, and Trzcinka 2011) and for commodities, see (Marshall, Nguyen, and Visaltanachoti 2012).

liquidity risk (Lee 2011).

1. Measurement of FX Liquidity

1.1 High-frequency benchmark

This section presents our high-frequency measure of liquidity, which we later use as a benchmark to compare different low-frequency measures.

Hereafter, we will use the abbreviations *LF* and *HF* to refer to low-frequency and high-frequency. We obtain HF data from ICAP that runs the leading interdealer electronic FX platform called Electronic Broking Services (EBS). The EBS data set spans January 2007 to May 2012. All EBS quotes are transactable. Best bid and ask quotes as well as transaction prices and volume indicators are available and the direction of trades is known. This is crucial for an accurate estimation of liquidity, because it avoids using any Lee and Ready (1991) type rule to infer trade directions. For each exchange rate, we process the irregularly spaced raw data to construct second-by-second time series, each containing 86,400 observations per day. For every second, we compute the midpoint of best bid and ask quotes or log-return based on the transaction price of deals. We exclude observations between Friday 10 p.m. and Sunday 10 p.m. GMT, since only minimal trading activity is observed during these non-standard hours. We also drop U.S. holidays and other days with unusually light trading activity from the data set.[5]

We use HF data on nine currency pairs, namely the AUD/USD, EUR/CHF, EUR/GBP, EUR/JPY, EUR/USD, GBP/USD, USD/CAD, USD/CHF, and USD/JPY. These exchange rates accounted for 71% of daily average trading volume in April 2013 (see Bank of International Settlements 2013) representing the vast majority of spot FX trading activity.

Following the previous literature, our benchmark measure of (the inverse of) liquidity is the effective cost (*EC*, as we will call it hereafter), which captures the cost of executing a trade. The *EC* measure is computed by comparing transaction prices with the quotes prevailing at the time of execution as

$$EC = \begin{cases} (P^T - P)/P, & \text{for buyer-initiated trades,} \\ (P - P^T)/P, & \text{for seller-initiated trades,} \end{cases} \tag{1}$$

[5] We run algorithm proposed by Brownlees and Gallo (2006) to clean the EBS data. This filtering procedure removed very few and obvious outliers. For a detailed description, see the Internet Appendix.

where P^T denotes the transaction price, superscripts A and B indicate the ask and bid quotes, and $P = (P^A + P^B)/2$ is the midquote price. We estimate effective cost for each month and each exchange rate by averaging the HF data over the month.

[Figure 1 about here.]

The average effective cost across all nine currency pairs is shown in Figure 1 (dotted line). Actually, the figure shows the negative of the effective cost—so as to illustrate liquidity (rather than illiquidity). The figure shows that liquidity was quite stable from January to July 2007. Afterwards, FX liquidity declined with a substantial drop from September 2008 to November 2008. The decline reflects the collapse of Lehman Brothers followed by a sustained turmoil. Liquidity gradually recovered during 2009 but it deteriorated again in early 2010 and mid-2011, which correspond to the peaks of the European sovereign debt crisis. During the first half of 2012, liquidity visibly improved and returned close to the pre-crisis level.

1.2 Finding the best low-frequency measures

Following the literature on market liquidity, in this section we identify the *best low-frequency FX liquidity measures*—defined as those with the consistently highest correlations with the high-frequency effective cost.[6] The aim is to find the most accurate measures of FX liquidity over a long time span and a large number of currencies (where only daily data are available), thus circumventing the limitations imposed by high-frequency data.

The LF data from Datastream Thomson Reuters contains daily high, low, bid, ask, and midquote prices, as well as quote frequencies. Daily close bid, ask, and midquote prices are snapped at 22:00 GMT based on the indicative data from the latest contributor. To guarantee a consistent comparison, we use the same nine currency pairs, time of the day, and time period (trading days) for LF and HF liquidity measures.

For each exchange rate, we compute five LF liquidity measures by averaging daily data over each month. Since these measures have been widely used in the literature on stock and bond liquidity, we provide only a short summary and relegate detailed descriptions to the Internet Appendix.

[6]For a similar approach, see Goyenko, Holden, and Trzcinka (2009), Hasbrouck (2009), Corwin and Schultz (2012), and Marshall, Nguyen, and Visaltanachoti (2012).

The five LF liquidity measures are *(1)* the relative bid-ask spread, *(2)* the bid-ask spread implied by the Roll (1984) model, *(3)* the Bayesian *Gibbs* sampler estimate of the transaction cost implied by the Roll model (Hasbrouck 2009),[7] *(4)* the Corwin-Schultz (*CS*) measure,[8] and *(5)* the *Effective Tick* (*Efftick*) from Holden (2009) and Goyenko, Holden, and Trzcinka (2009).[9]

[Table 1 about here.]

Table 1 shows the descriptive statistics of the EC benchmark and each LF liquidity for each exchange rate. The last column reports the descriptive statistics for an average across all nine currency pairs. For all measures considered in this section, a high value means low liquidity. The table shows that the scale of the LF liquidity measures differs from the effective cost—and they also differ among each other. This is a well-expected finding for at least two reasons. First, different liquidity measures that gauge diverse concepts of transaction cost produce different magnitudes (see, for instance, Stoll 2000). Second, EBS HF data comes from the most liquid segment of spot FX market whereas Thomson Reuters LF data cover broader and less liquid segments including over-the-counter (OTC). It is then to be expected that liquidity estimates in *levels* are different. However, we deem that these liquidity measures all capture movements in FX liquidity, so we will henceforth evaluate the accuracy of LF measures by studying how *changes* in these proxies correlate with changes in effective cost.

[Table 2 about here.]

Table 2 compares the LF liquidity measures with the EC benchmark. Panel A of Table 2 reports the times-series correlations of *changes* in each LF liquidity measure for

[7] Joel Hasbrouck generously provides the programming code of the Gibbs estimation procedure on his Web site. We run this code for our estimations, using 1,000 sweeps and discard the first 200 draws. The estimation uses a half-normal distribution, and we set (for each currency and month) the standard deviation of the transaction cost prior equal to the square root of the difference between the monthly averages of log ask and log bid prices. The estimates are robust to this choice, unless we choose a very small value.

[8] Corwin and Schultz (2012) show that the transaction cost can be estimated using high and low prices and assuming that the variance is proportional to the return horizon, whereas the bid-ask spread (negative autocovariance as in the Roll measure) is unaffected by the horizon.

[9] This method estimates the transaction cost from the clustering (relative frequency) of the last digits of the transaction prices. The basic idea is that price clustering signals more bargaining power of market makers and less-competitive quotes. We also analyzed the *LOT* and *Zeros* measure from Lesmond, Ogden, and Trzcinka (1999) and the *FHT* measure from Fong, Holden, and Trzcinka (2011). However, we discarded them because of the nearly complete absence of daily zero returns in our sample.

each exchange rate with the changes in their EC benchmarks. Boldfaced numbers are different from zero at the 5% significance level.[10] The average (across exchange rates) correlations are reported in panel B. The *CS* measure has the highest average correlation (0.53), followed by the *Roll* and *Gibbs* measures (0.43 and 0.40). The *BA* measure has a lower average correlation (0.22), while the *EffTick* shows poor performance with an average correlation close to zero. For the sake of comparison, Panel B also shows the average correlations between the HF effective cost and the LF liquidity measures in *levels*. Correlations are higher than for changes, but the ranking of the different measures remains the same.

[Table 3 about here.]

To construct a systematic (market-wide) measure of LF liquidity for each exchange rate, it is important to extract the common information across individual liquidity measures. To do this, we proceed as follows: we first standardize all liquidity measures (for each currency) by subtracting the time-series mean and dividing by the standard deviation. After the standardization process, we calculate an average across all nine currency pairs.[11] Table 3 shows how changes in LF liquidity proxies correlate with the changes in the average HF effective cost across all currencies. For the full sample (January 2007 to May 2012), shown on top of panel A, the findings are similar to those for individual currencies: the *CS*, *Roll*, and *Gibbs* measures outperform the *BA* and *EffTick*.

To study the consistency of performance across time, we divide the sample period into three sub-samples: *(a)* the pre-Lehman period (from January to June 2008); *(b)* the turmoil after the Lehman bankruptcy (from July 2008 to December 2009); *(c)* the European sovereign debt crisis (from January 2010 to May 2012). Correlation coefficients between the HF effective cost and LF liquidity measures are shown in the rest of panel A of Table 3. Despite the limited number of observations (only 18 months in each of the first two sub-periods) which cautions against drawing strong conclusions, some patterns are clear. First, the *CS*, *Roll* and *Gibbs* measures (once again) perform well in all three subperiods

[10] We apply a GMM based test using a Newey-West covariance estimator with four lags.

[11] Two main methods have been used in the literature to capture systematic liquidity across securities: simple averaging (e.g., Chordia, Roll, and Subrahmanyam 2000) or principal component analysis (PCA) (e.g. Hasbrouck and Seppi 2001). We experimented both and found very similar results. We also tried other methods to compute average liquidities. Applying GDP-/trade-/volume- weighting to construct a weighted average across all currencies gives similar results. See the Internet Appendix for details.

(the correlation with EC is always above 0.49). Second, the *BA* and *EffTick* show very inconsistent pattern across the subsamples. In particular, the *BA* has a -0.03 correlation with the EC during the European sovereign debt crisis period.

To summarize, Table 2 and panel A of Table 3 suggest that three LF liquidity measures (*CS*, *Roll*, and *Gibbs*) provide accurate and stable proxies of effective cost (our high-frequency benchmark). The other two LF measures (*BA* and *EffTick*) have low and/or unstable correlations with the EC benchmark.

The question that arises is why *BA* and *EffTick* demonstrated ability to measure liquidity of stocks and bonds (see, e.g., Goyenko, Holden, and Trzcinka 2009), but not that of currencies? The poor performance of the *EffTick* measure can be explained by the fact that there is little clustering of FX rates to some "round" numbers. The weak and unstable performance of the bid-ask spread deserves a closer inspection. The daily Thomson Reuters bid-ask spreads (snapped at 22.00 GMT) have very different time series properties compared to the daily effective cost retrieved by the HF EBS data. Consistent with the previous literature (e.g. Chordia, Roll, and Subrahmanyam 2001), the effective cost is a persistent series with high daily autocorrelation (on average 0.91 for the 2007–2012 sample). In contrast, the Thomson Reuters bid-ask spread has limited persistence (on average 0.17 for the 2007–2012 sample) and seems to follow a very noisy pattern.[12] Averaging daily Thomson Reuters bid-ask spread observations over a month mitigates some problems, but it still has distinctly less persistence than its benchmark, especially after 2009. Results for the bid-ask spread from an alternative data provider, WM/Reuters, based on the fixings at 16:00 GMT, are even worse. See the Internet Appendix for details.

In sum, the analysis shows that the *CS*, *Roll*, and *Gibbs* measures provide the best proxies for measuring FX liquidity, in the sense that these LF measures guarantee high and stable correlation with the HF liquidity benchmark. To illustrate this, we construct a systematic (market-wide) LF liquidity by taking a simple average across nine currency pairs, where the liquidity of each pair is the average across the three best LF liquidity measures (*CS*, *Roll*, and *Gibbs*).[13] Specification [1] of panel B of Table 3 shows that

[12]Additional tests indicate severe instability of the Reuters bid-ask spread. While the daily HF effective cost has consistently high persistence (above 0.7 for every possible 12 month period in our sample), the persistence of the BA measure is erratic—dropping dramatically from a subperiod to other (from 0.1 in 2007 to 0.6 in mid-2008 to mid-2009 and then back to below 0.1 for all 12 month periods from 2010 and onwards). In the 1991–2012 sample, the daily autocorrelation of the BA is around 0.3 in 1991–2, close to 0 in 1998–2000, as high as 0.6 in 2003, and then again approximately zero in 2006.

[13]Since all measures are standardized and have similar correlations, the simple average is very similar to

the correlation of the changes in systematic FX liquidity with the changes in the average effective cost across all currencies over the whole period is 0.73.

In the remaining part of panel B of Table 3, we consider alternative approaches to construct the systematic FX liquidity. Specification [2] uses fitted values from regressing the average (across currencies) HF effective cost on the average (across currencies) *Roll*, *Gibbs*, and *CS*.[14] Clearly, such approach to construct systematic LF liquidity gives the best possible fit and improves the correlation with the HF benchmark to 0.76. Specification [3] uses a simple average across only the best two LF measures, *CS* and *Roll*, and indicates a slight improvement as compared with the specification [1]. However, the average across the three best measures provides more consistent patterns across time (i.e. the correlations with the HF benchmark across different subperiods of Specification [1] are slightly more stable than that of Specification [3]). For the further analysis, we focus on the approach of specification [1] (taking simple average across the three best LF liquidity measures to get the systematic FX liquidity) because of its straightforwardness and simplicity.

To visualize these results, Figure 1 displays the systematic LF liquidity (the solid line) and the (negative of) HF effective cost (the dotted line), both in levels. Clearly, the systematic LF liquidity and its HF benchmark share very similar patterns over the 65 months of our sample period: the correlation is 0.92 for levels.

1.3 Finding the best LF measures: Robustness analysis

Here, we briefly describe some additional robustness checks. First, we used four HF liquidity measures as alternative benchmarks (the quoted bid-ask spread, order flow price impact (Kyle 1985), and return reversal (Campbell, Grossman, and Wang 1993), and price dispersion (Chordia, Roll, and Subrahmanyam 2001)) and we obtained very similar results. Second, we experimented with other ways to compute LF methods (number of sweeps and prior in *Gibbs*, different grids in *EffTick*, etc.), and found little or no improvements. However, we found that the optimal method to deal with negative two-day spreads in the (*CS*) measure is to exclude all such observations. Rather than imposing zeros or absolute values, this method substantially improves the measurement performance. Third, instead of using months, we considered shorter timeframes. As expected, the correlations of LF liquidity measures with the HF benchmark worsen at higher frequencies. However,

the first principal component.

[14]The *CS* measure has the highest weight at 92%.

our LF systematic measure (as in Specification [1] of Table 3) for the two-week frequency seems to be still effective in measuring FX liquidity. Fourth, we also considered liquidity measures based on the quote frequency. The main idea is approximate trading volume with the number of quote revisions. The Amihud (2002) and Amivest (Cooper, Groth, and Avera 1985 and Amihud, Mendelson, and Lauterbach 1997) measures perform relatively well, while the Pàstor and Stambaugh (2003) measure appears almost uncorrelated with effective cost. It should be noted, however, that data on quote revisions are available only from January 2007, so these quote-based measures are not helpful in calculating LF measures for a long sample period (which is our main goal). Further details about all our robustness checks are reported in the Internet Appendix.

1.4 Using the best LF liquidity measures in a larger sample

High-frequency data are available only for a small number of exchange rates and for very recent time periods. This severely restricts the possibility of calculating HF liquidity measures outside the major currencies and back in time. However, our previous analysis shows that it is possible to construct accurate liquidity proxies from low-frequency (daily) data. We now demonstrate the usefulness of this approach by considering a larger panel of exchange rates and by extending the sample period.

The source of the LF data (Datastream Thomson Reuters) naturally defines the limits of the cross-section and the length of the time series. For a sample starting in January 1991, 40 exchange rates are available (if we require data on high-low, needed to calculate the *CS* measure). However, we exclude nine pegged currencies since a pegged exchange rate implies very different liquidity dynamics and we also exclude Taiwan because of the limited availability some of the key macroeconomic and financial variables needed in the second part of the paper. For the rest of the paper we focus on the remaining thirty currency pairs.[15]

We compute monthly times series 1991–2012 of the *CS*, *Roll*, and *Gibbs* measures for each exchange rate. To create a measure of systematic FX liquidity, we first standardize each series and then take the average across the 90 data series (thirty currency pairs, three measures). We also investigate the effect of using just the nine main currencies, instead

[15]The EUR/USD is replaced with the DEM/USD prior to 1999. The other FX rates against the EUR are replaced with the quotes against the ECU prior to 1999 due to data availability in Thomson Reuters. The names of the used currencies are listed on the X-axis of Figure 4, more description is in the Internet Appendix.

of the full cross-section of thirty currencies. The results are very similar. For instance, the systematic liquidity measures from the nine and the thirty currencies have a correlation of 0.97. See the Internet Appendix for further details.

[Figure 2 about here.]

Figure 2 shows the time series of the systematic liquidity measure. The turmoil around the Lehman bankruptcy is associated with the largest drop in systematic liquidity. Substantial declines in systematic FX liquidity coincide with other major events, for instance, the European Exchange Rate Mechanism (ERM) crisis (1992), the Mexican peso crisis (1994), the Russian debt restructuring (1998), and 9/11 terrorist attacks (2001). On the other hand, the reaction of FX liquidity to more stock-specific events, such as the dotcom bubble burst (spring 2000) or the Enron scandal (2001), is less discernable. The prima facie evidence suggests that systematic FX liquidity correlates with global risk indicators. For instance, its correlation with the VIX and TED spread is 0.63 and 0.48, respectively. An in-depth inspection of the main drivers of FX liquidity will be conducted in the next sessions.

2. Hypotheses

In this section, we develop the hypotheses for our empirical tests. In Section 2.1, we discuss the possible drivers of FX liquidity. We review the relevant literature and set up testable hypotheses by taking into account three aspects. First, we consider how FX liquidity relates to the broad market conditions. Second, we attempt to isolate some representative variables to capture the demand-side and supply-side factors explaining FX liquidity. Third, we hypothesize which group of currencies is more exposed to liquidity drops. In Section 2.2, we discuss what can explain the temporal and cross-sectional variation in commonality of FX liquidity.

A note of caution must be stressed. While the literature below provides guidance on identifying some possible determinants of FX liquidity and its commonality, it is difficult to obtain empirical factors that isolate supply-side and demand-side sources of liquidity and causal inference depends on the validity of the identifying assumptions.

2.1 Drivers of FX liquidity

It is well known that bid-ask spreads are positively affected by return volatility due to higher adverse selection and inventory risk (see, e.g., Stoll 1978). Since a drop in asset prices increases financial leverage (Black 1976), liquidity can deteriorate after a price drop. Other reasons of larger bid-ask spreads are market power (e.g. Duffie, Garleanu, and Pedersen 2005) and search cost (e.g. Lagos and Rocheteau 2009), which may be particularly relevant for FX rates that are largely traded over-the-counter (OTC). For these reasons we empirically test whether FX liquidity decreases with FX volatility and depreciations of the quoted currency.

The contagion literature conjectures comovement patterns across markets and countries. For instance, Pavlova and Rigobon (2007) propose an open two-country economy with home-biased agents in which the FX market acts as a channel that propagates shocks across countries' stock and bond markets. We extend this mechanism to FX liquidity and test whether FX liquidity declines with *(a)* lower return on equity and bond markets or *(b)* higher volatility in stock and bond markets. Moreover, we test whether FX liquidity tends to decrease *jointly* with that in stock and bond markets suggesting cross-market spillovers in terms of market illiquidity. We will refer to *market conditions* when we analyze how FX liquidity reacts to returns, volatility, and liquidity in FX, stock and bond markets.

In addition to market conditions, we attempt to detect demand-side and supply-side sources of liquidity. We broadly think of the demand for FX liquidity coming from international investors rebalancing their portfolios. In traditional portfolio theory, assets in different currencies are considered to be imperfect substitutes so the demand for foreign exchange balances slopes downward (Kouri 1976). More recently, Hau and Rey (2006) offer micro-foundations of the portfolio balance theory which positively relates currency appreciations to net capital flows. Assuming that the demand of FX liquidity increases with international portfolio reallocations, we approximate demand-side dynamics with aggregate measures of trade and capital flows that should be positively related to FX liquidity. At the same time, the U.S. dollar acts as the reserve currency for the international monetary system (Maggiori 2012) and currencies of larger economies provide better hedge against shocks that affect a larger fraction of the world economy (Hassan 2013). Thus, we also test whether FX liquidity declines with *(a)* the deterioration of investors' sentiment, *(b)* the demand for U.S. safe assets and the dumping of foreign risky assets, and *(c)* depreciations of local currencies with respect to global reserve currencies.

As *supply-side sources of liquidity*, we broadly relate them to the propensity (reluctance) of financial intermediaries to provide liquidity in times of loose (tight) funding and monetary conditions. With respect to funding conditions, Brunnermeier and Pedersen (2009) demonstrate that market liquidity can evaporate with lower prices and higher volatility of collateral securities since financial intermediaries face losses and higher margins. A decrease in market liquidity may lead to further losses and/or margin increases, creating an "illiquidity spiral" or "feedback loop." Other important models that investigate the consequences of funding constraints of financial intermediaries for market liquidity include Garleanu and Pedersen (2007), Gromb and Vayanos (2002), Kyle and Xiong (2001), and more recently Kondor and Vayanos (2014). Hereafter, we call this new strand of the literature "liquidity spirals theories." Although the exact mechanisms in these models differ, they all predict that funding constraints and market illiquidity can generate spirals through fire-sales and increased risk. In our empirical analysis, we test whether FX liquidity decreases with indicators of funding strains including higher money market rates, TED spread (i.e. the difference between the interest rates on interbank loans and on short-term U.S. government debt) and the default spread on corporate bonds.

In addition, Gabaix and Maggiori (2014) propose a theory connecting exchange rates to banking liquidity whereby international financiers require a compensation to absorb the demand for financial assets due to international imbalances. Risk shocks impact on their balance sheets, thus affecting the FX market. Guided by this literature, we explore whether FX liquidity is positively related to *(a)* the returns on other international asset markets, and *(b)* to the equity return on the portfolio of the ten biggest FX dealers which, in the spirit of Hameed, Kang, and Viswanathan (2010), should capture their propensity to provide liquidity.

While the liquidity spirals theories focus on funding constraints of financial intermediaries, FX liquidity is also be related to general concepts of funding and monetary sources. In classical monetary models (e.g. Lucas 1982), monetary expansion leads to a depreciation of the domestic currency implying an increase of opportunity cost for FX liquidity. Thus, we empirical test if there is a negative link between FX liquidity and monetary aggregates as well as inflation.

The final question we address is *whether some currencies are more exposed to liquidity dry-ups*. First, a strand in the international finance literature finds that developed markets are more integrated and have higher exposure to common factors (Korajczyk

1996; Bekaert and Harvey 1995), while less-integrated and emerging countries tend to have more idiosyncratic patterns (Bekaert and Harvey 1997) that can disconnect currency-specific liquidity from FX market-wide liquidity. Second, the recent FX asset pricing literature documents that at least two risk factors are important for explaining excess currency returns or carry trade returns. Lustig, Roussanov, and Verdelhan (2011) find that the portfolio return of high-minus-low interest rate currencies is a pricing factor for carry trade returns, and Menkhoff, Sarno, Schmeling, and Schrimpf (2012) demonstrate the importance of volatility. Verdelhan (2013) shows that the USD return and carry trade risk factors also explain excess returns on individual exchange rates. Inspired by these papers, we test whether developed currencies and currencies bearing larger risk factors are more (negatively) exposed to liquidity drops.

2.2 Explanations for commonality in FX liquidity

Demand-side and supply-side factors also can help explain temporal and cross-sectional variation in commonality of currency liquidities.

The *demand-side explanation* links commonality in liquidity to the correlated trading behavior of international investors. Liu and Wang (2013) develop an equilibrium model in which correlated demands produce commonality in liquidity across different markets even if we assets' payoffs are independent. In the comovement literature (e.g. Barberis, Shleifer, and Wurgler 2005), it has been argued that co-movements can be explained by preferred habitats due to reasons, such as (currency) home bias (Mueller, Stathopoulos, and Vedolin 2012), international trading restrictions, and lack of information. Changes in risk aversion, sentiment, or liquidity needs would then alter their collective exposure to the currencies related to investors' habitat thereby inducing common patterns in security prices and liquidity. These aspects can be particularly relevant for the FX market since adverse shocks and deteriorations of investors' sentiment can trigger a rush to exit from FX speculative positions such as carry trade (Pedersen 2009). For these reasons, we test whether commonality in FX liquidity increases with measures of *(a)* capital and trade flows as well as net portfolio positions, *(b)* deteriorated investor sentiment, and *(c)* more general worsening of market conditions, such as higher volatility and losses on carry trade portfolios.

In addition to Brunnermeier and Pedersen (2009), the theoretical models supporting *supply-side explanations* include Kyle and Xiong (2001) and Cespa and Foucault (2014).

Kyle and Xiong (2001) show that if financial intermediaries supplying liquidity in two markets endure trading losses in one market, then they may reduce liquidity provision in both markets—thus increase the correlation among risky assets. Cespa and Foucault (2014) show that the learning process of informed market makers providing liquidity in assets with correlated payoffs may cause liquidity spillovers thus producing commonality in liquidity. In the spirit of these models, we test whether commonality increases with tighter funding and monetary conditions.

The theoretical background discussed above will guide us in specifying the regression models of the time-series and cross-sectional analysis of commonality in FX liquidity in the next sessions. A final consideration concerns the level of investor protection and the transparency of the information environment in a country (Morck, Yeung, and Wu 2000) which can cause correlated demands across securities thereby increasing commonality in FX liquidity. This hypothesis can only be tested in the cross-sectional analysis.

3. Explaining FX Liquidity

In this section, we try to determine the main drivers of FX liquidity over the last twenty years. The liquidity measure is (for each currency pair) the average across the three best LF measures (*Roll*, *Gibbs*, and *CS*) and has a monthly frequency. We proceed in four steps: first, we regress the monthly changes of FX liquidity (of the thirty currency pairs) on factors representing demand and supply forces as well as general market conditions. Second, we analyze whether some currency pairs are more exposed to liquidity dry-ups. Third, we study structural VAR models to trace out the dynamic response to demand and supply shocks. In the final part of this section, we conduct a simple event analysis. The description of the variables representing the demand- and supply-side sources of FX liquidity is available in Table 5 and those pertaining to the general market conditions in Table 5.

3.1 Explaining FX liquidity: panel regressions

We consider eight different variables representing possible *demand-side* sources of FX liquidity and eight variables for the *supply side*. Both sets are divided into three broad categories: current account, portfolio rebalancing, and investor sentiment proxies (demand side); funding conditions, monetary conditions, and banking liquidity (supply side).

As a first step, we perform simple panel estimations in which monthly *changes* of the liquidity of 30 currency pairs are regressed on *one factor at a time*. This exercise will permit us to determine the two most significant demand- and supply-side variables to be included in an encompassing (multiple) regression analysis. The sample period is January 1991 to May 2012 (257 months).[16] The dependent variable is (the change of) liquidity, which can be interpreted as a standardized version of the negative of effective cost. On the demand side, the results (not tabulated) indicate that changes in U.S. gross capital flows (per capita) and changes in VIX are the most significant demand side factors—suggesting that FX liquidity decreases with larger flows in U.S. securities and an increase in investor fear (as commonly proxied with the VIX index). These two variables will therefore be used to represent the demand side in the encompassing regression models below.

Evidence on the role of capital flows to explain aggregate movements in the FX market has been documented in several studies including Pavlova and Rigobon (2007), Hau and Rey (2004) and Froot and Ramadorai (2005) but none of the previous papers finds a (systematic) link between capital flows and FX liquidity. Our finding about a negative relation between FX liquidity and VIX extends Mancini, Ranaldo, and Wrampelmeyer (2013) who find a similar patter during the recent financial crisis. It also squares with Bao, Pan, and Wang (2011) who examine the properties of illiquidity in the corporate bond market and find that changes in bond liquidity are negatively related to changes in VIX.

We perform a similar analysis for the *supply-side* factors. Prior empirical research shows that FX liquidity and measures of funding conditions help explain currency (excess) returns (Christiansen, Ranaldo, and Söderlind 2011; Banti, Phylaktis, and Sarno 2012; Mancini, Ranaldo, and Wrampelmeyer 2013) and deviations from the Covered Interest rate Parity (Mancini-Griffoli and Ranaldo 2010). However, relatively little is known about the determinants of FX liquidity. We find (results are not tabulated) that the key supply-side determinants of FX liquidity come from the funding condition category rather than monetary and banking conditions. Among the eight variables considered, changes of the TED spread and the returns of the ten biggest FX dealers are the most significant, so they will be used to represent the supply side in the encompassing regression models. These results suggest that FX liquidity tends to decline when money market premiums

[16]Since the regressors are the same for all currencies, the estimates from the panel regression equal the cross-sectional average coefficients from currency specific regressions.

increases (TED spread increases) and FX dealers face tighter funding constraints.

Measures of *market conditions* include returns, volatility, and liquidity on FX, equity, and bond markets. In the simple regressions, three main results emerge. First, volatilities appear to be the most significant variables suggesting cross-market spillover effects from stock, bond, and FX volatilities to FX illiquidity. Second, stock and bond market liquidity are positively associated with FX liquidity, indicating cross-market commonality in liquidities. Chordia, Sarkar, and Subrahmanyam (2005) show that a nexus between stock and bond market liquidity. Our results reveal a systematic relation between FX liquidity and that of the bond and stock markets. Third, among the return variables we find that FX liquidity decreases when the U.S. dollar appreciates and MSCI global equity index declines. Overall, our results are in line with Hameed, Kang, and Viswanathan (2010) who provide evidence that negative market returns decrease stock liquidity.

[Table 4 about here.]

We now turn to multiple regressions. The results are summarized in Table 4. Each regression model [1]–[4] (different columns) uses one variable related to the supply- or demand-side explanations together with all *return* variables (as market conditions). All variables are standardized: a regression coefficient then shows how many standard deviations the dependent variable moves in response to a one standard deviation change in the regressor. The t-statistics (in brackets) are robust to heteroskedasticity, cross-sectional and serial correlations, using the Driscoll and Kraay (1998) covariance estimator.

Models [5]–[8] replicate model [1]–[4], but use *volatility* variables (as market conditions) instead of return variables. The same approach applies to models [9]–[12], but the market conditions now include stock, bond, and lagged FX *liquidity*.

There are three main results. First, both demand-side variables (changes of U.S. gross capital flows per capita and changes of VIX) have significantly negative coefficients in most models. For instance, in model [2] an increase of one standard deviation of VIX is associated with a 10.2% drop in FX liquidity, that is, a 10.2% increase in effective cost.[17] Second, (changes of) the TED spread (as supply-side variable) have a significantly

[17]Our LF liquidity measure (Liq) is a standardized version of EC, $Liq = (EC - \mu_{EC})/\sigma_{EC}$. We run regressions of standardized ΔLiq on standardized regressors Δx, $\Delta Liq/\sigma_{\Delta Liq} = \alpha + \beta \Delta x/\sigma_{\Delta x} + \varepsilon$. Combine these equations (disregarding the constant and the residual) to get $\Delta EC = \sigma_{EC}\sigma_{\Delta Liq}\beta\Delta x/\sigma_{\Delta x}$. For most variables (eg. for VIX), we measure the effect of a shock of size $\Delta x = \sigma_x$, but for returns we use $\Delta x = \sigma_{\Delta x}$. We quantify the economic effect as a percentage the EC by using the empirically estimated

negative coefficient in most models. For instance, in model [3] an increase of one standard deviation in the TED spread is associated with an increase in the effective cost of 3.5%. Third, the analysis of market condition variables indicate that FX liquidity decreases with negative stock returns, higher FX, and bond volatility as well as lower bond liquidity. Among the market condition variables, volatility and liquidity are more important than return factors in explaining FX liquidity, delivering three times higher R-squared values.

[Table 5 about here.]

We are now ready to construct an encompassing model that includes all significant variables that appeared relevant in Table 4. This is what we do in model [1] of Table 5. Three main results from the encompassing regression are discernable: *(a)* most of the market condition variables remain significant except for stock return and liquidity; *(b)* both demand-side factors (U.S. capital flow and VIX index) lose their significance, while *(c)* the supply-side variable (TED spread) remains negative and statistically significant.

A natural question arise whether *local* factors might contribute to explain FX liquidity—on top of the global variables. To address this issue, we add (one by one) local demand-side and supply-side factors[18] to the set of global factors. We find that most of them provide no additional ability to explain the movements of FX liquidity. A notable exception is the FX return (local currencies against SDR or base currency) that has a negative (significant) sign, implying that liquidity decreases when local currency depreciates (against SDR or base currency) — see model [2] of Table 5. However, the improvement in the fit is limited (R^2 increases from 0.195 in model [1] to 0.205 in model [2]).

In sum, the results in Table 4 and models [1] and [2] of Table 5 suggest the following three points: first, FX liquidity strongly comoves with global risk measures and liquidity on stock and bond markets—consistent with the contagion literature indicating the FX market is the crossroads of international risk spillovers (Pavlova and Rigobon 2007) and suggesting that FX liquidity is also impaired by flight-to-quality and flight-to-liquidity dynamics (Fleming, Kirby, and Ostdiek 1998 and Goyenko and Ukhov 2009). Second,

mean and standard deviation of the average (across currencies) effective cost over 2007–2012. We do the same for the Roll measure, but use the mean and standard deviation over 1991–2012.

[18]We analyze the following local factors: domestic interest rates, volatility of interest rates, money aggregates, inflation rates, bank returns, bilateral trade variables, net equity flows, gross capital flows, FX returns (denominated as local currencies against Special Drawing Rights (SDR) or base currency), stock returns, stock return volatility, stock turnover, commonality in stock liquidity, commonality in stock turnover, stock liquidity.

the TED spread remains (negatively) significant after controlling for all market conditions from FX and other markets—providing support to the supply-side explanation. Third, the demand-side variables (U.S. capital flow and sentiment) are useful for explaining FX liquidity movements, but they do not remain significant jointly with other market condition variables.

3.2 Currencies exposure to liquidity drops

The question we address in this subsection is whether some currencies are more exposed to liquidity drops. To answer this question, models [3]–[5] of Table 5 extend the analysis of movements in FX liquidity by interacting the global factors with dummy variables that capture different characteristics of the currencies

$$\Delta L_{ij,t} = \alpha + \beta' f_t (1 - D_{ij,t}) + \gamma' f_t \cdot D_{ij,t} + \varepsilon ij, t, \tag{2}$$

where $D_{ij,t}$ is a dummy variable for currency pair i, j in period t. The factors are the same as in model [1] of the same table.

In model [3] of Table 5, the dummy variable is equal to one for richer countries (above the median GDP per capita) in that month and zero otherwise. This means that the column labeled "High" ("Low") reports the estimates for richer (poorer) countries. The main result is that FX liquidity of richer countries is more adversely affected by an increase in FX volatility than that of poorer countries (a significant difference is indicated by the sign *). This finding is in line with the evidence in the international finance literature that developed markets are more integrated and are more affected by the fluctuations of global factors (e.g. Korajczyk 1996; Bekaert and Harvey 1995) and global liquidity risk (Lee 2011).

Inspired by the recent FX asset pricing literature, models [4]–[5] use dummies indicating "riskier" currencies. In model [4] we study the importance of being an investment currency in a typical carry trade, by using a dummy variable that is equal to one if a currency pair has a forward premium higher than the cross-sectional average in that month. Similarly, in model [5] we capture the volatility of the currency by a dummy that is equal to one if a currency pair has a higher realized volatility than the cross-sectional average in that month (model [5]). The evidence suggests that the liquidity of risky currencies is more (negatively) exposed to stock and FX volatility.

3.3 Explaining FX liquidity: vector autoregressions

[Table 6 about here.]

We now attempt to capture the dynamics affecting FX liquidity movements by using a structural Vector Autoregressive (VAR) model. We model the joint dynamics of FX liquidity with demand- and supply-side factors as well as capital market conditions in structural VAR models with the following order: VIX and TED first (implying that they cannot react to contemporaneous shocks to the other variables), market conditions second (i.e. they can react to contemporaneous shocks to VIX and TED) and FX liquidity last (it can react to contemporaneous shocks to all variables). The VAR is estimated for each 30 currency pairs, and we report the average impulse response functions. The order of VIX and TED or number of lags (we use 2) in the VAR model is not important for our results.

Panel A of Table 6 reports results from a five-equation model for VIX, TED, two market condition variables (FX and stock volatility) and liquidity. We report the impulse responses of FX liquidity to a one standard deviation shock in the VIX and TED at time $t = 0$. We find that shocks to VIX and TED at time $t = 0$ both have negative and significant effects on FX liquidity (and of similar magnitude to the earlier regression results), while the shock to the TED continues affecting FX liquidity in time $t = 1$ (the next month). The effects in further periods are typically small and insignificant (not tabulated). These results are essentially unchanged when we include two more market conditions (stock and bond liquidity) and estimate a seven-equation VAR, see panel B of Table 6.

In sum, the VAR analysis shows that our earlier results are robust to controlling for more dynamics. The effects of supply-side variables (represented by the TED spread) are persistent as postulated by the liquidity spirals theories.

3.4 Event study

The evidence presented above suggests that global factors are key drivers of FX liquidity. However, some episodes can affect currencies asymmetrically. A clear advantage of having a long time series of FX liquidity for a large panel of currencies is the opportunity to perform event studies in order to (1) determine which currency suffered a liquidity decline, and (2) disentangle the effects of demand- and supply-side liquidity shocks as well as that of broader market conditions.

To illustrate these points, we select four events, which are *(a)* the GBP-crisis (Black Wednesday) in September 1992; *(b)* the Asian financial crisis in July 1997; *(c)* announcement of the MSCI global equity index redefinition in early December 2000; and *(d)* the unexpected joint decisions of several central banks to lower the pricing on the U.S. dollar liquidity swap arrangements by 50 basis points at the end of November 2011. For each event, we divide currencies into two groups: those directly affected by the event and those not (others).

[Figure 3 about here.]

Figure 3 shows the change in the estimated effective cost around the event. To estimate the effective cost (basis points) from the LF liquidity measures, we use the link between the LF measure and the effective cost observed during the period 2007–2012.

We consider the first two events as representative examples of deteriorating market conditions. During the *GBP-crisis*, the estimated effective cost of the currencies involving GBP in the pair (directly affected) almost doubled (from 0.53 to 0.93 basis points) from August to October 1992 (see top left chart of Figure 3). This increase is twice as large as that for currency pairs that do not involve the GBP. The *Asian crisis* in July 1997 started in Thailand and then spread to the other Asian countries. From June to September 1997, the estimated effective cost to trade the Asian currencies increased by 0.32 bp, which is once again twice as much as the increase for the non-Asian currencies (see top right chart of the Figure 3).

Now we examine two events that might be considered more genuine shocks of the demand and supply of FX liquidity. As discussed in Hau, Massa, and Peress (2010), the announcement of the *MSCI global equity index redefinition* 1st December 2000 can be seen as an exogenous *demand* for FX liquidity.[19] The new index rules prompted a broad reshuffling of international portfolios—creating demand pressure and higher transaction cost for those currencies with the largest absolute weight change in the MSCI index. The left bottom chart of Figure 3 shows that the estimated effective cost of the affected currencies increased by 0.07 bp over November–December 2000, while that of the other currencies remained almost unchanged.

With a joint announcement at the end of November 2011, six central banks unexpectedly relaxed the funding conditions of the *USD swap line* accessible for financial

[19]We thank Harald Hau for providing us with the MSCI index data.

intermediaries in their jurisdictions. The right bottom chart of Figure 3 shows that the estimated effective cost for the currencies affected by this *supply* shock decreased by 0.15 bp from November to December 2011. In contrast, the estimated effective cost of the other FX rates remained virtually unchanged.

To sum up, this simple event-study shows how FX liquidity reacted to two crisis episodes and two representative events with demand and supply shocks.

4. Explaining commonality in FX liquidity

In this section, we analyze common movements of FX liquidity and relate this commonality to possible demand- and supply-side drivers. We proceed in three steps: First, we measure commonality in FX liquidity. Second, we study the commonality in distressed markets and across time. Third, we test the ability of demand- and supply-side factors to explain the cross-sectional variation in FX commonality.

4.1 Measuring commonality in FX liquidity

Following Chordia, Roll, and Subrahmanyam (2000), we regress the changes of currency-pair liquidity measures on changes of FX systematic liquidity

$$\Delta L_{ij,t} = \alpha_{ij} + \beta_{ij}\Delta L_{M,t} + \varepsilon_{ij,t}, \tag{3}$$

where $\Delta L_{ij,t}$ is the monthly change of the liquidity of the currency pair i and j, and $\Delta L_{M,t}$ is the concurrent change of the systematic LF liquidity (the average across 29 exchange rates, excluding the left hand side variable). We run the regressions over 257 months, from January 1991 to May 2012. All estimated slope coefficients are positive and statistically significant at any conventional level.[20]

[Figure 4 about here.]

As in Karolyi, Lee, and Dijk (2012), we use the R^2 as an indicator of commonality in liquidity. Figure 4 shows the R^2_{ij} for thirty currencies organized into three groups: (1) developed and much traded currency pairs (based on market share of FX market turnover

[20]Including one lead and one lag of the systematic LF liquidity as additional regressors does not affect the results materially. See the Internet Appendix for details.

by currency pair taken from the Bank of International Settlements (2013) ordered from the most to the least traded); (2) developed, but less-traded currency pairs; and (3) emerging currencies.

The figure delivers three main messages. First, commonality in FX liquidity is strong. The average R^2_{ij} across our sample of thirty currencies is 34%. Only two exchange rates have an R^2_{ij} lower than 15% (INR/USD, MXN/USD), suggesting that liquidity comoves for the vast majority of the currencies. This implies that there are periods when the entire FX market is systematically liquid or illiquid. Second, commonality in the FX market is stronger than that found on the stock market. For instance, Korajczyk and Sadka (2008) find adjusted R^2_{ij} values ranging from 4% to 26%. Third, FX commonality is stronger for developed currencies (R^2_{ij} values of around 38% compared with around 19% for emerging currencies) confirming the finding in Mancini, Ranaldo, and Wrampelmeyer (2013) about nine developed currencies and that in Banti, Phylaktis, and Sarno (2012) based on customer data from State Street Corporation (SSC). This is also in line with earlier findings that developed markets are more integrated and have higher exposure to common factors (Korajczyk 1996; Bekaert and Harvey 1995). This finding holds even if we compare the emerging currencies with those developed currencies that are relatively less traded (according to the BIS turnover data; see the middle group in the figure).

4.2 Time series determinants of FX commonality

In the spirit of Hameed, Kang, and Viswanathan (2010), we test whether commonality in FX liquidity increases in distressed markets, associated with an increase in the VIX index (representing a demand-side factor) and in the TED spread (representing a supply-side factor) as well as worsened market conditions (high FX and stock market volatility, and losses of carry trade portfolios). Specifically, we extend the commonality regression (3) by adding the FX systematic liquidity interacted with a proxy for market stress (D_t)

$$\Delta L_{ij,t} = \alpha_{ij} + \beta_{ij} \Delta L_{M,t} + \gamma_{ij} \Delta L_{M,t} \cdot D_t + \varepsilon_{ij,t}. \quad (4)$$

[Table 7 about here.]

Table 7 reports average (across currency pairs) regression coefficients. The t-statistics (reported in brackets) are robust to heteroskedasticity as well as serial and cross-sectional correlations. In panels A and B the market stress variable (D_t) is either a continuous version or logistic transformation[21] of the risk factor, while in panel C it is a dummy variable equal to one if the risk factor is more than one standard deviation above its mean in period t. Applying a stricter cutoff of 1.5 standard deviations gives very similar results (not tabulated).

The overall evidence suggests a significant increase in commonality in periods of market stress. The (average) γ_{ij} coefficient is significantly positive in most specifications, which means that liquidity of exchange rate ij is more strongly linked to the systematic FX liquidity in periods of market stress. For instance, the results of the dummy variable regression using the TED spread as stress indicator (panel C) indicate that the average R^2 increases from 0.33 to 0.43 when TED spread is large. The results for the other risk factors are similar. In short, market stress (as captured by demand- and supply-side variables, as well as general market conditions) is associated with higher commonality.

We corroborate this evidence by estimating panel models of a time-varying (logit transformation of) commonality $R^2_{ij,t}$ on the same risk factors as before

$$\ln[R^2_{ij,t}/(1 - R^2_{ij,t})] = \alpha + \beta' f_t + \varepsilon_{ij,t}. \tag{5}$$

To do this, we first compute a monthly series of commonality of each currency pair ij, $R^2_{ij,t}$, by running recursive commonality regressions on expanding data windows, but where old data is down weighted with exponentially declining weights ($\lambda = 0.7$). This is similar to the RiskMetrics approach. The logit transformation avoids issues with the restricted range of the R^2 measures (see Karolyi, Lee, and Dijk 2012).

[Table 8 about here.]

Table 8 shows the results of these panel regressions. Model [1] includes VIX together with the market condition variables (FX and stock market volatility, and losses of carry trade portfolios). Model [2] uses the TED spread instead of VIX. The evidence suggests that VIX is not significant, but both the TED spread and FX volatility have significantly positive coefficients. For instance, an increase of one standard deviation of the TED spread is associated with a drop of commonality $R^2_{ij,t}$ by 3.7 percentage points. Model [3] includes only TED spread and FX volatility, and both of them remain significant. As

[21] The logistic transformation of the risk factor x_t is $1/[1+\exp(-\gamma x_t)]$, where γ determines the steepness of the function. We set γ equal to 1. Setting γ to the alternative values from 1 to 5 does not affect our results materially.

for the time-series analysis of FX liquidity performed above, we analyze whether *local* factors help explain time-series evolution of commonality in FX liquidity. We apply the same procedure, that is, we add (one by one) local variables to the set of global factors. As reported in Model [4] of Table 8, we find that only the gross capital flow (divided by GDP) is significant—suggesting that commonality in FX liquidity increases with larger capital flows.

In sum, our analysis of FX commonality extends the previous literature that focuses only on specific events such as the redefinition of the MSCI Global Equity Index (Hau, Massa, and Peress 2010) or central bank announcements (Fischer and Ranaldo 2011) inducing common demand for FX liquidity across currencies. The results in Table 8 indicate that commonality in FX liquidity increases across time with larger capital flows providing further support to demand-side hypotheses. However, it systematically increases with tighter funding conditions and higher FX volatility supporting the supply-side explanation as well.

4.3 Cross-sectional determinants of FX commonality

As a final step, we investigate the ability of demand-side and supply-side variables to explain cross-sectional differences in commonality in FX liquidity. To do this, we run simple cross-sectional regressions of (a logit transformation of) commonality on a potential supply-side or demand-side variables described in Table 5

$$\ln[R_{ij}^2/(1 - R_{ij}^2)] = \alpha + \beta' z_{ij} + \varepsilon_{ij}, \tag{6}$$

where R_{ij}^2 is from the commonality regression (3) and z_{ij} are characteristics of the currency pair.

Our strategy is similar to that applied in section 3. First, we run single regressions of commonality in FX liquidity on all potential demand-side variables, supply-side variables, as well as control variables. Then, for each of these three categories we choose the best variable according to the highest t-statistics. Since the cross-section only contains 30 data points, we limit the multiple regression model to include only one variable from each category. That is, we jointly use no more than three regressors to perform multiple cross-sectional regression models.

[Table 9 about here.]

Table 9 presents the main results. Specification [1] includes the good government index (representing the demand-side variable) and log GDP per capita (a control variable), both of which are significant and capture 69% of cross-sectional variations in commonality. Specification [2] uses the local money market interest rate (representing the supply-side variable) and log GDP per capita, while model [3] includes all the three variables together. The money market interest rate is not significant in any of models, while the good government index and log GDP per capita remain significant. These two variables have correlation of 82%, suggesting that both of them capture similar (but not identical) characteristics, which is the level of country integration and development. Table 9 also shows the economic magnitude of the effects of demand- or supply-side factors—as measured by the effect of an increase of one standard deviation in the country-specific variable. In particular, column [1] shows that a one-standard-deviation increase in the good government index is associated with an increase in commonality R^2_{ij} of 7 percentage points.

In sum, the results in this section suggest that *(1)* commonality in FX liquidity is stronger for wealthier and developed countries rather than for emerging currencies, *(2)* commonality in FX liquidity strengthens in distressed markets and the time-variation in commonality is strongly linked to the TED spread and FX market volatility consistent with theoretical models where stricter funding conditions lead to stronger commonality in illiquidity, *(3)* commonality in liquidity is stronger in countries with better quality of institutions and openness supporting the demand-side hypothesis that these institutional features can induce common patterns in security prices and liquidity.

5. Concluding Remarks

In this paper we provide a comprehensive and in-depth study of FX liquidity. We first show how low-frequency (daily) data can be used to measure FX liquidity over more than two decades and a large cross-section of currencies. We demonstrate that three low-frequency liquidity proxies mimic best the effective cost calculated from a unique data set of high-frequency data. These low-frequency measures are the bid-ask spread implied by the Roll (1984) model, a Bayesian version of the Roll model (Hasbrouck 2009), and the high-low measure by Corwin and Schultz (2012).

Second, we show that FX liquidity decreases with tighter funding conditions as predicted by the theoretical models relating the supply of market liquidity to the funding conditions of financial intermediaries. Additionally, our findings show that there are considerable cross-market spillovers, in the sense that *(1)* FX liquidity declines with higher volatility in stock, bonds, and FX markets, and *(2)* it decreases at the same time with stock and bond market liquidity. These findings suggest a new dimension to the contagion literature, i.e. flight-to-quality or flight-to-liquidity dynamics involve impairment of FX liquidity as well. We also show that some currencies are systematically more exposed to liquidity drops, namely, *(a)* currencies of developed countries, *(b)* currencies representing the investment leg of a classical carry trade strategy, and *(c)* and more volatile FX rates.

Finally, we document that commonality in FX liquidity (comovement of liquidity of one currency with market-wide FX liquidity) has been systematically strong over the last two decades, and stronger for developed currencies. Our results clearly indicate that commonality in FX liquidity increases in distressed markets, especially when funding conditions are tight and volatility is high, providing further support to the supply-side explanations. Furthermore, commonality in FX liquidity tends to increase when currency carry trade strategies incur substantial losses, i.e. exactly when FX speculators "rush to exit" their positions. The cross-sectional analysis of commonality in FX liquidity indicates that wealthier countries with high quality of institutions are more subject to FX commonality, supporting the idea that common incentive to trade, such as higher degrees of investor protection and transparency can strengthen the demand for liquidity.

Our findings are relevant for investors, policy makers, and researchers. First, the liquidity measures analyzed in this study should help estimate transaction costs in FX markets. Second, this study highlights another channel of risk spillovers, that is, from risk intensification in stock, bond, and money markets to illiquidity in another (the FX market, in this case). Third, the empirical evidence of significant temporal and cross-sectional variation in currency liquidities documented in this paper challenges the static approach pervasive in the new liquidity requirements, such as Basel III. Fourth and finally, researchers try to shed light on intricate market mechanisms, including the spiral dynamics between market liquidity and funding liquidity. All this calls for reliable methods and accessible data to gauge FX liquidity and an in-depth understanding of liquidity issues on currency markets.

Appendix

See Tables A.1–A.3.

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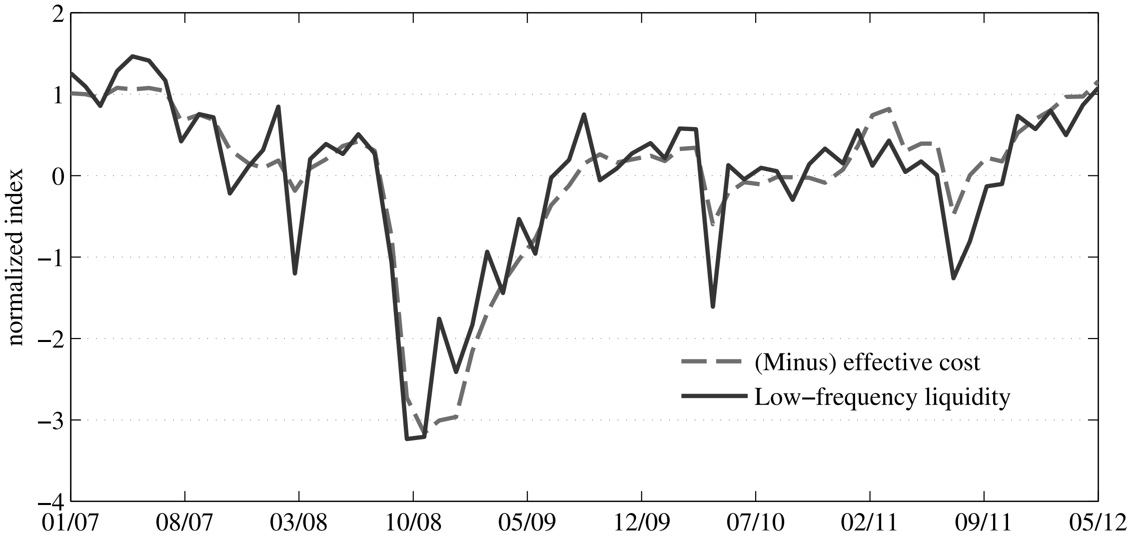

Figure 1: **Effective cost and systematic LF liquidity.** The figure shows the average high-frequency effective cost (dotted line) and the low frequency systematic liquidity (solid line). The EC is the average across nine currency pairs. The LF systematic liquidity is the average across nine currency pairs, where the liquidity of each pair is the average across the three best LF liquidity measures (*CS*, *Roll*, and *Gibbs*). Both measures are standardized. The sign of each measure is adjusted so that it represents liquidity rather than illiquidity. The sample is January 2007 – May 2012, i.e. 65 months.

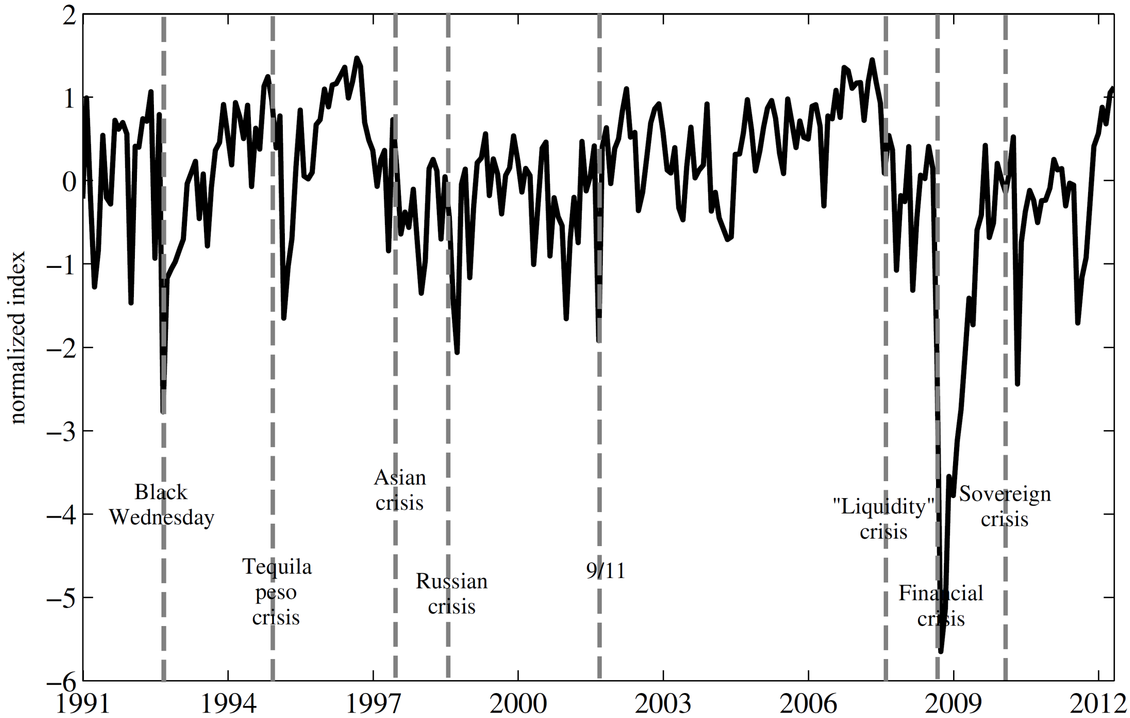

Figure 2: **Systematic LF liquidity over 1991–2012.** The figure depicts the monthly systematic LF liquidity. It is calculated as the average across thirty currency pairs, where the liquidity of each pair is the average across the three best LF liquidity measures (*CS*, *Roll*, and *Gibbs*). The measure is standardized and the sign is adjusted so that it represents liquidity rather than illiquidity. The dotted lines denote dates of some major events. The sample is January 1991 – May 2012, i.e. 257 months.

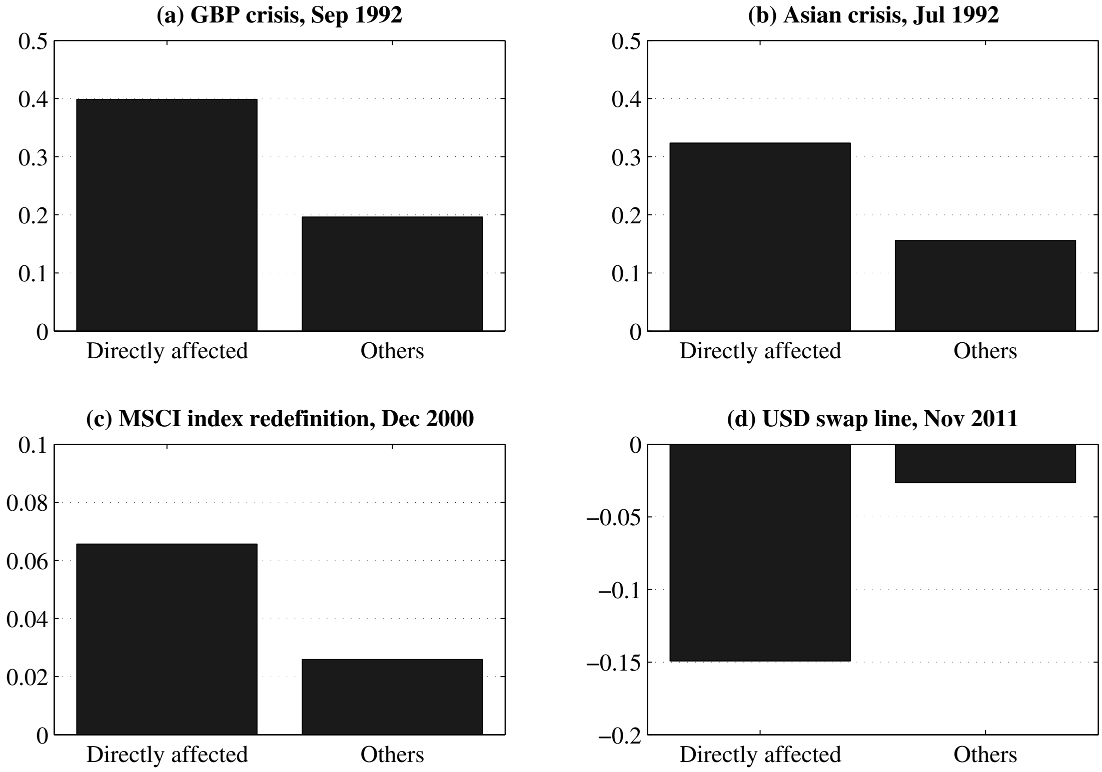

Figure 3: **Change in effective cost around four selected events.** The figure shows the change in effective cost around the four events: *(a)* the GBP-crisis in September 1992, *(b)* the Asian crisis in July 1997, *(c)* the announcement of the MSCI global equity index redefinition on the 1st December 2000, and *(d)* the USD swap line announcement by central banks in late November 2011. The change in the effective cost is shown for two groups of currencies: those directly affected by the event and the rest (others). The directly affected currencies for the four events are: *(a)* the ones which contain GBP either as quoted or as base currency (GBP/USD, GBP/EUR, AUD/GBP, CAD/GBP, JPY/GBP, NZD/GBP, NOK/GBP, SGD/GBP, ZAR/GBP, SEK/GBP, CHF/GBP), *(b)* the ones which contain Asian currency (SGD/USD, JPY/EUR, SGD/EUR, JPY/GBP, SGD/GBP), *(c)* the ones which experienced the largest absolute change in index weight due to the MSCI global equity index redefinition (CHF/USD, CHF/EUR, CAD/USD, AUD/GBP, AUD/USD, SGD/USD, SGD/GBP, JPY/EUR, NZD/EUR, GBP/USD, EUR/USD, NOK/EUR, MXN/USD, SGD/EUR, INR/USD), *(d)* the ones involved in the USD swap line establishment (CAD/USD, JPY/USD, CHF/USD, GBP/USD, EUR/USD).

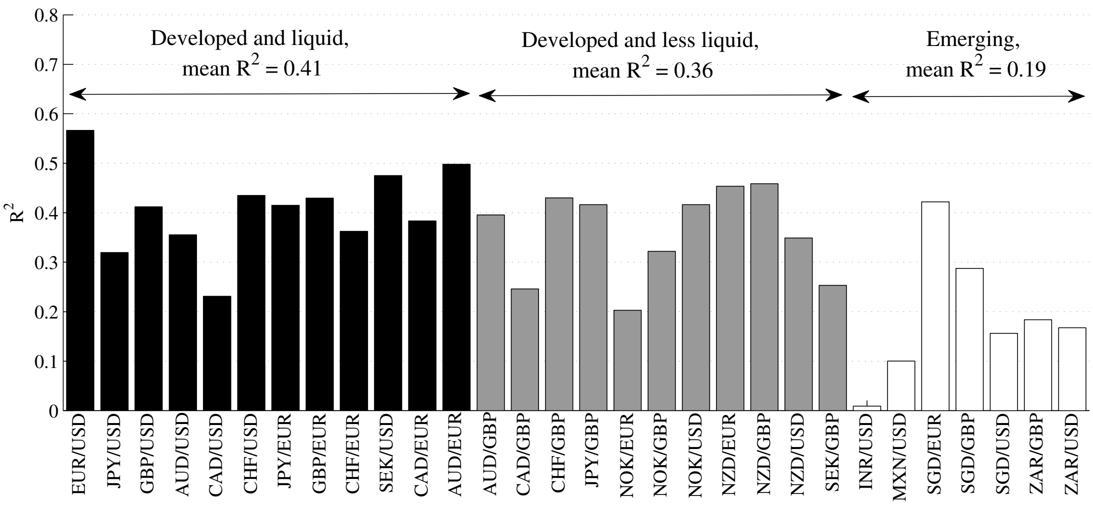

Figure 4: **Commonality in liquidity for each currency pair.** The figure shows the R^2_{ij} from regressing the liquidity of a currency pair on the systematic liquidity $\Delta L_{ij,t} = \alpha_{ij} + \beta_{ij}\Delta L_{M,t} + \varepsilon_{ij,t}$, where $\Delta L_{ij,t}$ is the monthly change of the liquidity of the currency pair i and j, and $\Delta L_{M,t}$ is the concurrent change of the systematic LF liquidity (the average across 29 exchange rates, excluding the left hand side variable). The liquidity of each currency pair is the average across the three best LF liquidity measures (*CS*, *Roll*, and *Gibbs*). The exchange rates in the developed and liquid group are sorted according to their FX market turnover in April 2013 (Bank of International Settlements 2013), starting from the highest turnover (on the left). The exchange rates in all the other groups are sorted alphabetically. The sample is January 1991 – May 2012, i.e. 257 months.

	AUD/USD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	USD/CAD	USD/CHF	USD/JPY	Average liquidity
					Effective cost (HF), bp					
Mean	1.119	0.388	0.760	0.460	0.292	0.693	1.074	0.473	0.401	0.629
Median	0.953	0.373	0.693	0.446	0.281	0.576	1.008	0.461	0.406	0.578
Std. dev.	0.652	0.125	0.260	0.132	0.053	0.381	0.406	0.094	0.091	0.222
					Bid-ask spread (LF), bp					
Mean	2.300	3.687	2.402	3.069	1.192	1.212	2.081	2.453	1.841	2.249
Median	2.224	3.903	2.362	3.062	1.196	1.152	2.082	2.521	1.786	2.348
Std. dev.	0.433	0.882	0.416	0.480	0.226	0.221	0.195	0.724	0.336	0.324
					Roll measure (LF), bp					
Mean	0.831	0.386	0.474	0.753	0.548	0.520	0.565	0.593	0.580	0.583
Median	0.660	0.324	0.428	0.621	0.496	0.477	0.496	0.575	0.537	0.518
Std. dev.	0.619	0.312	0.203	0.435	0.240	0.238	0.266	0.254	0.291	0.253
					Gibbs estimate (LF), bp					
Mean	0.378	0.167	0.193	0.330	0.258	0.239	0.266	0.274	0.252	0.262
Median	0.279	0.128	0.180	0.244	0.210	0.197	0.237	0.236	0.228	0.224
Std. dev.	0.293	0.137	0.088	0.217	0.149	0.121	0.129	0.163	0.151	0.126
					Corwin-Schultz high-low estimate (LF), bp					
Mean	0.193	0.115	0.133	0.190	0.144	0.137	0.155	0.165	0.153	0.247
Median	0.282	0.141	0.201	0.293	0.232	0.203	0.226	0.245	0.216	0.234
Std. dev.	0.097	0.062	0.057	0.088	0.056	0.058	0.056	0.060	0.068	0.090
					Effective tick (LF), bp					
Mean	0.813	0.451	0.733	0.522	0.478	0.413	0.672	0.640	0.278	0.556
Median	0.679	0.386	0.631	0.444	0.401	0.345	0.582	0.531	0.198	0.539
Std. dev.	0.396	0.199	0.294	0.244	0.186	0.266	0.302	0.311	0.239	0.073

Table 1: **Monthly effective cost and LF liquidity measures.** The table shows summary statistics for the high-frequency (HF) effective cost and five low-frequency (LF) measures of liquidity. Effective cost is the benchmark measure for HF liquidity. Bid-ask (*BA*) is the average over daily relative bid-ask spread. The *Roll* measure is from Roll (1984). The *Gibbs* measure is computed as in Hasbrouck (2009). The Corwin-Schultz (*CS*) measure is from Corwin and Schultz (2012). All the measures are in basis points (bp). The last column shows the statistics for an average across currencies (for non-standardized measures). The sample covers 65 months, January 2007 – May 2012.

	BA	Roll	Gibbs	CS	EffTick
Panel A. Correlations of changes in liquidity measures of individual currencies					
AUD/USD	**0.353**	**0.775**	**0.649**	**0.593**	**0.024**
EUR/CHF	**0.180**	**0.439**	**0.548**	**0.699**	0.021
EUR/GBP	**0.226**	**0.365**	**0.257**	**0.484**	**-0.080**
EUR/JPY	**0.143**	**0.432**	**0.446**	**0.614**	**-0.024**
EUR/USD	**0.197**	**0.494**	**0.340**	**0.372**	**0.093**
GBP/USD	**0.253**	**0.444**	**0.213**	**0.630**	**0.025**
USD/CAD	**0.034**	**0.358**	**0.353**	**0.406**	0.029
USD/CHF	**0.231**	**0.137**	**0.374**	**0.528**	**-0.018**
USD/JPY	**0.349**	**0.462**	**0.399**	**0.411**	**-0.223**
Panel B. Average correlations					
Changes	0.219	0.434	0.398	0.526	-0.017
Levels	0.548	0.736	0.696	0.779	0.050

Table 2: **Correlations between monthly effective cost and five LF liquidity measures.** *Panel A* of the table shows (for each exchange rate) the correlations of changes in five low-frequency liquidity measures with changes in effective cost. The monthly low-frequency liquidity proxies are: *BA* is the relative bid-ask spread, *Roll* from Roll (1984), *Gibbs* from Hasbrouck (2009), *CS* from Corwin and Schultz (2012), and *EffTick* from Holden (2009). Effective cost is estimated by averaging the HF data over the month. The bold correlations in *Panel A* are statistically significant at the 5% level (GMM based test using a Newey-West covariance estimator with 4 lags). *Panel B* shows the average correlations (across currencies) for both changes and levels. The sample is January 2007 – May 2012, i.e. 65 months.

	Panel A. Average Liquidity				*Panel B. Systematic Liquidity*		
BA	Roll	Gibbs	CS	EffTick	[1]	[2]	[3]
Whole sample (Jan 2007 - May 2012), 65 months							
0.376	**0.686**	**0.605**	**0.760**	**-0.035**	**0.734**	**0.762**	**0.748**
Pre-crisis (Jan 2007 - Jun 2008), 18 months							
0.597	**0.837**	**0.819**	**0.851**	**-0.159**	**0.865**	**0.858**	**0.870**
Financial crisis (Jul 2008 - Dec 2009), 18 months							
0.630	**0.739**	**0.495**	**0.842**	**0.032**	**0.758**	**0.842**	**0.803**
Sovereign debt crisis (Jan 2010 - May 2012), 29 months							
-0.034	**0.622**	**0.800**	**0.735**	**-0.133**	**0.778**	**0.790**	**0.715**

Table 3: **Correlations between effective cost and five LF liquidity measures.** Panel A of the table shows correlations between the changes in average (across currencies) LF liquidity measures and changes in average (across currencies) effective cost. The results are for the whole period (Jan 2007 – May 2012, 65 months) and over three subperiods: pre-crisis (Jan 2007 – Jun 2008, 18 months), financial crisis (Jul 2008 – Dec 2009, 18 months) and European sovereign debt crisis (Jan 2010 – May 2012, 29 months). Panel B shows times-series correlations between the changes of average (across currencies) *EC* and changes of five measures of systematic LF liquidity: [1] simple average across *Roll*, *Gibbs*, and *CS*, [2] fitted values from regressing the average (across currencies) EC on the average (across currencies) *Roll*, *Gibbs*, and *CS*, [3] simple average only across the *Roll* and *CS*. The monthly low-frequency liquidity proxies are: *BA* is the relative bid-ask spread, *Roll* from Roll (1984), *Gibbs* from Hasbrouck (2009), *CS* from Corwin and Schultz (2012), and *EffTick* from Holden (2009). The bold correlations are statistically significant at the 5% level (GMM based test using a Newey-West covariance estimator with 4 lags). The sample is January 2007 – May 2012, i.e. 65 months.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Demand-side factors												
Δ U.S. Gross capital flow / GDP	**-0.138**				-0.048				**-0.088**			
	[-4.230]				[-1.505]				[-2.316]			
Δ VIX		**-0.303**				-0.010				**-0.290**		
		[-5.295]				[-0.188]				[-4.886]		
Supply-side factors												
Δ TED spread			**-0.118**				-0.052				**-0.136**	
			[-3.083]				[-1.913]				[-3.560]	
Return on the 10 biggest FX dealers				-0.012				-0.063				0.076
				[-0.204]				[-1.655]				[1.773]
Market conditions												
USD appreciation	-0.052	-0.049	-0.048	-0.050								
	[-1.100]	[-1.226]	[-1.008]	[-1.056]								
MSCI return	**0.111**	-0.057	**0.110**	0.134								
	[1.902]	[-1.164]	[1.904]	[1.850]								
Δ AAA bond rates	-0.014	0.004	0.004	-0.002								
	[-0.298]	[0.108]	[0.072]	[-0.031]								
Δ FX volatility					**-0.225**	**-0.217**	**-0.220**	**-0.237**				
					[-4.862]	[-4.209]	[-4.893]	[-4.849]				
Δ MSCI volatility					**-0.215**	**-0.226**	**-0.220**	**-0.246**				
					[-4.046]	[-4.191]	[-4.398]	[-5.023]				
Δ Bond volatility					0.006	-0.003	0.011	-0.011				
					[0.189]	[-0.105]	[0.319]	[-0.349]				
Δ Stock liquidity									0.095	-0.022	0.098	**0.103**
									[1.751]	[-0.491]	[1.738]	[2.279]
Δ Bond liquidity									**0.252**	**0.148**	**0.234**	**0.223**
									[3.903]	[3.312]	[3.265]	[3.728]
Δ FX liqudity lagged									**-0.166**	**-0.199**	**-0.185**	**-0.190**
									[-3.491]	[-5.690]	[-4.651]	[-4.683]
Economic effect (using EC scale), bps	-0.045	-0.064	-0.022	-0.001	-0.016	-0.002	-0.010	-0.007	-0.029	-0.061	-0.025	0.009
Economic effect (using Roll scale), bps	-0.034	-0.048	-0.016	-0.001	-0.012	-0.002	-0.007	-0.005	-0.022	-0.047	-0.019	0.006
Economic effect, as a % of mean EC	-7.1%	-10.2%	-3.5%	-0.2%	-2.5%	-0.3%	-1.5%	-1.1%	-4.6%	-9.8%	-4.0%	1.4%
Economic effect, as a % of mean Roll	-6.8%	-9.7%	-3.3%	-0.2%	-2.4%	-0.3%	-1.4%	-1.1%	-4.3%	-9.3%	-3.8%	1.3%
R^2	0.044	0.083	0.039	0.025	0.155	0.153	0.155	0.156	0.107	0.147	0.118	0.105

Table 4: **Explaining liquidity.** This table shows results from panel regressions of liquidity on 30 FX rates on its drivers $\Delta L_{ij,t} = \alpha + \beta' f_t + \varepsilon_{ij,t}$, where $\Delta L_{ij,t}$ is, for the FX rate between currencies i and j, the change in liquidity from month $t-1$ to t, f_t denotes the demand-, and supply-side factors as well as market conditions. The liquidity of each currency pair is the average across the three best LF liquidity measures (*CS*, *Roll*, and *Gibbs*). The t-statistics are reported in brackets. They are based on the standard errors robust to conditional heteroscedasticity, cross-sectional and serial (up to one lag) correlation as in Driscoll and Kraay (1998). Bold numbers are statistically significant at the 5% level. The economic effect uses empirically estimated mean and standard deviation of the average (across currencies) *EC* and *Roll* liquidity measures and reflects the impact of each demand- or supply-side variable on the dependent variable. The sample for specifications [1]–[4] is Jan 1991 – May 2012, the sample for specifications [5]–[8] is April 1992 – May 2012, the sample for specifications [9]–[12] is January 1995 – December 2009. The USD appreciation is against 17 currencies, the FX volatility is JP Morgan's global implied volatility index, and the bond volatility is Merril's MOVE implied volatility index for Treasury bonds.

	[1]	[2]	[3] Low GDP per capita	[3] High GDP per capita	[4] Low Forward premium	[4] High Forward premium	[5] Low FX volatility	[5] High FX volatility
Demand-side								
Δ U.S. Gross capital flow / GDP	-0.012	-0.016	-0.003	-0.022	-0.019	-0.001	0.012	-0.035
	[-0.351]	[-0.450]	[-0.089]	[-0.565]	[-0.386]	[-0.026]	[0.335]	[-0.847]
Δ VIX	-0.110	-0.117	-0.095	-0.127	-0.147	-0.060	-0.055	-0.171
	[-1.496]	[-1.603]	[-1.352]	[-1.529]	[-1.766]	[-0.719]	[-0.978]	[-1.616]
Supply-side								
Δ TED spread	**-0.066**	**-0.064**	**-0.071**	-0.060	**-0.080**	-0.050	**-0.080**	-0.049
	[-2.519]	[-2.497]	[-2.569]	[-1.841]	[-2.896]	[-1.073]	[-3.963]	[-1.199]
Market conditions								
MSCI return	-0.033	-0.054	-0.043	-0.022	-0.040	-0.025	-0.004	-0.068
	[-0.763]	[-1.271]	[-0.936]	[-0.486]	[-0.684]	[-0.562]	[-0.096]	[-1.167]
Δ FX volatility	**-0.216**	**-0.205**	**-0.159**	**-0.278***	-0.138	**-0.322**	**-0.122**	**-0.347***
	[-3.990]	[-3.928]	[-2.708]	[-4.583]	[-1.584]	[-6.563]	[-1.958]	[-5.760]
Δ MSCI volatility	**-0.132**	**-0.128**	**-0.159**	-0.101	-0.060	**-0.236***	**-0.134**	**-0.127**
	[-2.473]	[-2.420]	[-2.848]	[-1.704]	[-0.872]	[-4.470]	[-2.488]	[-2.031]
Δ Stock liquidity	-0.071	-0.074	-0.052	**-0.091**	-0.067	-0.082	-0.044	-0.101
	[-1.722]	[-1.838]	[-1.210]	[-2.016]	[-1.355]	[-1.767]	[-1.131]	[-1.866]
Δ Bond liquidity	**0.104**	**0.098**	**0.108**	**0.098**	**0.146**	0.042	0.074	**0.138**
	[2.360]	[2.252]	[2.033]	[2.446]	[2.529]	[0.996]	[1.836]	[2.489]
Δ FX liqudity lagged	**-0.132**	**-0.133**	**-0.126**	**-0.139**	**-0.152**	**-0.099**	**-0.085**	**-0.176**
	[-3.530]	[-3.573]	[-3.085]	[-3.600]	[-3.123]	[-2.990]	[-2.027]	[-4.190]
FX return (local factor)		**-0.101**						
		[-3.334]						
R^2	0.195	0.205	0.198		0.212		0.237	

Table 5: **Explaining liquidity: encompassing models.** This table shows results from panel regressions of liquidity on 30 FX rates on its drivers. Specification [1] runs panel regressions with global factors $\Delta L_{ij,t} = \alpha + \beta' f_t + \varepsilon_{ij,t}$, where $\Delta L_{ij,t}$ is, for the FX rate between currencies i and j, the change in liquidity from month $t-1$ to t, f_t denotes the demand-, and supply-side factors as well as market conditions. Specification [2] uses also the local FX return. Specifications [3]–[5] extend the analysis of movements in liquidity by interacting the global factors with dummy variables that capture different characteristics of the currencies $\Delta L_{ij,t} = \alpha + \beta' f_t (1 - D_{ij,t}) + \gamma' f_t \cdot D_{ij,t} + \varepsilon_{ij,t}$, where D_{it} is a dummy variable for currency pair i, j in period t. The dummy in specification [3] is one for the currency pairs of countries with GDP per capita above the median in that month. The dummy in specification [4] is one if a currency pair has forward discount higher than the cross-sectional average in that month. The dummy in specification [5] is one if a currency pair has a higher realized volatility (mean of daily absolute returns) than the cross-sectional average in that month. The coefficients in the columns labeled "Low" ("High") show the effect of the factors on the FX liquidity for countries with low (high) GDP per capita in specification [3], low (high) forward premium in specification [4], and low (high) realized FX volatility in specification [5]. The sign * near the coefficient in the "High" column indicates that the difference between the "High" and "Low" is statistically significant. The t-statistics are reported in brackets. They are based on standard errors, robust to conditional heteroscedasticity, spatial, and serial (up to one lag) correlations as in Driscoll and Kraay (1998). Bold numbers are statistically significant at the 5% level. The sample is January 1995 – December 2009 (based on the availability of data for stock liquidity).

Panel A. Five-equation structural VAR *[VIX, TED, FX vol, stock vol, FX liq]*		
period	VIX shock	TED shock
0	**-0.258**	**-0.084**
	[-5.302]	[-2.580]
1	0.014	**-0.086**
	[0.351]	[-2.173]
2	0.059	0.013
	[1.795]	[0.409]
Panel B. Seven-equation structural VAR *[VIX, TED, FX vol, stock vol, stock liq, bond liq, FX liq]*		
period	VIX shock	TED shock
0	**-0.252**	**-0.106**
	[-5.749]	[-3.262]
1	-0.006	**-0.106**
	[-0.178]	[-2.959]
2	0.038	-0.016
	[1.196]	[-0.492]

Table 6: **Impulse responses of liquidity on the supply- and demand-side factors.** This table shows impulse responses of a panel of 30 FX rate liquidities with respect to shocks of 1 standard deviation in the demand-side (VIX) and supply-side (TED) factors. *Panel A* shows impulse responses based on a five-equation structural VAR with two lags, where the variables are ordered as VIX, TED, FX volatility (FX vol), stock volatility (stock vol), and FX liquidity (FX liq). *Panel B* shows the impulse responses based on a seven-equation structural VAR, where the variables are ordered as VIX, TED, FX volatility, stock volatility, stock liquidity (stock liq), bond liquidity (bond liq) and FX liquidity. All variables are in the changes. The shock to the VAR system is given at time $t = 0$. Bold numbers are statistically significant at the 5% level. The t-statistics are in brackets and are based on bootstrapped standard errors using 5000 simulations. The sample for Panel A is April 1992 – May 2012 (based on the availability of FX volatility), the sample for Panel B is January 1995 – December 2009 (based on the availability of stock liquidity).

	Demand-side	Supply-side	Market conditions		
	VIX	TED spread	FX volatility	MSCI volatility	Carry trade losses
	[1]	[2]	[3]	[4]	[5]
Panel A. Continuous factors					
Mean(β_{ij})	**0.562**	**0.562**	**0.560**	**0.560**	**0.557**
Mean(γ_{ij})	**0.009**	**0.007**	**0.010**	**0.008**	**0.012**
t-stat of mean(γ_{ij})	[2.544]	[6.150]	[4.853]	[6.826]	[4.585]
Panel B. Logistically transformed factors					
Mean(β_{ij})	**0.542**	**0.540**	**0.526**	**0.530**	**0.525**
Mean(γ_{ij})	0.044	**0.053**	**0.067**	**0.063**	**0.067**
t-stat of mean(γ_{ij})	[1.619]	[2.213]	[2.485]	[2.744]	[2.845]
Panel C. Dummy for the extreme values of factors					
Mean(β_{ij})	**0.560**	**0.562**	**0.561**	**0.559**	**0.554**
Mean(γ_{ij})	0.021	**0.031**	**0.025**	**0.026**	**0.031**
t-stat of mean(γ_{ij})	[1.953]	[2.494]	[2.051]	[2.239]	[2.716]
Mean R^2 calm periods	0.317	0.333	0.311	0.319	0.281
Mean R^2 distressed periods	0.404	0.426	0.442	0.388	0.440
Sum(D_t)	30	25	22	25	38
Number of obs.	255	255	241	255	255

Table 7: **Commonality in liquidity in distressed markets.** This table shows results from regressing liquidity on 30 FX rates $\Delta L_{ij,t}$ (one by one) on the systematic FX liquidity $\Delta L_{M,t}$ and $\Delta L_{M,t}$, interacted with a variable D_t capturing distressed market periods, $\Delta L_{ij,t} = \alpha_{ij} + \beta_{ij}\Delta L_{M,t} + \gamma_{ij}\Delta L_{M,t} \cdot D_t + \varepsilon_{ij,t}$, where $L_{ij,t}$ is, for the FX rate between currencies i and j, the change from month $t-1$ to t in liquidity, $\Delta L_{M,t}$ is the average across 29 out of 30 exchange rates (excluding the left hand side variable $L_{ij,t}$). In *Panel A*, D_t is equal to a continuous version of the risk factors. In *Panel B*, D_t is a logistic transformation of the risk factors. In *Panel C*, D_t is a dummy equal to one if the risk factor is more than one standard deviation above its mean in period t. The intercepts are not tabulated. The t-statistics for testing the hypothesis of the cross-sectional mean coefficients being equal to zero are calculated using a GMM based method that accounts for serial and cross-sectional correlations and reported in brackets. Bold numbers are statistically significant at the 5% level. The sample for specifications [1], [2], [4], and [5] is January 1991 – May 2012, the sample for specification [3] is April 1992 – May 2012. FX volatility is JP Morgan's global implied volatility index, losses on a carry trade portfolio are computed as minus mean FX return at time t on 3 currencies with the highest forward discount at time $t-1$ plus mean FX return at time t on 3 currencies with the lowest forward discount at time $t-1$.

	[1]	[2]	[3]	[4]
Demand-side				
VIX	-0.127			
	[-0.803]			
Supply-side				
TED spread		**0.165**	**0.171**	**0.247**
		[2.084]	[2.509]	[4.271]
Market conditions				
FX volatility	**0.254**	**0.203**	**0.212**	**0.139**
	[2.607]	[2.398]	[2.915]	[2.429]
MSCI volatility	0.157	-0.010		
	[1.326]	[-0.104]		
Losses on a CT portfolio	0.054	0.053		
	[0.885]	[0.901]		
Gross capital flow / GDP (local factor)				**0.116**
				[2.470]
Economic effect I	-0.027	0.037		
Economic effect II	-0.206	0.283		
R^2	0.019	0.022	0.022	0.030

Table 8: **Explaining time-series variation in commonality.** This table shows the results from panel regressions of logit transformation of commonality $R^2_{ij,t}$ on 30 FX rates on its drivers $\ln[R^2_{ij,t}/(1-R^2_{ij,t})] = \alpha + \beta' f_t + u_{ij,t}$. Specifications [1]–[3] use global drivers (demand- and supply-side factors and market conditions), while specification [4] also uses the local gross capital flow scaled by GDP. The commonality $R^2_{ij,t}$ is calculated by running recursive commonality regressions on expanding data windows, but where old data is down weighted with exponentially declining weights ($\lambda = 0.7$). Economic effect I is the impact on the commonality $R^2_{ij,t}$ of the change in the demand- or supply-side factor of interest by one standard deviation. This effect is calculated as follows. The regression is of the type $\ln[R^2_{ij,t}/(1-R^2_{ij,t})] = \alpha + \beta x/\sigma_x + \varepsilon$, where the regressor has a zero mean and is divided by its standard deviation, σ_x. The effect of a shock of size $\Delta x = \sigma_x$ on $R^2_{ij,t}$ is $\exp(\alpha+\beta)/[1+\exp(\alpha+\beta)] - \exp(\alpha)/[1+\exp(\alpha)]$. Economic effect II is economic effect I scaled by standard deviation of $R^2_{ij,t}$. The t-statistics are reported in brackets. They are based on standard errors, robust to conditional heteroscedasticity, spatial, and serial (up to one lag) correlations as in Driscoll and Kraay (1998). Bold numbers are statistically significant at the 5% level. The sample for specifications [1]–[3] is April 1992 – May 2012 (based on the availability of FX volatility). The sample for specification [4] is January 1995 – December 2009 (based on the availability of gross capital flow / GDP).

	[1]	[2]	[3]
Good government index	**0.297**		**0.343**
	[2.985]		[2.326]
Money market interest rate		-0.030	0.085
		[-0.228]	[0.557]
ln (GDP pro capita)	**0.509**	**0.731**	**0.529**
	[2.837]	[3.153]	[2.862]
Economic effect I	0.067	-0.006	
Economic effect II	0.514	-0.049	
R^2	0.686	0.653	0.690

Table 9: **Explaining cross-sectional variation in commonality.** This table shows the results from regressing logit transformation of commonality R^2_{ij} for 30 currency pairs on the fundamental factors $\ln[R^2_{ij}/(1-R^2_{ij})] = \alpha + \beta z_{ij} + \varepsilon_{ij}$. The commonality R^2_{ij} is taken from regression (3). The fundamental factors z_{ij} are based on the data on countries with the quoted currency. Economic effect I is the impact on the commonality R^2_{ij} of the change in the demand- or supply-side factor of interest by one standard deviation. For calculation of economic effect, see caption of Table 8. Economic effect II is economic effect I scaled by standard deviation of R^2_{ij}. The t-statistics are in brackets. They are based on the standard errors, robust to conditional heteroscedasticity and serial correlation up to one lag as in Newey and West (1987). Bold numbers are statistically significant at the 5% level.

Variable	Description	Source
Demand-side factors		
a) Current account		
Δ U.S. (Export+Import)/GDP	Changes in monthly sum of the U.S. FAS exports and imports scaled by the U.S. GDP	Datastream
Δ U.S. Export/GDP	Changes in monthly U.S. FAS exports scaled by the U.S. GDP	Datastream
b) Portfolio balances		
Δ U.S. central bank reserves / GDP	Changes in monthly U.S. total foreigners reserve assets held by central banks scaled by the U.S. GDP	Datastream
Δ U.S. Gross capital flow / GDP	Changes in monthly U.S. gross capital flow (sum of gross foreigners purchases of the U.S. securities plus gross U.S. citizens purchases of the foreign securities) scaled by the U.S. GDP	TIC data, Datastream
Δ Gross foreigners purchases of the U.S. treasuries / GDP	Changes in gross foreign purchases of the U.S. Treasury bonds and notes scaled by the U.S. GDP	TIC data, Datastream
Δ Gross U.S. citizens purchases of the foreign stocks and bonds / GDP	Changes in gross U.S. citizens purchases of foreign stocks and bonds scaled by the U.S. GDP	TIC data, Datastream
c) Sentiments		
Δ U.S. investor sentiment index	Changes in the sentiment index is from Baker and Wurgler (2007), downloaded from Wurgler's website. Lower scores indicate more pessimistic investor sentiment	Wurgler's website
Δ VIX	Changes in the Chicago Board Options Exchange Market Volatility (VIX) Index, which measures implied volatility of S&P 500 index options.	Bloomberg
Supply-side factors		
a) Funding conditions		
Δ TED spread	Changes in the difference in the interest rates between the three-month US Treasury bill and the three-month Eurodollar LIBOR.	Bloomberg
Δ U.S. commercial paper spread	Changes in the difference between the 90-day financial commercial paper rate and the 90-day US Treasury yield.	Federal Reserve Bank of St. Louis
Δ U.S. default spread	Changes in the percentage difference between Moody's corporate bond index BAA and AAA yields.	Bloomberg
Return on the 10 biggest FX dealers	We construct a portfolio long stocks of the top-10 FX dealers according to the annual Euromoney FX survey. The portfolio is rebalanced annually. The return on this portfolio should capture propensity of dealers to fund FX positions.	Own calculations based on Euromoney FX survey
b) Monetary conditions		
Δ U.S. Monetary aggregates	Changes in the U.S. monetary base	Datastream
U.S. Inflation	Changes in the consumer price index in the U.S.	Datastream
c) Banking		
Δ U.S. Bank deposits / GDP	Change in the amount of bank deposits scaled by the U.S. GDP	Datastream
Δ Financial commercial paper rate	Changes in 30-day AA Financial Commercial Paper Interest Rate	Federal Reserve

Table A.1. Description of the demand-side and supply-side factors to explain liquidity and commonality in liquidity.

Variable	Description	Source
USD appreciation	Mean FX return from investing into the U.S. Dollar is computed as the average return across 17 FX rates against the USD, higher values mean appreciation of the U.S. Dollar	Datastream
MSCI return	Return on the MSCI World Index, which captures large and mid cap representation across 24 Developed Markets countries.	Bloomberg
Δ AAA bond rates	Changes in Moody's long-term AAA corporate bond yields.	Bloomberg
Δ FX volatility	Changes in the JP Morgan Global FX volaility index, which tracks implied volatility of three-month at-the-money forward options on major and developed currencies.	Bloomberg
Δ MSCI volatility	Changes in the realized volatility (based on the daily returns) on the MSCI World index	Own calculations based on the data from Bloomberg
Δ Bond volatility	Changes in the Merrill's MOVE Index, which reports 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.	Bloomberg
Δ Stock liquidity	The changes in the stock market liquidity, computed as the average across price impact proxies of the monthly Amihud (2002) measure for each country. A country stock liquidity is calculated as the value-weighted average of all individual stocks withing the country.	Karolyi, Lee, and Dijk 2012
Δ Bond liquidity	The bond market liquidity is the off-the-run 10-year liquidity premium, i.e. the yield difference between less and more liquid ("off-the-run" from Gurkaynak, Sack, and Wright 2007 and "on-the-run" from FRED) ten-year nominal Treasury bonds.	Federal Reserve, Gurkaynak, Sack, and Wright (2007)
Δ FX liqudity lagged	Lagged changes in the market FX liquidity, which is based on the mean across the three best liquidity measures (CS, Roll, Gibbs)	Own computations

Table A.2. Description of the monthly market conditions to explain liquidity and commonality in liquidity

Variable	Description	Source
Demand-side factors		
(Export + Import)/GDP	Export plus import of countries i and j as a fraction of GDP, mean across annual data over 1991–2012	Datastream
Export QC to BC / GDP QC	Export from the country of the quoted currency (QC) to the country with the base currency (BC), scaled by the GDP in the country of the QC	Datastream
Export BC to QC / GDP BC	Export from the country of the BC to the country with the QC, scaled by the GDP in the country of the BC	Datastream
Trade flow (gravity model)	Trade flow between country with quoted and base currency, measured as ln GDP QC plus ln GDP BC minus ln (Geographical distance ij)	IMF, http://www.distancefromto.net/, own calculations
b) Portfolio balances		
International debt issues / GDP	Overall international debt issues (all issuers) as a fraction of GDP, mean across annual data over 1991–2012	Datastream
CB reserves / GDP	Central bank reserves to GDP, mean across annual data over 1991–2012	Datastream
Net foreign assets / GDP	Overall net foreign assets (foreign assets minus liabilities) as a fraction of GDP, mean across annual data over 1991–2012	Datastream
Gross capital flow / GDP	Gross capital flow as a fraction of GDP, mean across annual data over 1991–2012	Datastream
c) Institutional setting		
Good government index	The good government index is defined as the sum of the following three indices from the International Country Risk Guide (each ranging from zero to ten): (i) government corruption, (ii) the risk of expropriation of private property by the government, and (iii) the risk of the government repudiating contracts. Lower scores for each index indicate less respect for private property	La Porta, de Silanes, Shleifer, and Vishny (1998)
Financial disclosure	Assessment of the prevalence of disclosures concerning research and development (R&D) expenses, capital expenditures, product and geographic segment data, subsidiary information, and accounting methods. Lower scores indicate less disclosure.	Karolyi, Lee, and Dijk 2012
Supply-side factors		
a) Funding conditions		
Volatility of the FX rate return	Monthly realized volatility of daily FX rate returns, mean across monthly data over 1991–2012	Datastream
Local money market interest rate	Short-term money market interest rate, mean across annual data over 1991–2012	Datastream
Local money market interest rate volatility	Volatility of annual interest rate data over 1991–2012	Datastream, own calculations
b) Monetary conditions		
Money supply/GDP	Monetary base scaled by country GDP, mean over 1991–2012	Datastream
Inflation	CPI, mean over 1991–2012	Datastream
c) Banking		
Bank deposits / GDP	Bank deposits scaled by country GDP, mean over 1991–2012	Datastream
Controls		
ln (GDP pro capita)	Logarithm of the GDP per capita, mean over 1991–2012	Datastream
GDP growth volatility	Volatility of annual GDP growth over 1991–2012	Datastream, own calculations
ln GEO size	Logarithm of the surface area of the countries in square kilometers	United Nations Environmental Indicators
Stock market cap / GDP	Stock market capitalization to GDP, mean over 1991-2012.	Datastream

Table A.3. Description of the cross-sectional factors to explain commonality in liquidity