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UNDERSTANDING FX LIQUIDITY

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Abstract

We provide a comprehensive study of the 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 and readily-available data. Second, we demonstrate that FX liquidity declines with funding constraints and global risk, supporting theoretical models relating funding and market liquidity. In these distressed circumstances, liquidity tends to evaporate more for developed and riskier currencies. Finally, we show stronger comovements of FX liquidities in distressed markets, especially when funding is constrained, volatility is high, and FX speculators incur losses. (*JEL* C15, F31, G12, G15)

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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 in liquidity of individual currencies ("commonality"). This paper provides a study of FX liquidity and its commonality over more than two decades and thirty exchange rates. We first identify accurate measures of 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 FX liquidity patterns may differ from those of other asset markets. For instance, the FX market is characterized by limited transparency, heterogeneity of participants, and market fragmentation. In addition, FX spot transactions demand little or no margin requirements, allowing FX traders to take highly leveraged positions (e.g. Galati, Heath, and McGuire 2007). However, currency liquidity can deteriorate in crises episodes because haircuts increase, causing leveraged positions to be unwound in FX and related markets such as derivatives and money markets.[1] Finally, FX rates are normally closely connected to central bank operations.

This paper contributes to the international finance literature in three ways. First, it provides a *methodological* contribution to the measurement of FX liquidity. Using precise high-frequency (intraday) data (from Electronic Broking Services) to calculate benchmark measures, we show that it is possible to gauge FX liquidity using daily and readily-available data (from Bloomberg, Thomson Reuters, and WM/Reuters). The possibility to use a low-frequency measure circumvents a number of severe limits related to high-frequency data.[2] Several studies compare low-frequency and high-frequency liquidity measures for stocks and commodities.[3] But, to our knowledge, there is no such study of

[1]This was the rationale of the central banks' swap lines during the recent financial crisis organized by the U.S. federal reserve and the Swiss National Bank to provide U.S. dollar and Swiss franc liquidity, respectively.

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

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

FX liquidity.

The *second contribution* is to explain the significant temporal and cross-sectional variation in currency liquidity. So far, FX liquidity has been comprehensively analyzed only over short periods (Mancini, Ranaldo, and Wrampelmeyer 2013) or using specific measures, such as the order flow[4] or the bid-ask spread based on indicative quotes.[5] 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 our case, thirty exchange rates). Furthermore, little research has been conducted on the fundamental sources of FX liquidity. We contribute to this literature by studying supply-side and demand-side sources of FX liquidity. For instance, we investigate whether FX liquidity deteriorates with funding constraints and higher volatility, as postulated by recent theoretical models (e.g., Brunnermeier and Pedersen 2009; Vayanos and Gromb 2002), or demand shocks inducing portfolio reshuffling (e.g. Hau, Massa, and Peress 2010). Since the FX market is at the crossroads of any international portfolio allocation (e.g. Pavlova and Rigobon 2007), we propose a research design that explores cross-market linkages between FX liquidity on one hand and volatility as well as liquidity pertaining to the global stock and bond markets on the other hand.

The *third contribution* is an analysis of commonality in FX liquidity. 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 tight funding constraints and high global risk. Then, we analyze the cross-sectional variation of commonality in FX liquidity by looking at the main market features and institutional characteristics of every currency.

Some clear results emerge from our study. First, the low-frequency liquidity measures coming from *bid-ask spreads* and the *Corwin-Schultz* model (Corwin and Schultz 2012) offer the highest correlations with the high-frequency benchmark. Combining these measures in the same vein as Korajczyk and Sadka (2008), we then provide monthly estimates of liquidity for individual exchange rates and for the entire FX market from January 1991 to May 2012.

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

[4]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 Breedon and Vitale (2010), Breedon and Ranaldo (2012), Berger, Chaboud, Chernenko, Howorka, and Wright (2008) and Banti, Phylaktis, and Sarno (2012).

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

Second, we find that FX liquidity systematically worsens with more severe funding constraints and global risk—pointing to the importance of supply-side factors. These effects are economically significant. For instance, an increase of one standard deviation of (changes of) VIX and TED spread is associated with an increase of average cost of executing a FX trade ("effective cost") of 17% and 5%, respectively. Among the global risk measures, we find that FX liquidity tends to deteriorate with volatility and illiquidity of both global stocks and bonds—revealing cross-market linkages that go beyond the volatility linkages in the stock, bond, and money markets (e.g. Fleming, Kirby, and Ostdiek 1998) or stock-bond liquidity relationships (Chordia, Sarkar, and Subrahmanyam 2005; Goyenko and Ukhov 2009). We also find which currencies suffer larger liquidity drops when global risk increases. More specifically, when global stock and FX volatility increases, FX liquidity of developed and riskier currencies tend to evaporate more. By riskier currencies, we refer to FX rates bearing 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).

Third, we find that commonality in FX liquidity increases in distressed markets, similarly to what Hameed, Kang, and Viswanathan (2010) and Karolyi, Lee, and Dijk (2012) find for the stock market. Commonality strengthens with volatility in global stock and FX markets, and short-term funding constraints, providing further support to the supply-side hypothesis. It is also stronger when FX carry trade strategies incur large losses thereby exacerbating the adverse effects of "the rush to exit" from carry trade positions (e.g. Brunnermeier, Nagel, and Pedersen 2009 and Ranaldo and Söderlind 2010). Finally, we find that developed currencies are more subject to commonality in FX liquidity, especially when they are highly rated (by rating agencies), suggesting that these institutional features encourage common international trading.

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 evaluate 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 important for an accurate estimation of liquidity, because it avoids using a Lee and Ready (1991) 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. Using the last quotes and transaction prices for every second, we compute the midpoint of best bid and ask quotes and 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.[6]

We use HF data on nine exchange rates, 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

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

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 mid-quote price. We estimate effective cost for each month and each exchange rate by averaging the HF data over the month.

As a comparison, we also estimated four alternative HF liquidity measures (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). Although they capture different facets of liquidity, they are all highly correlated with effective cost (around 0.95 for levels and 0.80 for changes) on the monthly frequency.

[6]We run the 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.

The choice of HF benchmark is therefore not important. (See the Internet Appendix for details.)

[Figure 1 about here.]

The time profile of the average (across exchange rates) EC is illustrated in Figure 1 (dotted line). The figure shows that EC was quite stable from January to July 2007. Afterwards, EC increased with a substantial jump from September 2008 to November 2008. This reflects the collapse of Lehman Brothers followed by a sustained turmoil. EC gradually fell back during 2009 but increased again in early 2010 and mid-2011, which correspond to the peak of the European sovereign debt crisis. During the first half of 2012, EC visibly improved and returned close to the pre-crisis level.

1.2 Finding accurate low-frequency measures

Following the literature on market liquidity, in this section we identify *accurate low-frequency FX liquidity measures*—defined as those that have high correlations with the high-frequency effective cost.[7] The aim is to find accurate LF measures of FX liquidity over a long-time span and a large number of currencies. Such LF data are only available for the over-the-counter (OTC) segment of the FX market, where the convention is to collect data on indicative quotes. Trade prices are not available from common LF data providers.

We analyze data from three leading providers: Bloomberg, Thomson Reuters, and WM/Reuters (the last two can be accessed from Datastream). In the main analysis we use daily bid and ask quotes as well as daily high and low quotes, but we will comment also on other data. To guarantee a consistent comparison, we use the same nine currency exchange rates and time period (trading days) as for the EC benchmark. For each exchange rate, we compute monthly LF liquidity measures from daily data.

Panel A of Table 1 compares several LF liquidity measures (discussed below) with the EC benchmark, by reporting the times-series correlations of *changes* in each LF liquidity measure with changes in their respective EC benchmarks. Boldfaced numbers are different from zero at the 5% significance level, applying a GMM based test using a Newey-West covariance estimator with four lags.

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

The first measure we consider is the relative bid-ask spread (*BA*), which we calculate from Bloomberg's bid and ask quotes snapped at 5 p.m. EST time.[8] The first column of Table 1 shows that the BA has fairly high correlations with the EC benchmark, but with some variation across exchange rates. The average correlation (last row) is 0.44.[9] Using data snapped at other times of the day (Bloomberg at 6 p.m. GMT and 8 p.m. JST) or from other data providers (Thomson Reuters at 9 p.m. GMT and WM/Reuters at 4 p.m. GMT), the average correlations between the LF bid-ask spreads and the EC benchmark always remain below 0.25. See Table A.1 of the appendix to the paper for further details.

[Table 1 about here.]

Our second approach is the Corwin and Schultz (2012) measure (*CS*), which combines high and low values over one day with high and low values over two days—assuming that the high price is buyer-initiated and that the low price is seller-initiated. Both Bloomberg and Thomson Reuters provide data where the high is an ask quote and the low is a bid quote, so the CS measure can be readily applied. To handle negative spreads, our CS measure treats negative two-day spreads as missing, which gives a somewhat higher correlation with the EC benchmark than setting the negative spreads to zero (see Corwin and Schultz 2012, p. 727 for a discussion).

The second column of Table 1 shows CS based on Thomson Reuters (9 p.m. GMT). The correlations with EC are consistently high across exchange rates, with an average of 0.53. In this case, using Bloomberg data at any of the three time snaps give very similar results (see Table A.1 of the appendix to the paper). We choose to report results based on Thomson Reuters, since this data provider guarantees broader coverage in the early 1990s—which will be useful in the second part of the paper.

In short, both BA and CS are accurate at capturing how liquidity changes over time, as demonstrated by the high correlations with the EC benchmark. However, the choice of data provider and time snap is important for the BA measure. To illustrate the performance, Figure 1 displays a measure of systematic ("market") LF illiquidity which is the

[8] Bloomberg runs two methods to compile the collected quotes called *BGN* and *CMPN*. The former relies on a larger number of contributors. We consider both and use the *BGN* throughout the paper given the higher correlation with EC benchmark. See Table A.1 for more details.

[9] The correlation of the levels of average (across currencies) BA with the levels of average EC is 0.94, which well compares with the correlations reported in other papers (for instance, Goyenko, Holden, and Trzcinka 2009 report 0.95 correlation of the levels of their best measure with the HF benchmark).

average across BA and CS and across exchange rates (solid line). As before, the dotted line is the average EC. Clearly, the two series have very similar patterns over our sample period 2007–2012 (the correlation is 0.96 for levels and 0.84 for changes).

[Table 2 about here.]

Table 2 reports descriptive statistics of the EC benchmark and the LF liquidity measures. The table shows that the bid-ask spreads (which are divided by 2) are considerably higher than the EC. This is expected, since the EC comes from the most liquid segment of spot FX market whereas LF data cover broader and less liquid segments, in particular, OTC. The table also shows that the scale of the CS is much lower than EC. This is also reasonable since different liquidity measures that gauge diverse concepts of transaction cost produce different magnitudes (e.g. see Stoll 2000 and Marshall, Nguyen, and Visaltanachoti 2012). When we compare the time-series average of BA across exchange rates, then it is clear that the ranking differs from the ranking of EC (Spearman's rank correlation is 0.2). The results for CS are slightly better (a rank correlation of 0.4). These results suggest that the LF measures are not well-suited for capturing the levels of transactions costs. However, they do track FX liquidity changes over time. For this reason, the analysis of the second half of the paper will be based on results from BA and CS.[10]

The literature on liquidity on other markets have considered a large number of LF measures. The rest of this section will therefore provide a brief discussion of some of the commonly applied methods. We first consider the Roll (1984) measure (*Roll*) and the Bayesian *Gibbs* sampler estimate of it (Hasbrouck 2009). The Roll model is formulated for trade prices, so as to measure the bid-ask bounce by the autocovariance of price changes. As discussed above, trade prices are not provided by common LF data sources, so we instead use mid-quotes. For this reason, the results cannot capture the essence of the Roll model (the bid ask bounce), but they may still be of interest.

The third column of Table 1 shows that Roll has a low correlation with EC (on average 0.16). The presence of positive autocorrelations (we use the standard approach of setting them to zero) and the use of mid-quotes are possible explanations. The results are similar across time snaps and data sources.

[10]We also studied shorter time frames. As expected, the correlations of LF liquidity measures with the EC worsen at higher frequencies. However, the BA works reasonably well even on the daily frequency and CS on the three-day frequency. See Internet Appendix for more details.

The Bayesian approach (Gibbs) is one way of overcoming the problem with positive autocorrelations (by restricting the prior to positive values of the implied transaction cost).[11] The fourth column of Table 1 shows fairly high correlations of the Gibbs estimates and the EC, with an average of 0.4.

Other alternative LF measures like the so-called Effective Tick (Holden 2009 and Goyenko, Holden, and Trzcinka 2009), LOT, Zeros (Lesmond, Ogden, and Trzcinka 1999) and FHT (Fong, Holden, and Trzcinka 2011) turned out to be only weakly correlated with effective cost (not tabulated).

Finally, we also considered liquidity measures based on the quote frequency. The main idea is approximate trading volume with the number of quote revisions, which are available from January 2007. This means that the quote-based measures are not helpful in calculating LF measures for a long historical sample period (which is our main goal), but as a comparison, they are still of interest. The results (see the Internet Appendix) show that the Amihud (2002) and Amivest (Cooper, Groth, and Avera 1985 and Amihud, Mendelson, and Lauterbach 1997) measures are fairly strongly correlated with effective cost, while the Pàstor and Stambaugh (2003) measure is not.

To sum up, we find that the bid ask spread and the Corwin-Schultz measures are highly correlated with the EC benchmark. The choice of time snap and data provider is important only for the bid-ask spread. Other LF measures are either poor at tracking the HF benchmark, are inconsistent with the available data, or the data sets are limited.

1.3 Finding accurate low-frequency measures: a larger and longer sample

High-frequency data are available only for a small number of exchange rates and for 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 extend the analysis by considering a larger panel of exchange rates and longer sample period.

The source of the LF data naturally defines the limits of the cross-section and the

[11] 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 an extremely small value.

length of the time series. For a sample starting in January 1991, 40 exchange rates are available in Thomson Reuters (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 of some of the key macroeconomic and financial variables needed in the subsequent analysis. For the rest of the paper, we focus on the remaining thirty exchange rates.[12]

The previous analysis has demonstrated that there are some accurate LF liquidity measures, in the sense of being strongly correlated with the EC benchmark. For the rest of our analysis, we choose to focus on an average between the BA (from Bloomberg, 5 p.m. EST) and the CS measure (Thomson Reuters, 9 p.m. GMT) for two main reasons: both methods perform well and they are well-suited for the kind of data that is available. In practice, this means using only CS before 1996 (since there is little BA data then) and an average of the two methods afterwards. Averaging is a simple way to extract the common component and to reduce the noise.

Since the BA and CS estimates have different scales (and different standard deviations), we employ a simple approach to combine them: each measure is first standardized (to have zero mean and unit variance) and then we form an average. This creates a LF liquidity measure for each of the 30 exchange rates. As the final step to create a measure of systematic (market) FX liquidity, we simply average over the 30 exchange rates.[13]

Panel B of Table 1 shows that the averaging (of BA and CS, see column 5) works very well: the correlations with EC are consistently high and 0.6 on average. This is clearly better than using either BA or CS separately. Adding the Gibbs measure (column 6) or considering a weighted average of BA and CS (defined by OLS regression coefficients, column 7) seem to add little. For the further analysis, we focus on the average between BA and CS because of its straightforwardness and high correlation with the EC benchmark.

[12]The names of the used currencies are listed on the X-axis of Figure 4. It must be noted that 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. More description is in the Internet Appendix.

[13]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 with 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.

[Figure 2 about here.]

Figure 2 illustrates the systematic (market) LF *illiquidity* 1991–2012, based on the BA and CS measures for 30 exchange rates. The figure shows that substantial drops in FX liquidity (that is, increases in illiquidity shown in the graph) coincide with the Lehman bankruptcy and other major events such as the European Exchange Rate Mechanism (ERM) crisis (1992), the Mexican peso crisis (1994), the Russian debt restructuring (1998), and 9/11 terrorist attacks (2001). In contrast, the reaction of FX liquidity to stock-specific events, such as the dotcom bubble burst (spring 2000) or the Enron scandal (2001), is less discernible. However, the time series pattern suggests that systematic FX illiquidity correlates with global risk indicators. For instance, its correlation with the VIX and TED spread is 0.69 and 0.42, respectively. An in-depth inspection of the main drivers of FX liquidity will be conducted in the next sections.

2. Hypotheses

In this section, we set up the hypotheses for our empirical tests. In Section 2.1, we discuss the possible drivers of FX liquidity by taking into account three aspects: broad market conditions, demand-side, and supply-side factors explaining FX liquidity. In Section 2.2, we discuss what can explain the temporal and cross-sectional variation in commonality of FX liquidity.

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). Thus, our first hypothesis is that FX liquidity decreases with FX volatility.

The international finance literature conjectures comovement patterns across markets and countries and that the FX market acts as a channel that propagates shocks across countries' stock and bond markets (e.g. Pavlova and Rigobon (2007)). We assume that these shocks prompt international portfolio reshuffling that we approximate with lower return on global stock and bond markets, and higher volatility in the same markets. Thus, we test whether FX liquidity declines with these price movements. Moreover, we test whether FX liquidity tends to decrease *jointly* with stock and bond liquidity, suggesting cross-market linkages in terms of market liquidity. 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 general market conditions, we attempt to disentangle demand-side and supply-side sources of liquidity. 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. Hau and Rey (2006) offer micro-foundations of the portfolio balance theory relating currency appreciations to capital flows. Furthermore, financial intermediaries of the most financially developed countries can benefit from better funding conditions and higher leverage—producing asymmetric risk sharing and flight to quality during financial crises (Maggiori 2012). At the same time, currencies of larger economies provide better hedge against global shocks (Hassan 2013). These arguments not only suggest a connection between capital flows and FX liquidity but they also predict that flight-to-quality dynamics affect FX rates, that is, capital flows are diverted towards reserve currencies when global risk increases. Thus, we 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 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. Recent theoretical models including 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 "liquidity spirals." [14] These spirals can also materialize in FX markets, e.g. when FX speculators hit funding constraints (Brunnermeier, Nagel, and Pedersen 2009 and Ranaldo and Söderlind 2010), the risk bearing capacity of international financiers is impaired (Gabaix and Maggiori 2014), or when carry trade positions are unwound in a coordination-failure fashion (Plantin and Shin 2011). In our empirical analysis, we test whether FX liquidity decreases with higher *(a)* money market rates, *(b)* TED spread (i.e. the difference between the interest rates on interbank loans and on short-term U.S. government debt) and *(c)* monetary

[14] 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), and more recently Kondor and Vayanos (2014).

aggregates.[15] In addition, we predict that FX liquidly is positively related to the return on the portfolio of the ten biggest FX dealers, as an indirect proxy of their propensity to provide FX liquidity (similarly to Hameed, Kang, and Viswanathan 2010).

The final question we address is *whether some FX rates suffer larger drops in liquidity* (than other FX rates) when demand-side and supply-side factors as well as general market conditions deteriorate. There can be two main reasons: First, international financial integration may increase the transmission of crises across countries (e.g. Devereux and Yu 2014). Given that developed countries are characterized by high degrees of financial integration, we test whether the FX liquidity of developed currencies is more exposed to global risk factors. Second, the recent FX asset pricing literature indicates that some currencies have larger exposure to risk factors. Two risk factors have been well documented. 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. Menkhoff, Sarno, Schmeling, and Schrimpf (2012) demonstrate the importance of volatility. Verdelhan (2013) shows that these risk factors also explain excess returns on individual exchange rates. The reason why FX liquidity of "riskier" currencies can be more exposed to global risk comes from the adverse effects of unwinding carry trade dynamics. More precisely, we test whether liquidity of currencies having larger exposure to risk factors deteriorates more when global risk increases.

2.2 Explanations for commonality in FX liquidity

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

The *demand-side explanation* links commonality in liquidity to correlated trading behaviors of international investors. Co-movements can then be explained by investors' preferred habitats (e.g. Barberis, Shleifer, and Wurgler 2005) that originate from key institutional characteristics such as the sovereign credit risk (assessed by credit rating agencies), central bank transparency and independence (Dincer and Eichengreen 2014). Following the previous literature (e.g. Karolyi, Lee, and Dijk 2012), we include these institutional factors among the demand-side variables and test whether these institutional features help explain the cross-sectional variation of commonality in FX liquidity. Across

[15] 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.

time, we test whether commonality in FX liquidity increases with deteriorations of global risk and investor sentiment as well as stronger international portfolio movements.

On the *supply-side*, the liquidity spiral mechanisms discussed above also apply to multiple-asset settings. 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. Cespa and Foucault (2014) show that funding constraints for dealers in one asset can propagate to other assets and decrease market liquidity. In the spirit of these models, we test whether commonality increases with tighter funding constraints, proxied by local money market interest rate.

A note of caution must be stressed. While the literature above 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.[16]

3. Explaining FX Liquidity

In this section, we try to determine the main drivers of FX liquidity over the last twenty years. For each currency pair, the liquidity measure is the negative of the average across standardized *BA* and *CS* measures and has a monthly frequency. We proceed in four steps: first, we regress the monthly changes of FX liquidity (of each of the thirty exchange rates) on factors representing demand and supply forces as well as general market conditions. Second, we analyze whether the liquidity of some FX rates are more exposed to these factors. Third, we study Structural Vector Autoregressive (SVAR) 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 is available in the appendix of this paper. More precisely, Table A.2 describes the sets of variables representing the demand-side and supply-side sources of FX liquidity and Table A.3 explains those pertaining to the general market conditions.

[16]For instance, here the VIX is considered as a demand-side factor since it is commonly used as a investors' sentiment proxy (e.g. Brunnermeier, Nagel, and Pedersen 2009). However, as a volatility indicator it could also fall into the broad category of market conditions.

3.1 Explaining FX liquidity: panel regressions

We consider eight different variables representing possible *demand-side* sources of FX liquidity and seven variables for the *supply-side*. Both sets are divided into three broad categories: on the demand side, these are *(a)* current account (export and import data), *(b)* portfolio rebalancing (central bank reserves, U.S. gross capital flows, gross purchases of the U.S. treasuries by foreigners, and gross purchases of the foreign stocks and bonds by U.S. citizens), and investor sentiment proxies (U.S. investor sentiment index and VIX).

On the supply side, the categories are *(d)* funding conditions (return on the 10 biggest FX dealers and the spreads of TED and of U.S. commercial papers), *(e)* monetary conditions (U.S. monetary aggregates and inflation), and *(f)* proxies of banking liquidity (U.S. bank deposits and financial commercial paper rate). Volume variables are divided by GDP and when used as regressors, expressed in changes.

As a first step, we perform simple panel estimations in which monthly *changes* of the liquidity of each of the 30 exchange rates are regressed on *one factor at a time*. This exercise will permit us to determine the two most significant demand-side and supply-side variables to be included in a multiple regression analysis. The sample period is January 1991 to May 2012 (257 months).[17] 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[18] and changes in VIX are the most significant demand-side factors—suggesting that FX liquidity decreases with flight-to-quality dynamics and investor fears. These two variables will therefore be used to represent the demand side in the multiple regression models below.

Evidence on the role of capital flows in explaining aggregate movements of FX rates 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

[17] 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.

[18] U.S. gross capital flows tend to decrease in terms of stress, especially after the Lehman bust. We analyze both gross and net capital flows and find that only the former significantly explains FX liquidity. A possible explanation can be that gross capital flows better capture stop and retrenchment episodes and effects of global risk increases such as contagion and flight-to-quality dynamics; see Forbes and Warnock (2012).

relation between FX liquidity and VIX extends Mancini, Ranaldo, and Wrampelmeyer (2013) who find a similar pattern 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 covered interest rate parity (Mancini-Griffoli and Ranaldo 2010). However, relatively little is known about how FX liquidity relates to supply-side factors. 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 funding 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 multiple regression models. These results suggest that FX liquidity tends to decline when money market premiums increases (TED spread increases) and FX dealers face tighter funding constraints.

Measures of *market conditions* include returns, volatility, and liquidity on FX, global stock and bond markets. In the simple regressions, three main results emerge. First, volatilities appear to be the most significant variables, suggesting cross-market linkages between FX illiquidity and stock-bond volatilities. Second, stock and bond market liquidity tends to be positively associated with FX liquidity, indicating a wide cross-market commonality in liquidities and extending the stock-bond commonalty documented in the literature (Chordia, Sarkar, and Subrahmanyam 2005; Goyenko and Ukhov 2009). Third, among the return variables we find that FX liquidity decreases when the U.S. dollar appreciates and global stock prices decline. Overall, these results are consistent with our prediction that FX liquidity decreases in flight-to-quality episodes (captured by U.S. dollar appreciations) and when global risk increases (i.e. negative global stock returns), adding to Hameed, Kang, and Viswanathan (2010) who show that stock liquidity decreases with negative stock returns.

[Table 3 about here.]

We now turn to multiple panel regressions of the type

$$\Delta L_{ij,t} = \alpha + \beta' f_t + \varepsilon_{ij,t}, \tag{2}$$

where $\Delta L_{ij,t}$ is the change (from period $t-1$ to t) in the liquidity measure for currency pair ij and f_t is a vector of factors.

The results are summarized in Table 3. Each regression model [1]–[4] (different columns) uses one variable related to the demand-side or supply-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 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 an increase of effective cost by 0.1 bps, which corresponds to almost a fifth (17%) of the average effective cost.[19] Second, (changes of) the TED spread (as supply-side variable) have a significantly negative coefficient in most models. In model [3] an increase of one standard deviation in the TED spread is associated with an increase in the effective cost of 0.3 bps, which corresponds to 5% of the average effective cost. Third, the analysis of market condition variables indicate that FX liquidity decreases with negative global stock returns, higher FX and stock volatilities, as well as lower bond liquidity. Among the market condition variables, volatility and liquidity appear more important than return factors in explaining FX liquidity, delivering three times higher R-squared values.

[Table 4 about here.]

[19]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 mean and standard deviation of the average (across currencies) effective cost over 2007–2012.

We are now ready to construct an encompassing model that includes all significant variables that appeared relevant in Table 3. This is what we do in model [1] of Table 4. Three main results from the encompassing regression are discernible: *(a)* several of the market condition variables remain significant, especially FX volatility and bond liquidity; *(b)* both demand-side factors (U.S. capital flows and VIX index) lose their significance, while *(c)* the supply-side variable (TED spread) remains negative and statistically significant.

A natural question arises 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 to the set of global factors.[20] We find that none of them provides additional information, supporting the idea that FX liquidity is mainly driven by global shocks.

In sum, the results in Table 3 and model [1] of Table 4 suggest the following three points: first, FX liquidity correlates with global risk measures and with liquidity on global bond markets—consistent with the idea that the FX market is the crossroads of international risk spillovers and suggesting that FX liquidity declines with flight-to-quality patterns. Second, 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 to explain FX liquidity movements, but they do not remain significant jointly with other market condition variables.

3.2 Explaining FX liquidity: more exposed currencies

The question we address in this subsection is whether the liquidity of some FX rates are more exposed to the factors analyzed above. To answer this question, models [2]–[4] of Table 4 extend the analysis of movements in FX liquidity by interacting the global risk factors with dummy variables that capture different characteristics of the currencies

$$\Delta L_{ij,t} = \alpha + \beta' f_t (1 - D_{ij,t}) + \gamma' f_t \cdot D_{ij,t} + \varepsilon_{ij,t}, \tag{3}$$

[20] 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.

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

In model [2] of Table 4, we identify the most developed currencies with a dummy variable equal to one for richer countries (above the median annual GDP per capita) in that month and zero otherwise.[21] The column labeled "High" ("Low") reports the estimates for the richer (poorer) countries. The main result is that FX liquidity of more developed currencies is more adversely affected by an increase in FX volatility than that of less developed currencies (a significant difference is indicated by the sign *). This finding is in line with the idea that the transmission of crises can be more severe for advanced countries because their financial systems are more internationally integrated.

Inspired by the recent FX asset pricing literature, models [3]–[4] use dummies indicating "riskier" currencies. In model [3] 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 [4] 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. The evidence suggests that FX liquidity of riskier currencies is more affected by an increase of global FX risk, supporting the prediction that riskier currencies endure more severe liquidity dry-ups when carry trade positions are unwound.

3.3 Explaining FX liquidity: vector autoregressions

[Table 5 about here.]

We now attempt to capture the dynamics of FX liquidity by using SVAR models. We model the joint dynamics of FX liquidity with demand-side and supply-side factors as well as capital market conditions in a structural VAR model with the following order: *changes* of VIX and TED first (implying that they cannot react to contemporaneous shocks to the other variables), changes of market conditions second (i.e. they can react to contemporaneous shocks to VIX and TED) and changes of FX liquidity last (can react to contemporaneous shocks to all variables). The VAR is estimated for each of the 30 exchange rates, and we report the average impulse response functions. The order of VIX

[21] We obtain very similar results when we use the IMF classification criterion to distinguish between advanced and emerging countries.

and TED or number of lags in the VAR model (we use 2, which is enough to make the residuals white noise) is not important for our results. Also, estimating the model on systematic liquidity (average liquidity across the 30 exchange rates), instead of on individual exchange rates, gives very similar results.

Panel A of Table 5 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 in Table 3), 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 5.

In sum, the VAR analysis shows that our earlier results are robust to controlling for more dynamics. In addition, 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 the 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 shocks presumably originated from demand- and supply-side of market liquidity 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 rescale LF liquidity measure (which is standardized to have unit variance) to have the same volatility as the effective cost over 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) increased by 0.5 basis points (a doubling) from August to October 1992 (see top left chart of Figure 3). This increase is almost twice as large as that for exchange rates 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 0.18 bps, while non-Asian currencies saw a very small increase (see top right chart of Figure 3).

We additionally 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* on December 1, 2000 can be seen as an exogenous *demand* for FX liquidity.[22] 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 0.05 bps over November–December 2000, while that of the other currencies increased by less than half of that.

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 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 0.05 bps from November to December 2011. In contrast, the estimated effective cost of the other FX rates increased by some 0.03 bps.

To sum up, this simple event study shows that *(1)* FX liquidity is impaired during crisis episodes and *(2)* FX liquidity reacts to seemingly exogenous shocks of demand and supply of liquidity. Consistent with supply-side hypotheses, FX liquidity increases

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

when funding conditions improve. On the other hand, FX liquidity decline with stronger demand pressure.

4. Explaining commonality in FX liquidity

In this section, we analyze common movements of FX liquidity. We proceed in three steps: First, we measure commonality in FX liquidity. Second, we study the commonality in distressed markets. Third, we analyze 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

$$\Delta L_{ij,t} = \alpha_{ij} + \beta_{ij} \Delta L_{M,t} + \varepsilon_{ij,t}, \tag{4}$$

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.[23]

[Figure 4 about here.]

As in Karolyi, Lee, and Dijk (2012), we use the R^2 as an indicator of commonality in liquidity (the adjusted R^2 is very similar since there are 255 data points and only two regressors). 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 by currency pair taken from the Bank of International Settlements 2013); (2) developed, but less-traded currency pairs; and (3) emerging currencies.

The figure delivers two main messages. First, commonality in FX liquidity is overall strong. The average R^2_{ij} across our sample of thirty currencies is 28%. Only two exchange rates have an R^2_{ij} lower than 10% (INR/USD, MXN/USD), suggesting that liquidity comoves for the vast majority of the currencies. This implies that there are periods

[23] 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.

when the entire FX market is systematically liquid or illiquid. Second, FX commonality is stronger for developed currencies (R^2_{ij} values of around 32% 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 consideration 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 (i.e. increase of global risk, as proxied by global stock and FX volatilities, and losses of carry trade portfolios).[24] Specifically, we extend the commonality regression (4) by adding the FX systematic liquidity interacted with a proxy for market stress (D_t)

$$\Delta L_{ij,t} = \alpha_{ij} + \beta_{ij} \Delta L_{M,t} + \gamma_{ij} \Delta L_{M,t} \cdot D_t + \varepsilon_{ij,t}. \tag{5}$$

[Table 6 about here.]

Table 6 presents results from panel regressions. (Average coefficients from individual regressions of specific FX rates are very similar.) The t-statistics (reported in brackets) are robust to heteroskedasticity as well as serial and cross-sectional correlations. Panel A uses the level of the market stress variable, panel B a logistic transformation,[25] and panel C a dummy variable equal to one if the stress variable is more than one standard deviation above its mean in period t.[26]

The overall evidence suggests a significant increase in commonality in periods of market stress. The γ_{ij} coefficient is significantly positive in all specifications, which

[24]As proxies of distressed markets, we also experimented with an increase in gross capital flows to GDP or a drop in FX dealer portfolio returns. The results are consistent with those reported in Table 6.

[25]The logistic transformation of the stress variable 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.

[26]Applying a stricter cutoff of 1.5 standard deviations gives very similar results (not tabulated).

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 (panel C) using the TED spread as stress variable indicate that the average R^2 increases from 26% to 43% when the TED spread is high. The results for the other stress variables are similar.

We corroborate this evidence by estimating panel models of a time-varying (logit transformation of) commonality $R^2_{ij,t}$ on the same stress variables as before.[27] The results (reported in the Internet Appendix) are consistent with those reported in Table 6.

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. Our findings show that commonality in FX liquidity increases with tighter funding constraints and higher global risk (proxied by global stock and FX volatilities), consistent with the supply-side explanation. Commonality also increases with losses of carry trade positions, evoking the risk borne by FX speculators to be caught into liquidity spirals and coordination-failure dynamics.

4.3 Cross-sectional determinants of FX commonality

As a final step, we investigate the cross-sectional determinants of commonality in FX liquidity. We run simple cross-sectional regressions of (a logit transformation of) commonality on country characteristics

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

where R^2_{ij} is from the commonality regression (4) and z_{ij} are characteristics of the currency pair.

Since the cross-section only contains 30 data points, we limit the multiple regression models to include no more than two variables that proved to be the most significant regressors in the single-regression analysis. Table A.4 in the appendix describes the variables that entered the single regressions, which are ordered in three broad groups: demand-side, supply-side variables, and controls. In turn, the demand-side and supply-side groups

[27]To perform this panel analysis, we compute $R^2_{ij,t}$ for each currency pair by running recursive commonality regressions on expanding data windows, but where old data is down weighted with exponentially declining weights.

are organized in three sub-categories (for the demand side: trade, portfolio balances, and institutional setting; for the supply side: funding, monetary, and banking conditions).

[Table 7 about here.]

Table 7 presents the main results. Higher central bank transparency and sovereign credit rating (both institutional variables), and higher GDP per capita (a control variable) are positively related with commonality, suggesting that these institutional features encourage common international trading. Intuitively, higher central bank transparency reduces adverse selection and inventory costs while better ratings decrease sovereign and currency risks attracting more international traders. On the other hand, commonality tends to be lower with higher local money market rates (a supply-side variable), suggesting that higher funding costs deter cross-border positions.[28] The R^2 values indicate that the credit ratings and GDP per capita have very high explanatory powers (61% and 56% respectively). The economic magnitude of these effects is considerable. In particular, an increase of one standard deviation in the central bank transparency index and in credit rating is associated with an increase in commonality R^2_{ij} of 9% and 15%; see column [1] and [2] in Table 7, respectively.

When combining the variables in multiple regressions, the GDP per capita and credit rating remain significant in all specifications. If we include all four variables, then none of them is significant (not tabulated). Despite the limited number of observations, the results in this section suggest that commonality in FX liquidity is stronger for developed currencies, especially those with good credit ratings, suggesting that these features induce common patterns across currencies.

5. Concluding Remarks

We provide an in-depth study of spot FX liquidity which has three main messages. First, FX liquidity can be measured accurately using low-frequency (daily) data that are readily available. This should help investors and researchers estimate transaction costs for a large panel of currencies going back more than two decades.

[28] All the regressors refer to the country representing the quoted currency. When we experimented with the sum the variables of both quoted and base currencies, we obtain similar results.

Second, FX liquidity is mainly affected by funding constraints and by global risk dynamics. This suggests that supply-side factors are important drivers of FX liquidity. It also suggests that FX traders are exposed to cross-market linkages, i.e. FX liquidity tends to decline with volatility and illiquidity of global stock and bond markets. These effects are even stronger for developed currencies and FX rates bearing larger exposure to risk factors such as those representing the investment leg of a classical carry trade strategy. These results suggest a new dimension of risk spillover effects, i.e. FX liquidity can be impaired in times of flight to quality and higher global risk. Furthermore, 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.

Third, supply-side factors are also important to explain commonality in FX liquidity (i.e. comovement of liquidity of one currency with systematic FX liquidity). Commonality increases in distressed markets, especially when funding constraints are tighter and global risk increases. Also, comovements strengthen when FX carry trade strategies incur substantial losses, i.e. exactly when FX speculators "rush to exit" and need liquidity to offload their positions. Commonality in FX liquidity is stronger for more developed currencies with better credit ratings. For policy makers, these results suggest that some institutional features typically highly praised such as financial integration and openness may expose currencies to global liquidity shocks.

Appendix

See Tables A.1–A.4.

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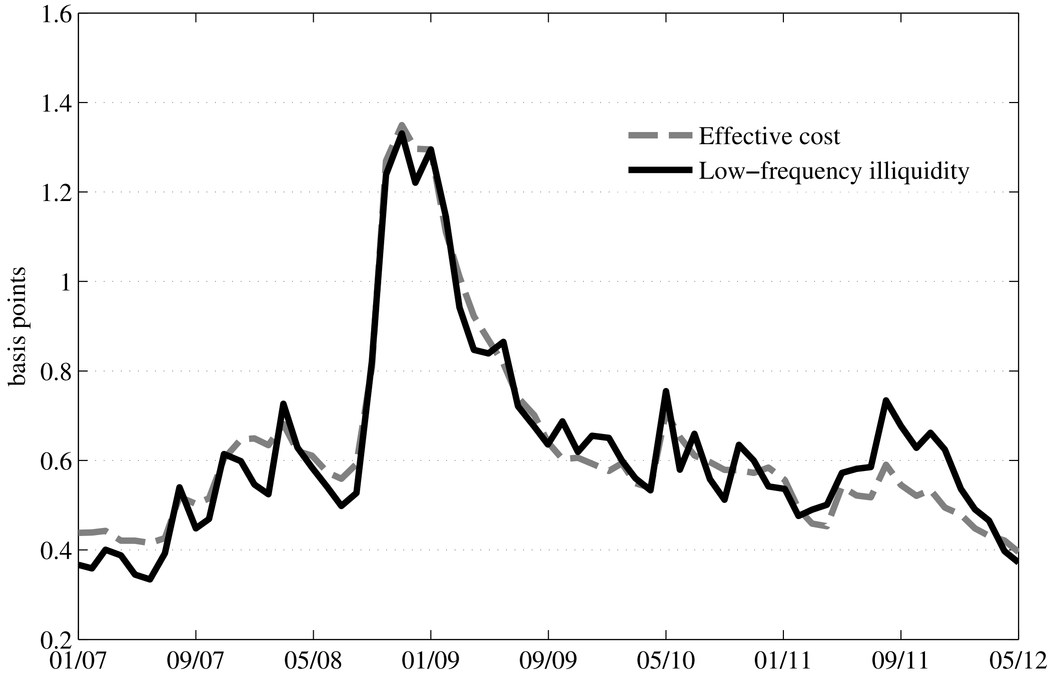

Figure 1: **Effective cost and systematic LF illiquidity.** The figure shows average (across exchange rates) high-frequency effective cost (dotted line) and systematic low-frequency (LF) illiquidity (solid line). The EC is the average across the nine exchange rates. The LF systematic illiquidity is constructed by first standardizing BA and CS for each exchange rate, calculating an average of them and then forming an average across the nine exchange rates. For illustrative purposes, the LF measure is then also rescaled to have the same average and volatility as the average EC. The sample is January 2007 – May 2012.

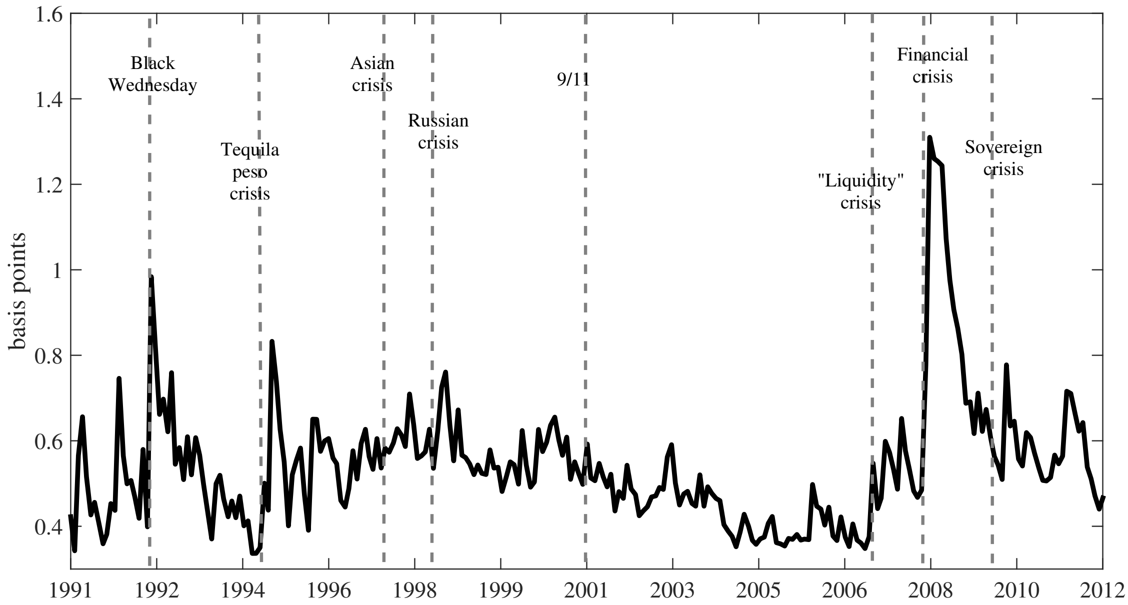

Figure 2: **Systematic LF illiquidity over 1991–2012.** The figure depicts the monthly average (across exchange rates) LF illiquidity. It is calculated as the average across thirty exchange rates, where the illiquidity of each exchange rates is the average of standardized LF BA and CS measures. The dotted lines indicate dates of some major events. The sample is January 1991 – May 2012.

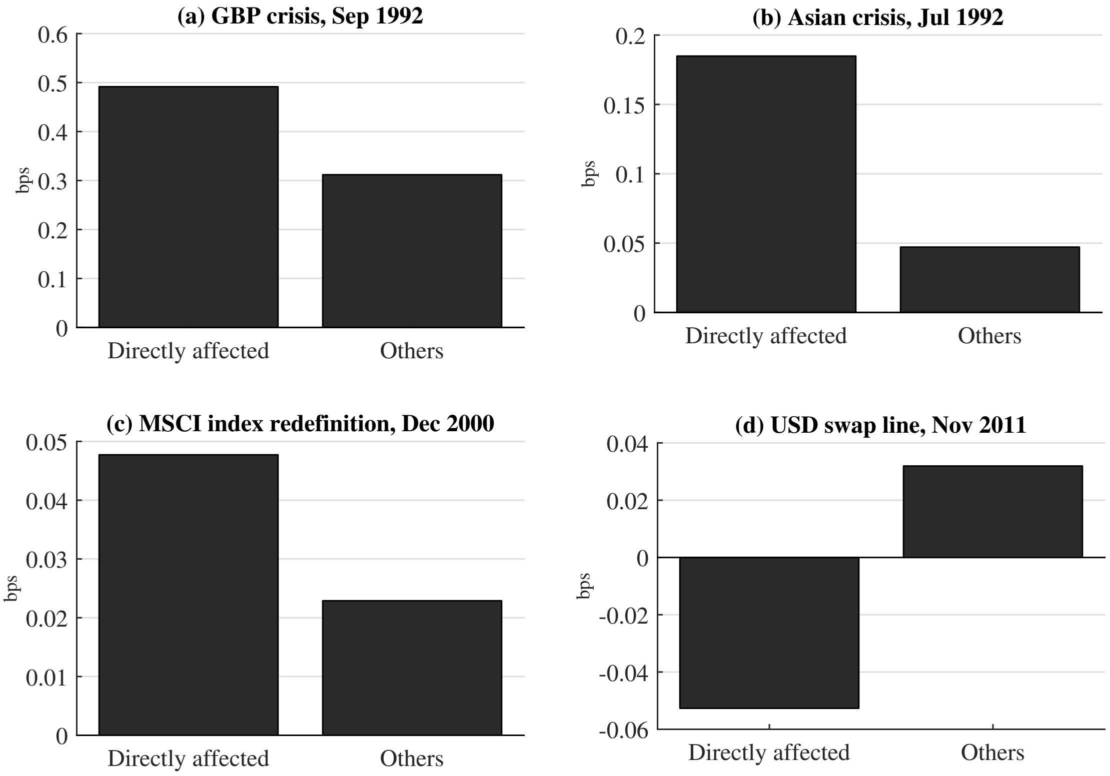

Figure 3: **Change in effective cost around four selected events.** The figure shows the change in effective cost around the four events: *(a)* the GBP-crisis in September 1992, *(b)* the Asian crisis in July 1997, *(c)* the announcement of the MSCI global equity index redefinition on December 1, 2000, 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).

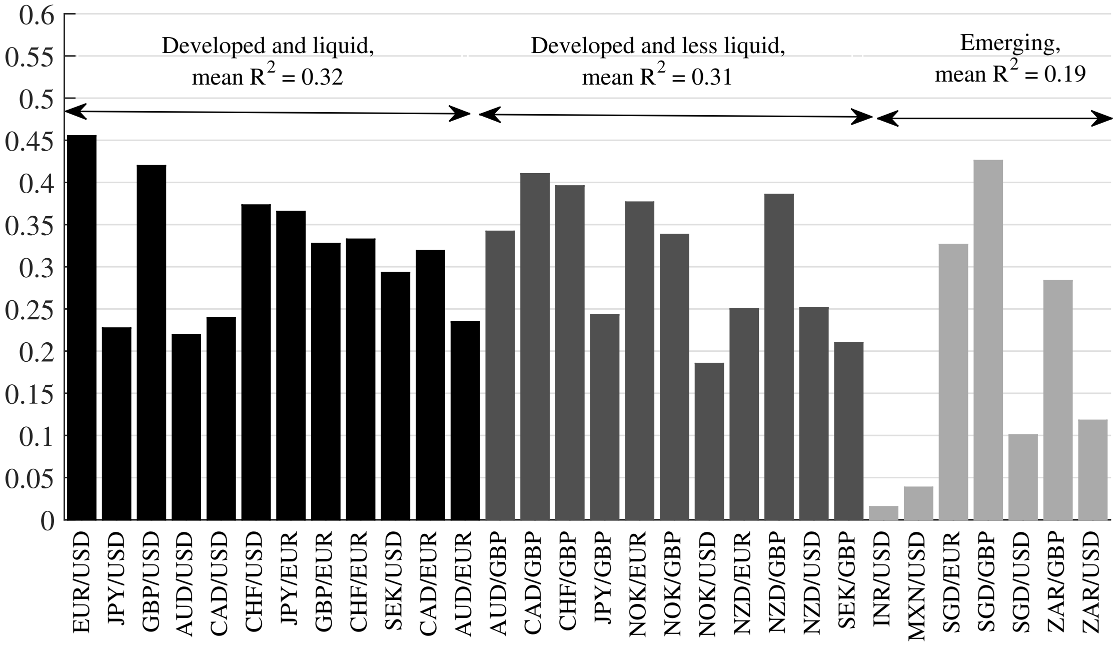

Figure 4: **Commonality in liquidity for each currency pair.** The figure shows the R^2_{ij} from regressing the liquidity of a currency pair on the systematic liquidity $\Delta L_{ij,t} = \alpha_{ij} + \beta_{ij}\Delta L_{M,t} + \varepsilon_{ij,t}$, where $\Delta L_{ij,t}$ is the monthly change of the 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 standardized *BA* and *CS*. 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.

	Panel A				*Panel B*		
	[1] BA	[2] CS	[3] Roll	[4] Gibbs	[5] Average of BA, CS	[6] Average of BA, CS, Gibbs	[7] OLS with BA, CS
AUD/USD	**0.70**	**0.59**	**0.62**	**0.65**	**0.77**	**0.79**	**0.79**
EUR/CHF	**0.49**	**0.70**	-0.04	**0.55**	**0.73**	**0.76**	**0.73**
EUR/GBP	**0.33**	**0.48**	**0.12**	**0.26**	**0.54**	**0.45**	**0.54**
EUR/JPY	**0.62**	**0.61**	**0.44**	**0.45**	**0.69**	**0.66**	**0.70**
EUR/USD	**0.44**	**0.37**	**0.23**	**0.34**	**0.51**	**0.57**	**0.54**
GBP/USD	**0.51**	**0.63**	**-0.07**	**0.21**	**0.69**	**0.54**	**0.70**
USD/CAD	**0.35**	**0.41**	**-0.11**	**0.35**	**0.50**	**0.51**	**0.50**
USD/CHF	**0.16**	**0.53**	-0.05	**0.37**	**0.50**	**0.58**	**0.54**
USD/JPY	**0.39**	**0.41**	**0.33**	**0.40**	**0.49**	**0.50**	**0.49**
Average	**0.44**	**0.53**	**0.16**	**0.40**	**0.60**	**0.60**	**0.61**

Table 1: **Correlations between monthly changes in effective cost and LF liquidity measures.** Panel A of the table shows (for each exchange rate) the correlations of changes in four low-frequency (LF) liquidity measures with changes of effective cost (*EC*). The monthly LF liquidity proxies are: *BA* is the relative bid-ask spread, *CS* from Corwin and Schultz (2012), *Roll* from Roll (1984) and *Gibbs* is from Hasbrouck (2009). The *BA* is from Bloomberg at 5 p.m. EST, while the other LF measures use Thomson Reuters at 10 p.m. GMT. *EC* is estimated by averaging the HF data over the month. Panel B of the table shows the correlations of three alternative versions of LF liquidity measures with changes in *EC*. The alternative versions are: [5] simple average across the *BA* and *CS*; [6] simple average across the *BA*, *CS*, and *Gibbs*; [7] fitted values from regressing the *EC* on the *BA* and *CS*. The bold correlations are statistically significant at the 5% level (GMM based test using a Newey-West covariance estimator with 4 lags).

	AUD/USD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	USD/CAD	USD/CHF	USD/JPY	Average
					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	0.577
Std. dev.	0.652	0.125	0.260	0.132	0.053	0.381	0.406	0.094	0.091	0.244
					Bid-ask spread/2 (LF), bp					
Mean	2.407	2.526	2.726	2.469	1.037	1.522	2.293	2.864	1.897	2.193
Median	1.925	2.396	2.222	2.359	0.893	1.370	2.013	2.493	1.703	1.931
Std. dev.	1.257	1.092	1.253	0.890	0.430	0.638	0.887	1.324	0.815	0.954
					Corwin-Schultz high-low estimate/2 (LF), bp					
Mean	0.323	0.167	0.211	0.311	0.238	0.233	0.249	0.250	0.240	0.247
Median	0.282	0.141	0.201	0.293	0.232	0.203	0.226	0.245	0.216	0.227
Std. dev.	0.173	0.095	0.088	0.139	0.099	0.112	0.102	0.085	0.103	0.111
					Roll measure/2 (LF), bp					
Mean	0.348	0.127	0.119	0.265	0.161	0.151	0.182	0.214	0.205	0.197
Median	0.670	0.324	0.428	0.621	0.496	0.477	0.496	0.575	0.537	0.514
Std. dev.	0.442	0.160	0.140	0.285	0.192	0.148	0.198	0.225	0.233	0.225
					Gibbs estimate/2 (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	0.215
Std. dev.	0.293	0.137	0.088	0.217	0.149	0.121	0.129	0.163	0.151	0.161

Table 2: **Monthly effective cost and LF illiquidity measures.** The table shows summary statistics for the high-frequency (HF) effective cost and four low-frequency (LF) measures of liquidity. Effective cost is the benchmark measure for HF illiquidity. Bid-ask (*BA*) is the average over daily relative bid-ask spreads from Bloomberg (snaps at 5 p.m. EST). The other LF measures use Thomson Reuters (at 10 p.m. GMT). The Corwin-Schultz (*CS*) measure is from Corwin and Schultz (2012), the *Roll* measure is from Roll (1984) and the *Gibbs* measure is computed as in Hasbrouck (2009). All the measures are in basis points (bp) and scaled to correspond to half the bid-ask spread. The last column shows the statistics for an average across currencies. The sample covers 65 months, January 2007 – May 2012.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
Demand-side												
Δ U.S. Gross capital flow / GDP	**-0.096**				-0.041				**-0.098**			
	[-3.281]				[-1.428]				[-2.726]			
Δ VIX		**-0.237**				-0.015				**-0.225**		
		[-3.958]				[-0.326]				[-3.954]		
Supply-side							-0.031					
Δ TED spread			**-0.088**				[-1.107]				**-0.109**	
			[-2.347]								[-2.527]	
Return on the 10 biggest FX dealers				0.026				-0.043				0.075
				[0.430]				[-1.201]				[1.879]
Market conditions												
USD appreciation	-0.055	-0.053	-0.052	-0.054								
	[-1.345]	[-1.514]	[-1.249]	[-1.310]								
MSCI return	0.097	-0.035	0.097	0.086								
	[1.715]	[-0.825]	[1.742]	[1.148]								
Δ AAA bond rates	0.015	0.028	0.028	0.024								
	[0.430]	[1.021]	[0.705]	[0.606]								
Δ FX volatility					**-0.281**	**-0.273**	**-0.276**	**-0.288**				
					[-5.093]	[-4.462]	[-5.007]	[-5.036]				
Δ MSCI volatility					**-0.092**	**-0.097**	**-0.099**	**-0.116**				
					[-2.315]	[-2.291]	[-2.369]	[-2.694]				
Δ Bond volatility					-0.004	-0.012	-0.004	-0.018				
					[-0.141]	[-0.390]	[-0.125]	[-0.585]				
Δ Stock liquidity									0.103	0.018	0.111	**0.113**
									[1.704]	[0.408]	[1.827]	[2.116]
Δ Bond liquidity									**0.225**	**0.142**	**0.207**	**0.196**
									[3.325]	[3.056]	[2.788]	[3.288]
Δ FX liqudity lagged									-0.074	**-0.110**	**-0.098**	**-0.102**
									[-1.854]	[-3.176]	[-2.656]	[-2.734]
Economic effect (using EC scale), bps	-0.060	-0.109	-0.031	0.006	-0.025	-0.007	-0.391	-0.009	-0.061	-0.103	-0.038	0.016
Economic effect, as a % of mean EC	-9.6%	-17.4%	-4.9%	0.9%	-4.0%	-1.1%	-62.1%	-1.5%	-9.8%	-16.4%	-6.1%	2.6%
R^2	0.030	0.057	0.029	0.021	0.121	0.119	0.120	0.121	0.085	0.105	0.088	0.082
Number of time periods	255	255	255	255	241	241	241	241	179	179	179	179
Number of exchange rates	30	30	30	30	30	30	30	30	30	30	30	30

Table 3: **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-side and supply-side factors as well as market conditions. The liquidity of each currency pair is the average across standardized *BA* and *CS* measures. 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 reflects the impact of each demand-side 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.

		Low	High	Low	High	Low	High
		GDP per capita		Forward premium		FX volatility	
	[1]	[2]		[3]		[4]	
Demand-side							
Δ U.S. Gross capital flow / GDP	-0.043	-0.042	-0.044	-0.064	-0.016	-0.027	-0.055
	[-1.406]	[-1.265]	[-1.348]	[-1.676]	[-0.569]	[-0.961]	[-1.412]
Δ VIX	-0.077	-0.086	-0.068	-0.089	-0.047	-0.043	-0.118
	[-1.493]	[-1.641]	[-1.117]	[-1.566]	[-0.782]	[-0.907]	[-1.668]
Supply-side							
Δ TED spread	**-0.056**	-0.046	**-0.068**	**-0.059**	-0.056	**-0.073**	-0.037
	[-2.066]	[-1.674]	[-2.186]	[-2.063]	[-1.624]	[-2.734]	[-0.904]
Market conditions							
MSCI return	-0.035	-0.049	-0.020	-0.036	-0.035	0.005	-0.083
	[-0.862]	[-1.126]	[-0.456]	[-0.642]	[-0.955]	[0.116]	[-1.618]
Δ FX volatility	**-0.306**	**-0.241**	**-0.377***	**-0.258**	**-0.389**	**-0.226**	**-0.411***
	[-5.098]	[-4.425]	[-5.113]	[-3.171]	[-7.249]	[-3.486]	[-6.560]
Δ MSCI volatility	-0.031	-0.042	-0.019	0.007	**-0.087**	-0.005	-0.058
	[-0.661]	[-1.027]	[-0.308]	[0.115]	[-2.098]	[-0.091]	[-1.110]
Δ Stock liquidity	-0.050	-0.017	-0.086	-0.059	-0.041	0.019	**-0.124**
	[-1.276]	[-0.405]	[-1.903]	[-1.421]	[-0.812]	[0.402]	[-2.768]
Δ Bond liquidity	**0.086**	**0.097**	0.073	**0.127**	0.028	0.059	**0.116**
	[2.186]	[2.059]	[1.891]	[2.631]	[0.638]	[1.471]	[2.319]
Δ FX liqudity lagged	-0.040	-0.065	-0.013	-0.044	-0.030	-0.030	-0.049
	[-1.102]	[-1.720]	[-0.305]	[-1.077]	[-0.772]	[-0.748]	[-1.196]
R^2	0.169	0.172		0.185		0.186	
Number of time periods	179	179		179		179	
Number of exchange rates	30	30		30		30	

Table 4: **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-side and supply-side factors as well as market conditions. Specifications [2]–[4] 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 [2] is one for the currency pairs of countries with GDP per capita above the median in that month. The dummy in specification [3] is one if a currency pair has a forward discount higher than the cross-sectional average in that month. The dummy in specification [4] 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 [2], low (high) forward premium in specification [3], and low (high) realized FX volatility in specification [4]. 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 [ΔVIX, ΔTED, ΔFX vol, Δstock vol, ΔFX liq]		
period	VIX shock	TED shock
0	**-0.210**	**-0.059**
	[-4.547]	[-2.802]
1	-0.023	**-0.101**
	[-0.672]	[-2.802]
2	-0.015	-0.032
	[-0.494]	[1.003]

Panel B. Seven-equation structural VAR [ΔVIX, ΔTED, ΔFX vol, Δstock vol, Δstock liq, Δbond liq, ΔFX liq]		
period	VIX shock	TED shock
0	**-0.227**	**-0.090**
	[-4.801]	[-2.296]
1	-0.040	**-0.128**
	[-0.221]	[-3.685]
2	-0.030	-0.014
	[-1.026]	[-0.454]

Table 5: **Impulse responses of liquidity on the demand-side and supply-side factors.** This table shows impulse responses of a panel of 30 FX rate liquidities with respect to shocks of one 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). All variables are in changes. *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. 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 number of time periods is 241, and the number of exchange rates is 30. The sample for Panel B is January 1995 – December 2009 (based on the availability of stock liquidity); the number of time periods is 179, the number of exchange rates is 30.

	Demand-side	Supply-side	Market conditions		
	VIX	TED spread	FX volatility	MSCI volatility	Carry trade losses
	[1]	[2]	[3]	[4]	[5]
Panel A. Linear factors					
β	**0.510**	**0.506**	**0.503**	**0.506**	**0.500**
γ	**0.013**	**0.012**	**0.012**	**0.010**	**0.015**
t-stat of γ	[5.031]	[7.214]	[5.546]	[5.920]	[6.583]
Panel B. Logistically transformed factors					
β	**0.466**	**0.450**	**0.438**	**0.450**	**0.451**
γ	**0.097**	**0.119**	**0.121**	**0.117**	**0.100**
t-stat of γ	[3.668]	[6.481]	[3.190]	[4.711]	[3.048]
Panel C. Dummy for the extreme values of factors					
β	**0.505**	**0.502**	**0.503**	**0.502**	**0.501**
γ	**0.046**	**0.058**	**0.047**	**0.055**	**0.038**
t-stat of γ	[2.866]	[4.414]	[2.865]	[3.879]	[2.044]
Sum(D_t)	30	27	22	25	38
Mean R^2 calm periods	0.259	0.257	0.231	0.253	0.233
Mean R^2 distressed periods	0.419	0.434	0.441	0.439	0.382
Number of time periods	255	255	241	255	255
Number of exchange rates	30	30	30	30	30

Table 6: **Commonality in liquidity in distressed markets.** This table shows results from panel regressions of liquidity on 30 FX rates $\Delta L_{ij,t}$ on the systematic FX liquidity $\Delta L_{M,t}$ and $\Delta L_{M,t}$, interacted with a variable D_t capturing distressed market periods, $\Delta L_{ij,t} = \alpha_{ij} + \beta \Delta L_{M,t} + \gamma \Delta L_{M,t} \cdot D_t + \varepsilon_{ij,t}$, 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 $L_{ij,t}$). In *Panel A*, D_t is the stress factor (in the respective column). In *Panel B*, D_t is a logistic transformation of the stress factor. In *Panel C*, D_t is a dummy equal to one if the stress factor is more than one standard deviation above its mean in period t. The intercepts are not tabulated. The t-statistics account for serial and cross-sectional correlations and is 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. Losses on a carry trade portfolio (three investment and three funding currencies) are based on sorting the currencies by their forward discounts in the previous month. The definitions of VIX, TED spread, FX volatility, and MSCI volatility are in Tables A.2 and A.3.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Demand-side							
Central bank transparency	**0.435**				0.217		
	[2.011]				[1.755]		
Sovereign credit ratings		**0.676**				**0.462**	
		[4.733]				[2.865]	
Supply-side							
Local money market rate			**-0.543**				-0.196
			[-3.949]				[-1.274]
Control							
ln (GDP pro capita)				**0.644**	**0.559**	**0.254**	**0.511**
				[4.371]	[4.684]	[1.999]	[2.724]
Economic effect I	0.091	0.147	-0.089	0.140			
Economic effect II	0.807	1.307	-0.790	1.238			
R^2	0.255	0.614	0.395	0.557	0.610	0.639	0.585
Number of exchange rates	30	30	30	30	30	30	30

Table 7: **Explaining cross-sectional variation in commonality.** This table shows the results from regressing logit transformations of commonality R^2_{ij} for 30 exchange rates on the fundamental factors, $\ln[R^2_{ij}/(1 - R^2_{ij})] = \alpha + \beta z_{ij} + \varepsilon_{ij}$. The commonality R^2_{ij} is from regression (4). The fundamental factors z_{ij} refer to the country representing the quoted currency. Economic effect I is the impact on the commonality R^2_{ij} of the change in the demand-side or supply-side factor of interest by one standard deviation. This effect is calculated as follows. The regression is of the type $\ln[R^2_{ij}/(1 - R^2_{ij})] = \alpha + \beta x/\sigma_x + \varepsilon$, 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} is $\exp(\alpha + \beta)/[1 + \exp(\alpha + \beta)] - \exp(\alpha)/[1 + \exp(\alpha)]$. Economic effect II is economic effect I scaled by the 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.

Measure	Source	Data frequency, time snap	Type of the data	Start of availability	Mean corr with EC
Effective cost (HF)	EBS	Second	Trade, Mid	2007	-
BA (LF)	B, BGN	Daily, 1700 EST	Bid, Ask, Mid	1996-1999	0.442
	B, BGN	Daily, 1800 GMT	Bid, Ask, Mid	1996-1999	0.162
	B, BGN	Daily, 2000 JST	Bid, Ask, Mid	1996-1999	0.100
	B, CMPN	Daily, 1700 EST	Bid, Ask, Mid	1996-1999	-0.017
	TR	Daily, 2100 GMT	Bid, Ask, Mid	1991	0.219
	WMR	Daily, 1600 GMT	Bid, Ask, Mid	1991	0.240
CS (LF)	B, BGN	Daily, 1700 EST	High, Low, Mid	1992-1999	0.513
	B, BGN	Daily, 1800 GMT	High, Low, Mid	1992-1999	0.504
	B, BGN	Daily, 2000 JST	High, Low, Mid	1992-1999	0.476
	B, CMPN	Daily, 1700 EST	High, Low, Mid	1992-1999	0.509
	TR	Daily, 2100 GMT	High, Low, Mid	1991	0.526
Roll (LF)	B, BGN	Daily, 1700 EST	Mid	1991	0.126
	B, BGN	Daily, 1800 GMT	Mid	1991	0.024
	B, BGN	Daily, 2000 JST	Mid	1991	0.049
	B, CMPN	Daily, 1700 EST	Mid	1991	0.123
	TR	Daily, 2100 GMT	Mid	1991	0.163
	WMR	Daily, 1600 GMT	Mid	1991	0.054
Gibbs (LF)	B, BGN	Daily, 1700 EST	Mid	1991	0.381
	B, BGN	Daily, 1800 GMT	Mid	1991	0.317
	B, BGN	Daily, 2000 JST	Mid	1991	0.292
	B, CMPN	Daily, 1700 EST	Mid	1991	0.379
	TR	Daily, 2100 GMT	Mid	1991	0.398
	WMR	Daily, 1600 GMT	Mid	1991	0.320

Table A.1. Description of the FX liquidity measures and data sources for their construction. The table uses the following abbreviations for the data source: EBS is Electronic Broking Services, B is Bloomberg, TR is Thomson Reuters, WMR is WM/Reuters. BGN and CMPN are two different methods used by Bloomberg to compile quotes, where CMPN uses fewer contributors. The last column shows the correlations between monthly changes in low-frequency (LF) liquidity measures and the high-frequency (HF) effective cost. The correlations are estimated on 65 months, January 2007 – May 2012. Effective cost is estimated by averaging the HF data over the month. The monthly LF liquidity proxies are: *BA* is the relative bid-ask spread, *CS* from Corwin and Schultz (2012), *Roll* from Roll (1984) and *Gibbs* is from Hasbrouck (2009).

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 U.S. 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 U.S. Treasury yield.	Federal Reserve Bank of St. Louis
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.	Own calculations based on Euromoney FX survey
b) Monetary conditions		
Δ U.S. Monetary aggregates / GDP	Changes in the U.S. monetary base scaled by the U.S. GDP	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.2. 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 stocks 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 BA and CS.	Own computations

Table A.3. Description of the monthly market conditions to explain liquidity and commonality in liquidity

Variable	Description	Source
Demand-side factors		
a) International Trade		
(Export + Import)/GDP	Export plus import of both countries forming the currency pair as a fraction of their GDP data; mean across annual data over 1991–2012	Datastream
Export QC to BC / GDP QC	Export from the QC country to the BC country, scaled by the QC GDP	Datastream
Export BC to QC / GDP BC	Export from the BC country to the QC country, scaled by the BC GDP	Datastream
Trade flow (gravity model)	Trade flow between QC and BC countries, measured as ln GDP of the QC country plus ln GDP of the BC country minus ln (Geographical distance between the two countries)	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 as a fraction of 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		
Central bank transparency	Index measuring the degree of transparency of the central bank on five fronts: political (openness about policy objectives), economic (economic information used for monetary policy), procedural (the way monetary policy decisions are taken), policy (prompt disclosure of policy decisions and indications of future actions), and operational; mean across annual data over 1998–2010	Dincer and Eichengreen (2014)
Central bank independence	Index measuring the degree of independence of the central bank's chief executive officer (CEO) in policy formulation and interventions as well as rules governing the appointment and dismissal of board members; data as of 2010	Dincer and Eichengreen (2014)
Sovereign credit ratings	Sovereign rating of the local currency long-term debt; average score across three main credit rating agencies S&P, Moody's and Fitch, across annual data over 1991–2012	Bloomberg
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
b) Monetary conditions		
Money supply / GDP	Monetary base scaled by GDP; mean over 1991–2012	Datastream
c) Banking		
Bank deposits / GDP	Bank deposits scaled by GDP; mean over 1991–2012	Datastream
Controls		
ln (GDP/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.4. Description of the cross-sectional factors to explain commonality in liquidity The table uses the following abbreviations: QC and BC denote Quoted and Base Currency forming the currency pair. Unless specified otherwise, the variables in this table refer to the country of the Quoted Currency.