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UNDERSTANDING FX LIQUIDITY

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Comments are welcome

Abstract

Previous studies of liquidity in the foreign exchange (FX) market span short time periods or focus on specific measures of liquidity. In contrast, we provide a comprehensive study of FX liquidity and commonality over more than two decades and a cross-section of forty exchange rates. After identifying the most accurate liquidity proxies based on low-frequency and readily available data, we show that commonality in FX liquidities is stronger for developed currencies and in highly volatile markets. We also show that FX liquidity deteriorates with risk in stock, bond and FX markets, and that riskier currencies are more exposed to liquidity drops.

Keywords: exchange rates, liquidity, transaction costs, commonality, low-frequency data.

JEL Classification: C15, F31, G12, G15

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1 Introduction

How does liquidity of the foreign exchange market (FX) evolve across time and how does it differ across currency pairs? Does FX liquidity deteriorate with an increase of risk in stock and bond markets? Do funding strains decrease FX liquidity? Does FX liquidity co-move with stock and bond market liquidities? Are riskier currencies more exposed to liquidity drops? Do common patterns in FX liquidity strengthen in highly volatile markets? In this paper, we address these relevant questions.

Financial markets need liquidity to function well. This is true also for the FX market that determines the relative values of currencies and any related assets. This paper provides a comprehensive study of FX liquidity and commonality. It defines the most accurate low-frequency liquidity measures and it offers a method to gauge FX liquidity on aggregate and currency-pair levels. More importantly, it documents when and for which currencies commonality in FX liquidities is stronger and which factors explain the time-series and cross-sectional variation of FX liquidity.

An in-depth understanding of FX liquidity is important for several reasons. First, illiquidity erodes asset returns and liquidity risk demands a premium (e.g. Amihud and Mendelson (1986)). This has been widely documented in the literature on stocks (e.g. Pàstor and Stambaugh (2003) and Acharya and Pedersen (2005)) and other assets but only recently on foreign exchange (Christiansen, Ranaldo, and Söderlind (2011), Banti, Phylaktis, and Sarno (2012), Mancini, Ranaldo, and Wrampelmeyer (2012)). However, a clear understanding of why and how FX illiquidity materializes is still missing. Second, a new strand of theoretical models (thereafter called "liquidity spirals theories") sheds light on the intricate linkages between market liquidity, funding liquidity and risk (e.g. Brunnermeier and Pedersen (2009) and Vayanos and Gromb (2002)). Empirically, Brunnermeier, Nagel, and Pedersen (2009) show that financial crises are typically associated with unwinding carry trade and liquidity drops (Brunnermeier, Nagel, and Pedersen (2009)) and Mancini, Ranaldo, and Wrampelmeyer (2012) show that after the Lehman bankruptcy, even the nine most liquid FX rates suffered from sharp liquidity drops. But more aspects need to be studied empirically. For instance, it is not clear how FX liquidity relates to developments of risk and return on the global asset markets and how individual FX rates react to distressed markets.

The FX market is the world's largest financial market with a daily average trading volume of four trillion U.S. dollars in 2013 (Bank of International Settlements (2013)). Liquidity in the FX market is crucial to guarantee efficiency and arbitrage conditions in many other markets including bonds and derivatives. Despite its importance, the literature on FX liquidity is scant or limited to specific measures such as the order flow[1] or the bid-ask spread based on indicative quotes.[2] Using high-frequency data from 2007 to 2009, Mancini, Ranaldo, and Wrampelmeyer (2012) provide an accurate measurement of FX liquidity. We closely follow this study to build our benchmark measures. However, none of the previous papers studies the possibility of accurately measuring FX liquidity and commonality in FX liquidities using low-frequency and readily available data. More importantly, none of the previous studies performs a comprehensive analysis of liquidity measures over an extended period of time (in our case, more than 20 years) and a large cross-section of currencies (in our case, forty exchange rates).

To address our research questions, we need to construct reliable liquidity measures from price data that are readily available on a daily frequency. Low-frequency liquidity measures are necessary since high-frequency data have several disadvantages, including a very limited access only to recent data, a restricted and delayed use, the need of time-consuming data handling and filtering techniques.

We use two main sources of data: first, low-frequency data from Thomson Reuters (a very common data provider) from which we compute many low-frequency liquidity measures widely used in the equity and bond literature. Second, high-frequency and sophisticated data from Electronic Broking Services (EBS), which is the leading platform for FX spot interdealer trading, from which we derive the benchmark measures of FX liquidity. Then, we compare the low-frequency and high-frequency measures on the nine mostly traded currency pairs over the period January 2007 to May 2012.

Due to the limited data sets with high-quality trade and quote data, researchers have for decades been looking for reliable low-frequency measures of market liquidity. Roll (1984) introduced a simple proxy for the effective spread that can be estimated using low-frequency data. A number of studies were later conducted to develop further liquidity proxies from daily data on the stock market (Lesmond, Ogden, and Trzcinka (1999),

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

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

Amihud (2002), Pàstor and Stambaugh (2003), Hasbrouck (2009), Holden (2009), Corwin and Schultz (2012)). With the increased importance of liquidity during the financial crisis, several papers addressed liquidity on the corporate bonds market (Bao, Pan, and Wang (2011), Dick-Nielsen, Feldhütter, and Lando (2012)), government bond market (Hu, Pan, and Wang (2012)), and OTC market (Deuskar, Gupta, and Subrahmanyam (2011)).[3]

Several studies compare low-frequency and high-frequency liquidity measures for stocks (Hasbrouck (2009), Goyenko, Holden, and Trzcinka (2009), Holden (2009), Fong, Holden, and Trzcinka (2011)) and commodities (Marshall, Nguyen, and Visaltanachoti (2012)), to provide a guide to the most accurate low-frequency measures in the absence of high-frequency information. But to our knowledge, there is no such study of FX liquidity. By identifying the best low-frequency liquidity measures, we therefore aim to fill a gap in the literature. This permits us to measure FX liquidity across a large panel of currency pairs, over an extended period of time.

We find that the *Corwin-Schultz* (Corwin and Schultz (2012)), the *Gibbs sampler estimate of Roll's model* (Hasbrouck (2009)), and *volatility* dominate other low-frequency measures in the sense of having the highest time-series correlation with the (high-frequency) benchmarks. For instance, the daily bid-ask spread based on daily snaps of indicative quotes and some other measures that often perform well in gauging liquidity in the stock and corporate bond markets work less well on the FX market.

Based on these findings, we construct a systematic low-frequency measure as the first principal component across the "best" low-frequency measures and across all currencies. Over January 2007 to May 2012, this measure has a 0.93 correlation with an effective cost liquidity measure constructed from the EBS data. We provide monthly estimates of the low-frequency FX liquidity measure based on forty currencies over January 1991 to May 2012.

[Figure 1 about here.]

The availability of reliable LF measures of FX liquidity is important in practice. For instance, one can estimate FX trading costs using the estimated coefficients by fitting low-frequency FX liquidity to high-frequency effective cost. To illustrate it, Figure 1 shows two historical cases, i.e. "the Black Wednesday" and "Lehman collapse" in September

[3] See Johann and Theissen (2013) for a recent and comprehensive survey.

1992 and 2008, respectively. In the earlier episode the British government was forced to withdraw the pound sterling from the European Exchange Rate Mechanism. The estimated effective spread on GBP/USD that was around 0.5 basis points in August 1992 increased approximately by three times. By the end of October 2008 after the Lehman bust, the effective spread measure on AUD/USD increased by 4 times (i.e. from 0.9 to 4.1 b.p.)! Both FX rates would have been involved in typical carry trade strategies since the money market rates in GBP and AUD were the highest (across the panel) while the USD money market rate was the lowest interest rates in August 1992 and the second-lowest rate in August 2008. Since any international portfolio position involves FX trading costs and eventually liquidity risk, LF measures of FX liquidities can help estimate (net) returns and risks related to international portfolio allocations.

After having found the most reliable low-frequency measures of FX liquidity, we can perform the main analysis of this paper, i.e. studying the properties of FX liquidity and commonality. First, we follow the previous literature on commonality in stock liquidities. We find strong commonality in FX liquidities, stronger than that on the stock market. Commonality is particularly remarkable for developed currencies and in highly volatile markets. We also find that FX liquidity comoves with stock and bond market liquidity suggesting cross-market liquidity movements.

Second, we find that FX systematic illiquidity can be explained by increases of risk in stock and bond markets in addition to FX risk–consistent with flight-to-quality or flight-to-liquidity episodes. Thus, we find that cross-markets linkages not only via volatility (Fleming, Kirby, and Ostdiek (1998)) but via illiquidity as well. These findings add to the extant literature on the interconnections between stock-bond illiquidity (Goyenko and Ukhov (2009)) by showing that FX liquidity is tied to stock and bond risk and liquidities. Our results are also in line with the liquidity spirals theories, i.e. an adverse shock and an increase in volatility trigger feedback loops between funding constraints and market illiquidity. In the last part of this paper, we analyze currency-pair liquidities. We find that riskier currencies are more exposed to liquidity drops. More specifically, liquidity of riskier currencies tends to decrease more with an increase of risk in stock and bond market as well as tighter funding constraints.

The paper proceeds as follows. Section 2 documents the data; sections 3 and 4 discusses the high-frequency and low-frequency methods, respectively; sections 5 and 6 present the results on FX systematic and currency-pair liquidities, respectively; section 7 concludes.

2 Data

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 and it is organized on a one-second basis (i.e. 86,400 observations per day). This rich source of information contains order and transaction data. From the order data, we use the prevailing bid and ask (offer) quotes. From the trading data, we keep track of the transaction price and trade direction (i.e. if the trade was buyer- or seller-initiated). From the trade direction, we compute the order flow as the number of buys minus the number of sells over a given period.

EBS quotes reliably represent the prevalent spot interdealer exchange rates. Dealers on the EBS platform are prescreened for credit and bilateral credit lines, which together with the continuously monitoring by the system, makes the potential counterparty risk virtually negligible.[4]

We use HF data on nine currency pairs, namely the AUD/USD, EUR/CHF, EUR/GBP, EUR/JPY, 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)). For every second, we compute log-returns using the midpoint of the best bid and ask quotes or alternatively, the transaction price. Observations between Friday 10 p.m. and Sunday 10 p.m. GMT are excluded, since only minimal trading activity is observed during these non-standard hours.[5]

The LF data are daily high, low, bid, ask and midquote prices as well as trading volumes from Datastream Thomson Reuters. Daily close bid, ask and midquote prices are snapped at 21:00 GMT. The data set covers 1991 to 2012 and it includes forty exchange rates (over 84% of daily average trading volume in April 2013). 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

[4]Chaboud, Chernenko, and Wright (2007) provide a descriptive study of the EBS data set.

[5]We drop U.S. holidays and other days with unusually light trading activity from the data set. We also remove a few obvious outlying observations. The internet appendix for Mancini, Ranaldo, and Wrampelmeyer (2012) discusses in detail the filtering procedure for the data.

Reuters.[6] To guarantee a consistent matching between HF and LF data, we consider the same set of trading days and we compute the daily measures from the EBS data taking 21:00 GMT as the end of the day. For one of our LF measures (*LOT*, see below), we also use the daily effective exchange rate computed by the U.S. Federal Reserve.

To link FX liquidity with the variables of the main asset classes, we use a large dataset of monthly return and risk measures on FX markets, US and global equity/corporate/government bond markets, money market and central bank rates. All the data are available from January 1991 except from JP FX implied volatility and stock market liquidity, which are accessible from April 1992 and January 1995, respectively. The description and sources of these variables is available in the internet appendix. The stock market liquidity is based on the PCA across price impact proxies of the monthly Amihud (2002) measure, calculated as the value-weighted average of all individual stock in each country. We use data from Karolyi, Lee, and Dijk (2012) to get the Amihud (2002) measure for each country, which currency appears in our sample of the forty exchange rates. The bond market liquidity is the off-the-run liquidity premium the yield difference between less and more liquid ("off-the-run" and "on-the-run") ten-year nominal Treasury bonds. The data on "off-the-run" bonds is from Gurkaynak, Sack, and Wright (2007), the data on "on-the-run" bonds is from the St. Louis FRED database.

3 High-frequency measures

The HF data allows us to compute very accurate estimates of liquidity in the FX market.

The effective cost (*EC*) captures the cost of executing a trade. The *EC* is computed by comparing transaction prices with the quotes prevailing at the time of execution as

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

with P denoting the transaction price, superscripts A and B ask and bid quotes, and $P = (P^A + P^B)/2$ the midquote price. Following the previous literature, we refer to the *EC* as the main benchmark measure for market liquidity.

[6] The ECU was an accounting unit made up of the sum of fixed amounts of 12 out of then 15 currencies of the European Union. The value of the ECU was calculated as weighted average of its component currencies, please see details at http://fx.sauder.ubc.ca/ECU.html. The ECU was replaced by the EUR on a one-for-one basis on 1 January 1999.

Another measure of transaction cost is the proportional quoted bid-ask spread, *BA*,

$$BA = (P^A - P^B)/P. \tag{2}$$

The price impact (*PI*) measures the FX return associated with the order flow (Kyle (1985)). Similarly, the return reversal (*RR*) shows the reversal of the price to the fundamental value after the initial price impact (Campbell, Grossman, and Wang (1993)). We estimate *PI* and *RR* from the linear regression

$$\Delta p_t = \vartheta + PI \times (\upsilon_{b,t} - \upsilon_{s,t}) + \sum_{k=1}^{5} \gamma_k(\upsilon_{b,t-k} - \upsilon_{s,t-k}) + \varepsilon_t, \tag{3}$$

where Δp_t is the change of the log midquote price between t and $t-1$, $\upsilon_{b,t}$ is the number of buyer-initiated trades and $\upsilon_{s,t}$ the number of seller-initiated trades at time t (i.e. the order flow). For each day, we estimate the parameter vector $[\vartheta, PI, \gamma_1 ... \gamma_5]$. The price impact *PI* is expected to be positive due to net buying pressure, while the return reversal *RR*= $\sum_{k=1}^{5} \gamma_k$ is expected to be negative.

The price dispersion (*PD*) or volatility is often used as an additional proxy for illiquidity (Chordia, Roll, and Subrahmanyam (2001)). To get a consistent and unbiased estimate, we use the two-scale nonparametric estimator (Aït-Sahalia, Mykland, and Zhang (2005)) of realized volatility.[7]

A liquid exchange rate is associated with a lower value of *EC*, *BA*, *PI*, *PD* as well as lower absolute value of (*RR*).

4 Low-frequency measures

For each exchange rate, we compute eight LF liquidity measures that are widely used in the literature on stock and bond liquidity. This section summarizes these measures, and more detailed information can be found in an internet appendix. We compute the LF measures for each month, but later we consider other granularities.

Roll (1984) shows that a transaction cost induces a bid-ask bounce, so the cost can be estimated from the (negative of the) autocovariance of the return process. Following

[7] We compute the effective cost, bid-ask spread, price impact, return reversal and price dispersion for each FX rate.

the previous literature, when the autocovariance is positive,[8] we substitute the transaction cost estimator with zero

$$Roll = \begin{cases} 2\sqrt{-\operatorname{Cov}(\Delta p_t, \Delta p_{t-1})}, & \text{when } \operatorname{Cov}(\Delta p_t, \Delta p_{t-1}) < 0, \\ 0, & \text{when } \operatorname{Cov}(\Delta p_t, \Delta p_{t-1}) \geqslant 0, \end{cases} \tag{4}$$

where Δp_t is the change of the log midquote price between t and $t-1$. The higher is the *Roll* spread, the lower is the liquidity. We compute the *Roll* estimate for each month in our sample using daily midquote prices.

The second LF liquidity measure is the gamma (*BPW*) measure put forward by Bao, Pan, and Wang (2011) to measure liquidity in the corporate bond market, defined as

$$BPW = -\operatorname{Cov}(\Delta p_t, \Delta p_{t-1}). \tag{5}$$

Clearly, this is very similar to the Roll measure. We compute the *BPW* measure for each month in our sample using daily midquote prices.

The third LF liquidity measure is the Bayesian *Gibbs* sampler estimate of the effective cost in the Roll model (Hasbrouck (2009)). The higher is the *Gibbs*, the lower is liquidity. We compute the *Gibbs* estimates for each month from the daily log midquote prices. We run each Gibbs sampler for 1000 sweeps and discard first 200 draws. We calibrate the prior for the transaction cost to get a good proxy of the HF benchmark.[9] Details are discussed in the robustness section.

The fourth LF liquidity measure is the relative bid-ask spread (*BA*) defined as in (2). A high *BA*, indicates low liquidity. We obtain monthly estimates of *BA* by averaging the daily bid-ask spreads.

The fifth LF liquidity measure is the high-low cost estimate *CS* from Corwin and Schultz (2012). The basic idea is that the bid-ask spread is unaffected by the horizon

[8]Positive autocovariances are not infrequent. For instance, Roll (1984) finds positive autocovariances in roughly half of his sample. Goyenko, Holden, and Trzcinka (2009) also use the modified version of the Roll estimator used in this paper.

[9]Joel Hasbrouck generously provides the programming code of the Gibbs estimation procedure on his web-site. We use this code for our estimations. This code uses a half-normal distribution - and we set (for each currency and month) the standard deviation of the transaction cost prior equal to $\sqrt{\overline{p}^A - \overline{p}^B}$, where $\overline{p}^A$ and $\overline{p}^B$ are the monthly averages of log ask and log bid prices, respectively. The estimates are robust to this choice, unless we choose a very small value.

while the variance scales with the horizon. The CS is calculated as

$$CS = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}}, \text{ with } \alpha = (1 + \sqrt{2})(\sqrt{\beta} - \sqrt{\gamma}), \tag{6}$$

where β is the sum (over two days) of the squared daily log(high/low) and γ is the squared log(high/low) but where the high (low) is over two days. To estimate on a monthly basis, we estimate spreads separately for each 2-day period and calculate the average across all overlapping 2-day periods in the month. The higher is the *CS*, the lower is the liquidity. Following Corwin and Schultz (2012), we correct for overnight returns and negative values (by setting the estimate to zero).

The sixth LF liquidity measure is the *Effective Tick* (*Efftick*) from Holden (2009) and Goyenko, Holden, and Trzcinka (2009). This method estimates the transaction cost from the clustering (relative frequency) of the last digits of the transaction prices. The basic idea is that price clustering signals more bargaining power of market makers and less competitive quotes. We implement the Holden method on daily midquote prices to get monthly estimates.

The seventh LF liquidity measure is the transaction cost estimator *LOT* from Lesmond, Ogden, and Trzcinka (1999). Its rationale is that the marginal investor trades only if expected gains outweigh the costs of trading. In this model, returns of a specific asset are benchmarked against market returns. We implement this idea by benchmarking currency-pair returns to the USD effective exchange rate.[10] In line with Lesmond, Ogden, and Trzcinka (1999), we define the three regions for FX returns (equal to zero, positive and negative) and we perform a maximum likelihood estimation on daily returns for each month.[11]

Finally, the eighth LF liquidity measure is an estimate of realized *Volatility*. Following Menkhoff, Sarno, Schmeling, and Schrimpf (2012a), we calculate monthly averages of the daily absolute returns. Although the microstructure theory relates transaction costs to volatility in various ways (e.g. directly as in Roll (1984) and through inventory risk (e.g., Stoll (1978)) and probability of informed trading (e.g., Glosten and Milgrom (1985)), volatility is clearly an indirect measure of FX liquidity that has been commonly used in the literature (e.g., Chordia, Roll, and Subrahmanyam (2001)).

[10] The USD effective exchange rate represents the "market" trade-weighted value of the USD against the other currencies.

[11] We are very grateful to David Lesmond for providing us with the code for computing the LOT measure.

5 Results on measuring FX liquidity

5.1 Results for high-frequency liquidity measures

Using the EBS data set over January 2007 – May 2012, we estimate effective cost and four alternative HF liquidity measures (bid-ask spread, price impact, return reversal, and price dispersion) for each month and each exchange rate.

The full descriptive statistics are found in an internet appendix, but the following are worth mentioning. First, average effective costs are smaller than average bid-ask spreads, reflecting within-quote trading. Second, the average return reversal (temporary price change accompanying order flow) is negative and the order flow price impact is positive for all exchange rates. Third, comparing liquidity estimates across currencies, we observe a substantial cross-sectional variation in which EUR/USD is the most liquid exchange rate, while AUD/USD is the least liquid.

For the subsequent analysis we standardize each monthly HF liquidity measure for each currency by subtracting the time-series mean and dividing by the standard deviation. After the standardization process, we use the first principal component to construct across-currencies liquidity measures (one for each method: *EC*, *BA*, *PI*, *RR*, and *PD*).

[Table 1 about here.]

The evidence in Table 1 indicate strong comovements among liquidity measures: the lowest correlation of different across-currencies measures is 0.89. This means that all these HF liquidity measures are very similar.

[Figure 2 about here.]

Looking at the dynamics of the HF effective cost in Figure 2 (dotted line, disregard the other line for now), it is clear that liquidity is fairly persistent (autocorrelated). Liquidity was quite stable from January 2007 to mid 2008, followed by a substantial drop in September 2008 to November 2008. The decline reflected the collapse of Lehman Brothers together with the increased turmoil and uncertainty after the bankruptcy. Liquidity gradually recovered during 2009, but was still below the pre-crisis level at the end of 2009. We observe a contraction of liquidity when the European sovereign debt crisis intensified in early 2010. During the first half of 2012, liquidity was visibly improving, being quite close to the pre-crisis level in May 2012.

5.2 Results for low-frequency liquidity measures

In this section, we identify the *best low-frequency FX liquidity measures*—defined as the ones with the highest correlation with the high-frequency benchmark. The aim is to give guidance for the estimation of FX liquidity over a long time span and many currencies (where only daily data is available) and to circumvent various other limitations imposed by high-frequency data.

We use daily midquote, bid, ask, high, and low prices from Thomson Reuters on the same nine currency pairs as above and over the same time period to compute eight different LF liquidity measures. We compute the liquidity measures for each month and for each exchange rate. The full descriptive statistics are found in an internet appendix, but it can be noticed that the LF measures have much larger cross-sectional differences than the HF measures.

Following the literature on evaluating the performance of LF liquidity measures (see e.g. Goyenko, Holden, and Trzcinka (2009) Hasbrouck (2009), Corwin and Schultz (2012), Marshall, Nguyen, and Visaltanachoti (2012)), we *compare the LF liquidities with the effective cost* computed from the high-frequency EBS data. Given the very high correlation between the HF liquidity measures (as demonstrated above), the choice of HF benchmark is not crucial.

[Table 2 about here.]

Table 2 reports the times-series correlations of each LF liquidity measure for each exchange rate with their respective HF effective cost benchmark. Boldfaced numbers are different from zero at the 5% significance level.[12] The *Volatility* measure has the highest average (across exchange rates) correlation at 0.81, followed by the *CS* and *Gibbs* measures with 0.71 and 0.70 average correlations. Notice also that, for each individual exchange rate, the correlation coefficients between these three best measures and the HF benchmark is always above 0.51 (the lowest value is *CS* for the EUR/USD). Among the other measures, *LOT* has a mild average correlation at 0.43. The *Roll*, *BPW*, and *EffTick* show poor performance, having average correlations with the effective cost measures of 0.30, 0.10, and 0.06, respectively.

To confirm the findings from individual exchange rates, we now consider the evidence for across-currencies measures. That is, for each standardized LF liquidity measure, we

[12] We apply a GMM based test using a Newey-West covariance estimator with 4 lags.

calculate the first principal component across exchange rates. We compare these LF measures with the HF across-currencies effective cost (the first principal component across currencies of the effective cost).

[Table 3 about here.]

Table 3 shows how the LF liquidities correlate with the across-currencies effective cost (*EC*). For the full sample (January 2007 to May 2012), shown on top, the findings are similar to those for individual currencies: the *CS*, *Gibbs* and *Volatility* measures outperform the other measures.

To study the consistency of performance across time, we break the time-series correlations down by sub-periods in the rest of Table 3. Specifically, we compute time-series correlations for three sub-periods: the pre-Lehman period, the Lehman bankruptcy and the successive turmoil, and finally, the European sovereign debt crisis. Despite the limited number of observations (only 18 months in each of the first two sub-periods) which cautions against drawing strong conclusions, some patterns are clear. In particular, the *BPW* and *EffTick* measures both perform poorly at the peak of the U.S. financial crisis. Thus, a weakness of these two measures is that their estimates of FX liquidity can severely be biased by market conditions. In contrast, the *CS*, *Gibbs* and *Volatility* measures (once again) perform well in all three sub-periods (the correlation with the HF benchmark is always above 0.76).

To summarize, Tables 2–3 suggest that some of the LF liquidity measures (*CS*, *Gibbs*, and *Volatility*) provide accurate proxies of the HF benchmark. The other LF measures have low and/or unstable correlations with the HF benchmark.

The previous evidence suggests that some LF measures perform worse on the FX market than on the stock and bond markets (see e.g. Goyenko, Holden, and Trzcinka (2009)). One reason for the poor performance of the *Roll* measure can be that the FX market is inherently more liquid. In this regard, Harris (1990) points to significant deterioration of the *Roll* estimator performance when the spread gets smaller (i.e. for more liquid stocks). Another problem could be due to the use of indicative quotes rather than actual transaction prices, as it is the case for FX data. Being estimated from daily midquote prices rather than transaction prices, the *Roll* measure may underestimate the transaction costs. The *BPW* measure, originally designed for corporate bond liquidity, may suffer for the same reasons. The indicative quotes probably affect also the *BA*. In addition, the timing

(21.00 GMT) of the daily bid-ask spread seems to lead to a noisy and unrepresentative measure of the transaction costs.[13] Finally, the poor performance of the *EffTick* measure as a proxy of FX liquidity may be due to the specific characteristics of the FX data. In fact, the number of digits after the point in daily bid and ask quotes can deviate from 1 to 5 during a single month, distorting the *EffTick* estimates.

To sum up, we provide evidence that the *CS*, *Gibbs*, and *Volatility* measures give the best proxies of the HF liquidity benchmark on the FX market. This conclusion is substantiated by the comparison between LF and HF measures, by consistent time-series patterns and by cross-sectional evaluations.

5.3 Quote-based measures

Trading volume data are not readily available for FX markets. A method to approximate trading volume proposed in FX literature is the quote frequency, i.e. the number of quote revisions over a given period (e.g. Melvin and Yin (2000)). In this section we apply this method to extend the set of LF liquidity measures by three quote-based measures of price impact, namely the liquidity measures proposed by Amihud (2002), Pàstor and Stambaugh (2003) and the so-called Amivest measure from Cooper, Groth, and Avera (1985) and Amihud, Mendelson, and Lauterbach (1997). These measures require daily number of quote revisions, which are available only from January 2007. They are therefore not useful for calculating LF measures for a long sample period (which is our main goal), but of independent interest.

Table 4 shows correlations of the across-currencies quote based LF measures with the HF effective cost benchmark. The *Amihud* performs relatively well: the correlation for the entire sample (January 2007 to May 2012) is 0.82, and the correlation coefficient is reasonably stable (0.65 to 0.92) across sub-periods. In contrast, the *Amivest* performs only modestly well and is less consistent (with correlations ranging from -0.37 to -0.82). The *Pastor-Stambaugh* measure is clearly the worst: it appears almost uncorrelated with the HF effective cost.[14]

[13]Thomson Reuters provides bid-ask quotes at 21:00 GMT based on the indicative data from the latest contributor, while the EBS data contains the best transactable bid and ask prices. Daily snaps of the EBS bid-ask at 21:00 GMT have weak correlations (0.04–0.28) with the Thomson Reuters daily bid-ask over the sample Jan 2007–May 2012, depending on the currency pair. The standard deviation of the Thomson Reuters bid-ask for the highly liquid FX rates (EUR/USD, EUR/CHF, USD/JPY) is more than twice as large as that from EBS.

[14]We also analyzed the Zeros measure from Lesmond, Ogden, and Trzcinka (1999) and the FHT measure

[Table 4 about here.]

The poor performance of the *Pastor-Stambaugh* is probably explained by two facts: it relies on a rough proxy of order flow (number of quote revisions signed by the direction of return) and it uses the lagged (instead of the contemporaneous) order flow.

5.4 Systematic low-frequency liquidity over 2007–2012

We now construct a systematic (market wide) LF liquidity (see Korajczyk and Sadka (2008)) by computing the first principal component across the nine exchange rates and the three best LF liquidity measures (*CS*, *Gibbs* and *Volatility*).[15] This is the solid line in Figure 2, while the dotted line is the HF effective cost discussed before. Clearly, the systematic LF liquidity and its HF benchmark share very similar patterns over the 65 months of our sample period: the correlation is 0.93.

[Table 5 about here.]

This evidence suggests that it is possible to measure systematic liquidity by combining the best LF measures by a principal component approach. Using an unweighted average instead of the first principal component gives very similar results (see robustness section for more details). However, it is not obvious that any of these methods attach the best weights to the different LF measures—in the sense of proxying for the HF measure as well as possible. We therefore also consider a regression approach.

Table 5, column 1, shows the regression of the monthly HF effective cost on the systematic LF liquidity. The coefficient is 0.93, highly significant and the coefficient of determination (R^2) is 0.86. Column 2 instead uses only LF volatility as the regressor—and it works equally well.

Columns 3 and 4 include also the other good LF measures–and that gives a small improvement in the R^2 (increases from 0.86 to 0.88). Given the high correlations between the different LF liquidity measures (potential multicollinearity issues), we orthogonalize the LF measures by applying rotating transformations before using them as regressors. In column (3) we let the first transformed factor be *Volatility*, while the second factor is

from Fong, Holden, and Trzcinka (2011). However, we discarded them due to the almost complete absence of daily zero returns.

[15]First principal component explains 59% of the total variation. For details, see internet appendix.

the residuals from regressing the *CS* on the *Volatility* and the third factor represents the residuals from regressing the *Gibbs* on the first two factors. In column (4), we switch the order of the *CS* (now third) and *Gibbs* (now second). The results suggest that both *CS* and *Gibbs* are useful.

Column (5) shows a specification based on only volatility and volatility interacted with a dummy that is one when there was an increase in volatility last month, and zero otherwise. This specification adds somewhat to the fit, but perhaps more interestingly, it shows that the relation between the HF effective cost and volatility is somewhat weaker when there has been a recent surge in volatility. Further nonlinear specifications give very small improvements in fit and therefore not reported.

Overall, the regression results shed light on which HF measures that are most important for proxying the HF effective cost and that a regression can improve the fit somewhat. However, it also shows that using the principal components approach is almost as good as the regression based "optimal" weights. Since the principal component approach is already well established in the literature (see eg. Korajczyk and Sadka (2008)), we will henceforth rely on this.

5.5 Granularity of the LF measures

The previous analysis shows that some LF measures provide good proxies of the HF effective cost on the *monthly frequency*. This section explores what happens at higher frequencies than a month.

This exercise is possible for only four measures. We compute the LF *Volatility* and *BA* on frequencies of 1 to 5 days as well as 1 to 4 weeks. In contrast, *CS* requires a minimum of two consecutive days and the *Gibbs* estimator seems to need at least five days of data to work.

[Figure 3 about here.]

Figure 3 plots the correlation of each of these four across-currencies LF measures with the across-currencies HF effective cost benchmark for different frequencies. Two findings emerge: first, as expected, the performance deteriorates at higher frequencies: the correlations with the HF benchmark are 0.66–0.93 on the four-week frequency and only 0.47–0.70 on the two-day frequency. However, the overall performance is fairly good down to the two-week frequency—and some of the measures (in particular, *Volatility*) seem to perform reasonably well even on the two-day frequency. Second, the systematic liquidity always provides the most precise technique to measure liquidity.

5.6 Systematic low-frequency liquidity over 1991–2012

High-frequency data is available only for a small number of exchange rates—and for very recent time periods. This severely restricts the possibility to calculate HF liquidity measures outside the major currencies and back in time. However, our previous analysis shows that it is possible to construct accurate liquidity proxies from low-frequency (daily) data. We now demonstrate the usefulness of that by considering a larger panel of exchange rates and by extending the sample period. The source of the LF data (Datastream Thomson Reuters) naturally defines the limits of the cross section and the length of the time series, which are 40 exchange rates and more than 20 years (from January 1991 to May 2012).

We compute monthly times series 1991–2012 of the *CS*, *Gibbs*, and *Volatility* measures for each exchange rate. For each measure, we also calculate the across-currencies measure (by the first principal component across the forty currency pairs). To create a measure of systematic FX liquidity we calculate the first principal component across the 120 data series (40 currency pairs, 3 measures).

[Table 6 about here.]

Table 6 shows the correlation coefficients between the LF measures. All correlations are very high, ranging from 0.81 to 0.97—so these different measures capture virtually the same time patterns.

Figure 4 shows the time series of the systematic liquidity measure. As references chosen arbitrarily, we have also indicated some major (financial and geopolitical) crises. While the turmoil around the Lehman bankruptcy caused the largest drop in systematic liquidity, there are also a number of other significant events, for instance, the ERM crisis (1992), the peso crisis (1994), the Russian default (1998) and 9/11 (2001). Looking at further details shows that the reaction to stock market events is mixed. There is a decline in FX liquidity after the October 1997 crash, perhaps some decline after the burst of the dotcom bubble (spring 2000) but very little response to the Enron scandal (Dec 2001). In addition, the systematic FX liquidity has a correlation of 0.67 with the VIX and only 0.51 with the TED spread. Overall, FX liquidity seems to share some time series patterns with other asset markets, but also contains some features that are not directly reflected by the stock market or measures of funding liquidity (TED spread). These preliminary findings motivate an in-depth understanding of the main drivers of FX liquidity that will be conducted in the next sessions.

[Figure 4 about here.]

5.7 Robustness checks

In this section, we briefly describe the main robustness checks and additional analysis. Further details are reported in an internet appendix.

First, we replicated our analysis by using other HF benchmarks than the HF effective cost. Overall, we obtain very similar results. Given the very high correlation between the HF liquidity measures (see Table 1), the choice of benchmark is not important.

Second, we changed the details of how the methods are implemented—and our main results are almost unchanged. For instance, in the Gibbs sampler, using a higher number of sweeps (up to 10000) or changing the prior of the transaction cost does not affect the mean parameter estimates materially. However, there are two exceptions to this finding: (a) setting the standard deviation of the prior to a very small value (eg. 0.001) gives estimates that are much less correlated with the HF benchmark; (b) when we study liquidity on a weekly instead of the monthly frequency, then the prior becomes more important. (The latter confirms the evidence in Hasbrouck (2009).) Similarly, in the LOT measure we replaced the effective exchange rate from the Fed with a simple average change in the dollar versus all the other currencies in the same spirit of "the dollar factor" (see Lustig and Verdelhan (2007)). The resulting LOT estimates have somewhat lower correlations with the effective cost benchmark.

Third, we have replaced the principal component analysis with straight or trimmed averages across currencies and/or liquidity measures. This has very small effects on our results, since the first principal component typically loads more or less equally on the currencies/measures. However, there is one exception to this finding: some of the across-currencies LF measures (for instance, in Table 3) have unequal (and even negative) loadings on the different exchange rates. This affects mostly the *BPW* and *EffTick* measures. When using a straight (or trimmed) average, these measures tend to perform even worse.

Fourth, we assessed the correlations of changes instead of levels for the different liquidity measures. Similarly to the analysis on levels, the *CS*, *Gibbs* and *Volatility* perform better than the other LF measures in terms of correlations with the HF effective cost benchmark.

Fifth, for the long sample 1991-2012, we also investigated the effect of using just the 9 main currencies instead of the full cross-section of 40 currencies. The results are very similar. For instance, the systematic liquidity measure from the 9 and the 40 currencies have a correlation of 0.97.

Finally, we found very similar results to those reported in Table 5 when we regress the across-currencies EC on LF liquidities using the quantile regression technique. Additionally, we found that the orthogonalized liquidity measures have significant coefficients in mid-quantiles, i.e. not when liquidity is extremely low or high.

6 Understanding FX liquidity

In the previous section, we showed that it is possible to accurately measure FX liquidity using low-frequency data. In this section, we try to understand FX liquidity by analyzing the commonality of FX liquidities and by relating FX liquidity to its possible drivers. We proceed in three steps: first, we study commonality in FX liquidity. Second, we regress FX systematic liquidity on returns, risk proxies and liquidites of the main asset classes. Finally, we extended this analysis to individual exchange rates. In most of our analysis, we take into separate consideration the few pegged currencies in our sample since a pegged exchange rate means that the central bank steps in as a liquidity provider.

6.1 Commonality in FX liquidity

Commonality in liquidity has been extensively analyzed in stock and bond markets (e.g. Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Chordia, Sarkar, and Subrahmanyam (2005), Korajczyk and Sadka (2008) and Karolyi, Lee, and Dijk (2012)). However, to our knowledge only two papers investigate commonality of FX liquidity. Mancini, Ranaldo, and Wrampelmeyer (2012) use HF data to study FX commonality of nine exchange rates during the recent financial crisis of 2007-9. Banti, Phylaktis, and Sarno (2012) use the institutional customer data provided by State Street Corporation to approximate the market order flow of 14 exchange rates over a period of 14 years and of six additional exchange rates over a shorter period. Here, we extend the FX literature by investigating FX commonality across a long period (1991-2012) and a large cross-section (40 currencies). This allows us to identify different patterns for developed and emerging currencies as well as the asymmetries of up- and down-markets.

We extend the analysis of commonality in FX liquidities following Chordia et al. (2000). We regress the changes of currency pair liquidity measures on changes of FX systematic liquidity

$$\triangle L_{j,t} = \alpha_j + \beta_j \triangle L_{M,t} + \varepsilon_{j,t} \tag{7}$$

where $\triangle L_{j,t}$ is, for FX rate j, the change from month $t-1$ to t in individual FX rate liquidity (obtained from the PCA across the three best LF liquidity proxies), and $\triangle L_{M,t}$ is the concurrent change in the systematic LF liquidity. We run the regressions over 257 months, Jan 1991 - May 2012. All estimated slope coefficients are positive and statistically significant at any conventional level.[16]

[Figure 5 about here.]

As in Karolyi, Lee, and Dijk (2012), we use the R-square as an indicator of commonality in liquidity. Figure 5 shows the R^2 for 40 currencies organized into three groups: (1) developed and much traded exchange rates (based on market share of FX market turnover by currency pair resulting from the Bank of International Settlements (2013)), (2) developed and less traded exchange rates and (3) emerging currencies. Solid black bars are for currencies that were not pegged at any time during our sample, shaded bars for currencies that were pegged for at least some time.

The figure has three main messages. First, commonality in FX liquidity is strong. The average R-square across our sample of 40 currencies is 36%. Only seven exchange rates have an R-square lower than 10% (several of which involved pegged currencies), suggesting that liquidity co-moves for the vast majority of the currencies. This implies that there are periods when the entire FX market is systematically illiquid or liquid.

Second, commonality of the FX market is stronger than that found in the stock market literature. Several papers find significant co-movement of liquidity in cross-sections of U.S. stocks (e.g. Datar, Naik, and Radcliffe (1998), Chordia, Roll, and Subrahmanyam

[16] Excluding exchange rate j in the computation of $\triangle L_{M,t}$ or including one lead and one lag of the systematic LF liquidity as additional regressors (i.e. $\triangle L_{M,t+1}$ and $\triangle L_{M,t-1}$) does not affect the results materially, see internet appendix for details.

(2000), Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001), A. (2005)). Karolyi, Lee, and Dijk (2012) show that commonality is also discernible across international stock markets. Our analysis suggests that comovement in liquidity is even more pervasive than previously documented for stocks (for instance, Korajczyk and Sadka (2008) find adjusted R^2 values ranging from 4% to 26%).

Third, our findings indicate that FX commonality is stronger for developed currencies (R^2 values of around 45% compared to around 20%). This holds also 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). Also, within the group of developed and liquid currencies (first group) there seem to be no relation between the more trading volume and commonality.

[Figure 6 about here.]

Figure 6 illustrates how the degree of commonality (for floating currencies) has changed across different time periods. Emerging currencies have lower commonality than developed currencies across all sub-periods, but they seem to be catching up. Since mid-2008 their average R^2 is 28%, compared with just 19% during the second half of the 1990s (when the Asian crisis drove down the liquidity for several of the emerging currencies in our cross-section).

[Table 7 about here.]

In the spirit of Hameed, Kang, and Viswanathan (2010), we test whether commonality in the FX market liquidity increases in distressed markets, associated with the drop in liquidity and tighter funding constraints. Specifically, we run the panel regression of individual FX rate liquidities on the FX systematic liquidity as well as the FX systematic liquidity interacted with a dummy for severely distressed markets.[17] Table 7 provides the evidence of significantly stronger FX market commonality in the periods of high volatility in FX, interest rate, stock markets as well as tighter funding conditions and sharp depreciation of exchange rates against the U.S. dollar.

[17] As in Hameed, Kang, and Viswanathan (2010), the dummy takes one if and only if the risk factor at time $t-1$ is more than 1.5 standard deviations above its unconditional mean

6.2 Explaining FX systematic liquidity

In this section, we try to identify some possible drivers of FX liquidity. The market microstructure literature suggests various frictions which may cause low liquidity, including participation and transaction costs, asymmetric information, imperfect competition, funding constraints and search costs. These frictions may be particularly relevant in a decentralized and opaque trading environment like the FX market.[18] These issues translate into several forms of risk (e.g. inventory and asymmetric information risks),[19] portfolio rebalancing and delegation that may affect time-variation and cross-sectional differences in FX liquidity.

One of the main tenets in FX literature is the parity condition, and that arbitrage trades push prices between two similar assets denominated in different currencies towards parity. This applies to fixed-income securities (e.g. covered and uncovered interest rate parity) and stocks (e.g. uncovered equity parity, as in Hau and Rey (2006)). No matter how trading strategies that exploit deviations from the parity condition are implemented, cross-market linkages between return and FX trading are likely to arise.

Market liquidity should also relate to risk. For instance, in flight-to-quality and flight-to-liquidity scenarios investors rebalance their portfolios toward less risky and more liquid securities (e.g. Beber, Brandt, and Kavajecz (2009)). A recent strand of the literature sheds light on the intricate dynamics between market liquidity, funding constraints and risk (e.g. Vayanos and Gromb (2002), Morris and Shin (2004), Vayanos (2004), Brunnermeier and Pedersen (2009), Garleanu and Pedersen (2007), Acharya and Viswanathan (2011)). While the exact mechanisms in the theoretical models above differ, they all predict that funding constraints and market illiquidity can generate spirals through fire-sales and increased risk.[20] This mechanism can spill over across various asset classes including FX markets, creating contagion and commonality in illiquidity (e.g. Xiong (2001) and Kyle and Xiong (2001)).

[Table 8 about here.]

[18]See Vayanos and Wang (2012) for excellent survey of the literature on market liquidity and Lyons (2001) for specific issues on FX microstructure.

[19]Inventory and the asymmetric information effects are documented in several papers, e.g. Lyons (2001) and Bjønnes and Rime (2005).

[20]The main idea behind these models is that large price fluctuations increase the demand for liquidity as agents liquidate their positions across many assets and reduce the supply of liquidity as liquidity providers hit their wealth or funding constraints.

On the one hand, the parity condition principle suggests that FX liquidity can be related to returns of FX and other assets such as bonds and stocks. On the other hand, the liquidity spirals theory implies a link between market illiquidity, risk and funding constraints. Below, we analyze whether FX liquidity is linked to returns and risk variables of the main asset classes, i.e. stocks, government and corporate bonds and FX. It should be kept in mind, however, that we make no attempts to control endogeneity and reverse causality, which may limit the economic interpretation of the analysis. We proceed in three steps: First, we construct a large dataset of monthly returns on FX markets, US and global equity/corporate/government bond markets, money market rates and central bank rates. Similarly, we consider several risk measures for each asset class. The list of these variables is available in the internet appendix. Second, we regress (changes of) FX systematic liquidity on each individual variable to identify the most significant variables within each asset class. Detailed results are reported in the internet appendix. The main idea is to isolate some possible "global factors" linked to FX liquidity. Third and finally, we estimate various encompassing models that include representative variables for the risk, return and liquidity of each asset class. Table 8 summarizes the main results. The regression models (1)-(4), (5)-(8) and (9)-(12) refer to the (changes of) FX systematic liquidity including all (floating) 32 currencies, developed currencies and emerging currencies, respectively.

Some clear patterns emerge. First, we can explain much of the variation in FX systematic liquidity. The R^2 values for the FX systematic liquidity for the 32 floating currencies are above 50% in several specifications. The separate analysis of (floating) developed and emerging currencies suggest that the global factors explain developed currencies better than the emerging currencies (higher R^2 values).

Second, the risk variables are more important than the return variables. A Wald test easily rejects the null hypothesis that the estimated coefficients of all risk variables are equal to zero. The coefficients of the risk variables have (with very few exceptions) negative signs, indicating that FX liquidity decreases with an increase of risk in each asset classes. In most specifications, the risk variables of bond and stock markets are significant (t-stats in brackets). This holds also when variables from the FX market are included. In addition, that FX liquidity of developed currencies is negatively related to the TED spread. Other measures of funding strains such as the Libor-OIS confirm the same result (see internet appendix). It is also worth noting that we replicated our analysis for all EUR and

GBP currency pairs. The results obtained taken the EUR and GBP as base currency are exactly in line with the findings reported here when the U.S. dollar is the base currency (see internet appendix). In general, our findings suggest that flight-to-liquidity dynamics and liquidity spirals theory explain better FX liquidity patterns. On the other hand, the parity condition theory, at least in its original risk-neutral framework, provides a weaker explanation for time-varying FX liquidity.

Third, we find significant commonality in liquidity between FX, stock and bond markets (see columns (3), (7) and (11) of Table 8). This finding extends the previous literature by showing that FX-stock-bonds commonality holds for both developed and emerging currencies. However, the importance of the stock liquidity is overshadowed by the other variables (see columns (4), (8) and (12)) — and the risk factors remain significant when we control for stock and bond liquidity.

6.3 Explaining FX currency-pair liquidities

This section extends the analysis in the previous section by studying the FX liquidity of individual exchange rates. We are particularly interested in whether the exposure to the global factors depends on the risk characteristics of the currency.

[Table 9 about here.]

The recent FX asset pricing literature shows that various types of risks are associated with FX excess returns. In the spirit of the factor model in Fama and French (1993), Lustig, Roussanov, and Verdelhan (2011) find that two risk factors can explain most of the variation in monthly carry trade returns. These factors are the U.S. dollar average currency return (denoted "FX return risk" thereafter) and the carry trade risk factor (denoted "carry trade risk"), given by a currency portfolio that is long in high interest rate currencies and short in low interest rate currencies. Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) show that "volatility risk" supplements the FX return and carry trade risk factors. Mancini, Ranaldo, and Wrampelmeyer (2012) illustrate that a "liquidity risk" factor also has a strong impact on carry trade returns. Motivated by these papers, we construct regression models referring to each one of the four risk categories discussed. We perform fixed-effect panel regressions in which (changes of) the liquidities of individual exchange rates are regressed on the global factors, interacted with dummies that represent the risk categories.

The t-stats of the coefficients are robust to cross-sectional correlations, using the Driscoll and Kraay (1998) covariance estimator. Table 9 presents the main findings.

As a validation of the panel approach, column 1 of Table 9 performs almost the same analysis as previously in Table 8, where the dependent variable was the change of the systematic liquidity for the floating currencies. However, there are two differences. First, the dependent variable is now a panel of currency-specific liquidities. Second, Table 9 applies a time-varying definition of whether a currency is floating or pegged. (In practice, this is done by interacting all global factors with a time-varying "floating dummy" and also with another "pegged dummy". The results for the latter are not reported.) Not surprisingly, the coefficients from the panel regression are in line with those found for the FX systematic liquidity: the same signs and the same degree of statistical significance as in Table 8.[21] However, the R-square is reduced to 0.12, since the panel contains much more idiosyncratic noise than the systematic liquidity.

The remaining columns in Table 9 introduce some specific dummy variables aimed at capturing risky currencies. Each specification is based in column (1), but adds a new dummy variable interacted with the global factors. For instance, the new dummy in column (2) in Table 9 is equal to one if a currency pair underperforms the cross-sectional average U.S. dollar return in that month (and the currency is floating). We interpret this dummy as capturing general FX return risk.[22] Hence, the new regression coefficients measure the extra exposure to the global factors for currencies that bear some FX return risk (and are floating).

In column (3) of Table 9, we instead use a carry trade risk dummy which is one if a currency pair has a forward premium (difference between monthly forward and current spot rate) higher than the cross-sectional average in that month (and the currency is floating).[23] In column (4), we use a volatility risk dummy which is equal to one if a currency pair has a higher realized volatility than the cross-sectional average in that month (and is floating). Volatility is measured as the monthly squared return. Finally, in column (5), liquidity risk is captured by a dummy variable equal to one if an exchange rate has

[21] The magnitude of the coefficients differs a bit compared to Table 8 since the various exchange rates are here given a different weighting than according to the principal component that defines the systematic liquidity.

[22] Conceptually, this variable can also be related to momentum strategies in FX markets, recently studied by e.g. Asness, Moskowitz, and Pedersen (2012), Burnside, Eichenbaum, and Rebelo (2011), and Menkhoff, Sarno, Schmeling, and Schrimpf (2012b).

[23] We exclude from the panel the observations, for which monthly forward data is not available.

stronger commonality (in terms of R^2 as in Figure 5) in FX liquidity than the sample average (and is floating). This last dummy variable is (in contrast to the other dummies) not time-varying.

The main result in Table 9 is that riskier currencies are more exposed to FX market liquidity drops. This pattern materializes in three ways. First, an increase in stock volatility and in default spreads is associated with more severe liquidity drops for those exchange rates that depreciate more against the U.S. dollar (column 2) and for those exchange rates with large volatility increases (column 4). Hence, the FX return risk and volatility risk strengthen the effects of the stock market and corporate bond risks. Second, the liquidity of those currencies more exposed to the carry trade risk deteriorates more with an increase of corporate bonds yields (column 3). Third, the liquidity risk appears to be more discernible in terms of funding liquidity risk, that is, as the TED spread increases (column 5), the liquidity tends to evaporate more for those currencies with stronger commonality in FX liquidity. Overall, these findings confirm that currency-pair liquidities and not only FX liquidity are related to global risk factors. Moreover, the exchange rates that bear larger risk premiums are more exposed to liquidity drops.

7 Concluding Remarks

This paper provides evidence that liquidity measures based on low-frequency (LF) data can reliably measure liquidity on the foreign exchange (FX) market. To do this, we compare LF measures based on readily available data to high-frequency (HF) measures based on data that are highly sophisticated but very limited and difficult to access.

We perform a comparative analysis between LF and HF measures using nine currency pairs that roughly captures three quarters of the daily average FX trading volume. Our sample period spans from January 2007 to May 2012, which includes a pre-crisis phase and the most recent financial turmoil. Comparing the monthly time series of eight LF liquidity measures to the HF effective cost (our benchmark), we find that three measures perform particularly well, namely *CS* (from Corwin and Schultz (2012)), *Gibbs* (from Hasbrouck (2009)), and *Volatility*. These liquidities measures have correlations of around 0.90 with the HF effective cost benchmark. Two other measures, the *LOT* measure from Lesmond, Ogden, and Trzcinka (1999) and the *BA* spread, do a worse, but still reasonably good job. In contrast, the *Roll* from Roll (1984), *BPW* from Bao, Pan, and Wang (2011) and *EffTick* from Holden (2009) are much less effective in gauging FX liquidity. We then combine the best LF measures for all currency pairs to construct an index of systematic FX liquidity. This index has a 0.93 correlation with the HF effective cost benchmark. This is evidence of that FX liquidity can be measured on the basis of readily available (daily) data and fairly simple methods.

In order to document the long-term pattern of FX liquidity, we compute the systematic LF liquidity index from 1991 across forty currency pairs. First, we analyze commonality in FX liquidities. Our results indicate strong commonality, especially for developed currencies and in highly volatile markets. Our findings also suggest that FX commonality is more pronounced than on stock markets and that FX liquidity of developed and emerging currencies is positively related to stock and bond market liquidity. Second, our study suggests that a substantial part of the common variation in currency liquidity is due to risk. FX illiquidity is tied to risk variables of the main asset markets consistent with the liquidity spirals theory and more in general, with flight-to-quality and flight-to-liquidity phenomena. Cross-sectionally, exchange rates bearing larger risk premiums identified by the recent FX asset pricing literature tend to be more exposed to liquidity drops.

Our findings are relevant for investors, policymakers and researchers. First, investors are interested in returns net of transaction costs. The liquidity measures analyzed in this study should help estimate transaction costs in FX markets. Second, for market participants the recent financial crisis has proved that liquidity can suddenly evaporate even on the FX market. More generally, our results suggest other channel of risk spillovers, i.e. from risk intensification in one market to illiquidity in another (the FX market, in this case). Third, liquidity issues dominate the agenda of policymakers, see e.g. the liquidity requirements in Basel III. Fourth and finally, researchers try to shed light on intricate market mechanisms, including the spiral dynamics between market liquidity and funding liquidity. All this calls for reliable methods and accessible data to gauge FX liquidity and in-depth understanding of liquidity issues on currency markets.

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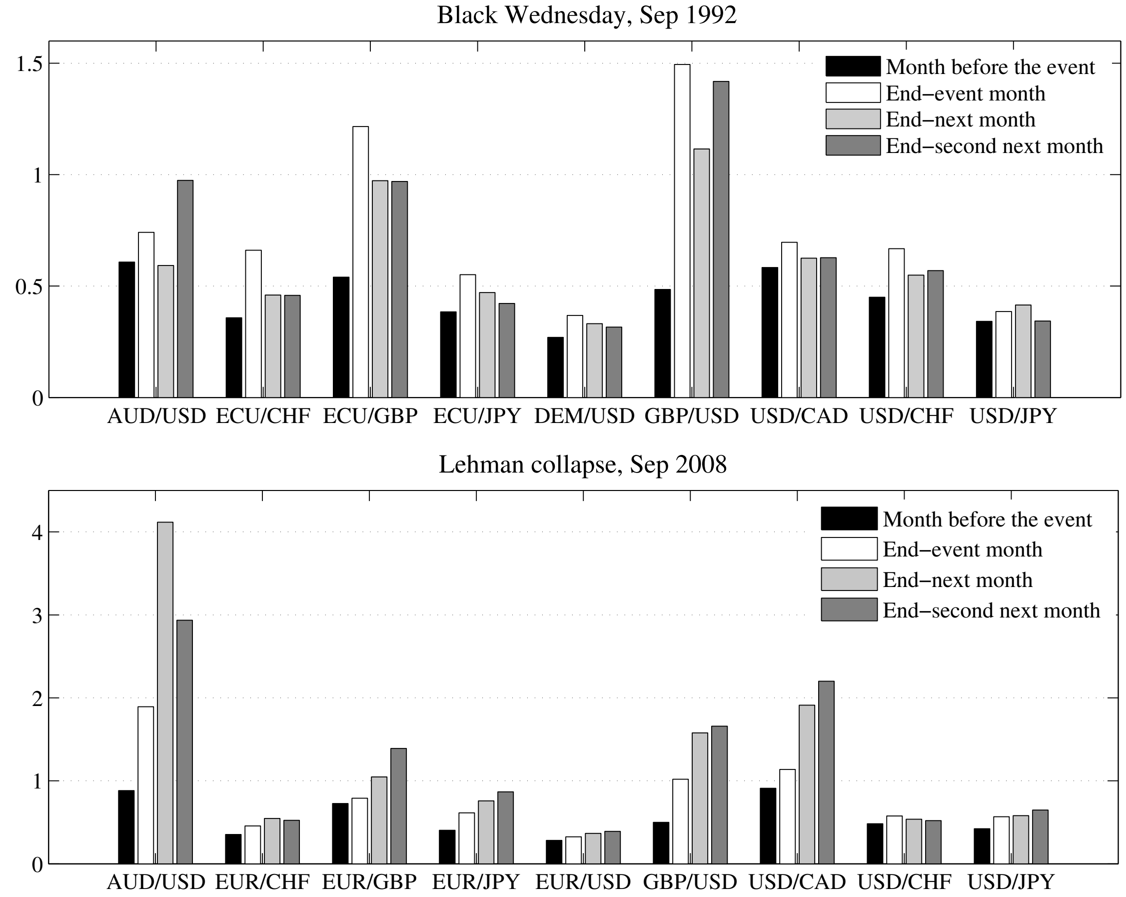

Figure 1: **Effect of the crisis events on the estimated EC.** Figure depicts the monthly estimated EC (in basis points) for 9 exchange rates before and after two crisis events: "the Black Wednesday" on 16 September 1992 and "Lehman collapse" on 15 September 2008. The estimated Effective Cost (EC) for FX rate i is calculated from $EC_i^{est} = \alpha + \beta L_i$, where L_i is the low-frequency currency pair liquidity ($i = 1...9$), α and β are taken from regressions $EC_i = \alpha + \beta L_i + \varepsilon$, performed over 2007 - 2012 with the actual high-frequency EC as the dependent variable. The R^2 values from these nine regressions range from 46% to 82% and are on average 66%. The low-frequency currency pair liquidity is obtained from the PCA across three best LF liquidity proxies (*CS*, *Gibbs* and *Volatility*).

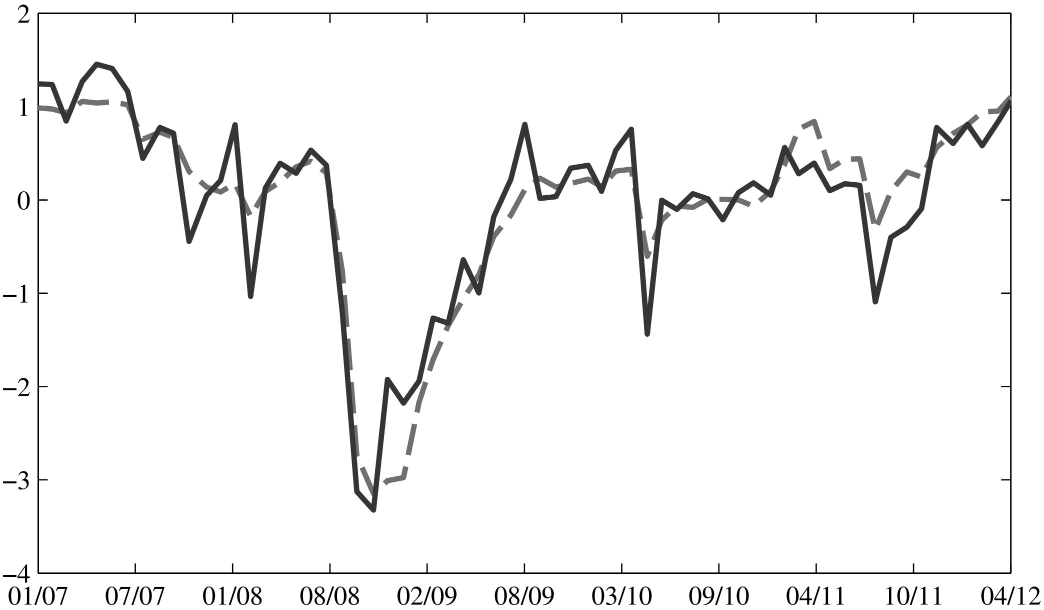

Figure 2: **Across-currencies effective cost (HF) vs. systematic low-frequency (LF) liquidity.** The across-currencies effective cost liquidity is obtained from the PCA across exchange rates (dotted line). The systematic LF liquidity is obtained from the PCA across exchange rates as well as three best LF liquidity measures (*CS*, *Gibbs* and *Volatility*). Both measures are standardized. The sign of each liquidity measure is adjusted such that the measure represents liquidity rather than illiquidity. The sample is January 2007 – May 2012, 65 months.

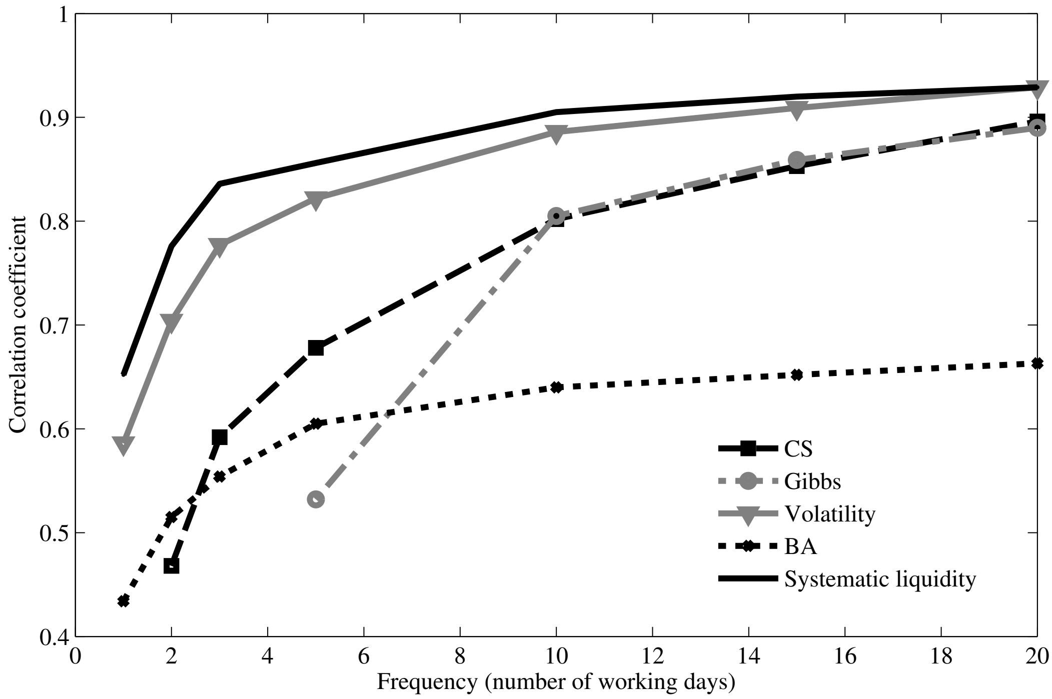

Figure 3: **Low-frequency (LF) liquidity measures based on different frequencies vs effective cost liquidity.** Each line represents the correlations of the LF liquidity measures based on different frequencies with the effective cost benchmark. Whenever it is possible, each liquidity measure is computed for one, two, three days and for one, two and four weeks. LF liquidity measures include across-currencies *CS*, *Gibbs*, *Volatility*, *BA*, and systematic LF liquidity. The systematic LF liquidity is based on the PCA across the FX rates as well as across the best LF measures available at each frequency (*Volatility* and *BA* on one-day; *Volatility*, *CS* and *BA* on two- and three-day; *Volatility*, *Gibbs* and *CS* from five-day frequency up). The sample is January 2007 – May 2012.

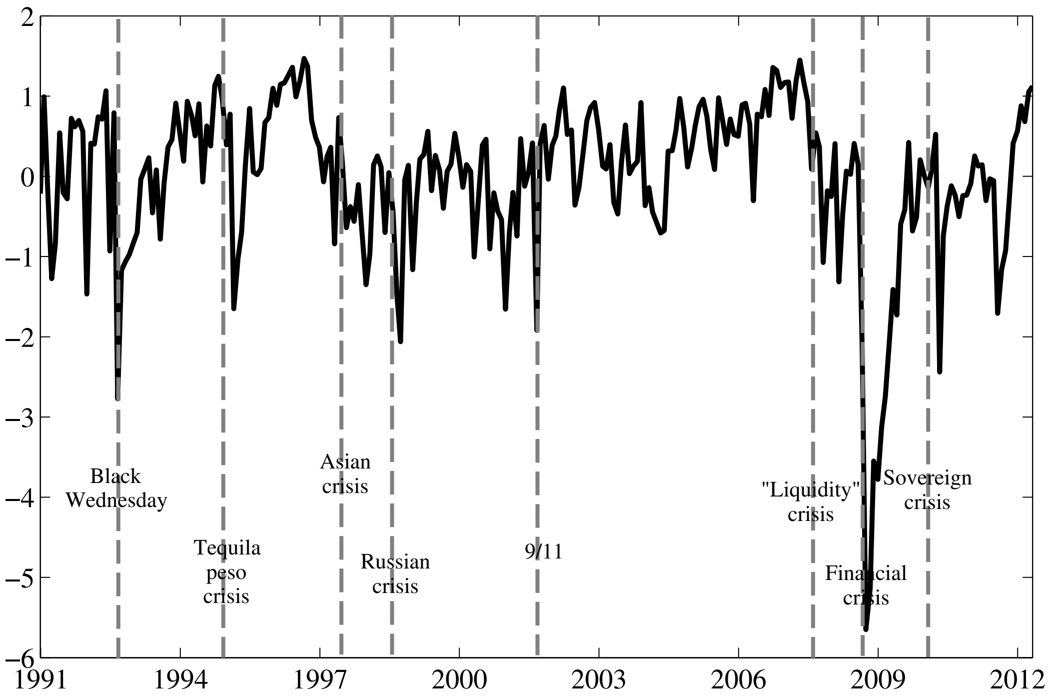

Figure 4: **Systematic low-frequency (LF) FX liquidity over 1991–2012.** Figure depicts the monthly standardized systematic LF liquidity obtained from the PCA across the 40 exchange rates as well as three best LF liquidity proxies (*CS*, *Gibbs* and *Volatility*). The sign of each liquidity measure is adjusted such that the measure represents liquidity rather than illiquidity. The dotted lines denote the dates of financial and geopolitical crises over 1991–2012. The sample is January 1991 – May 2012, 257 months.

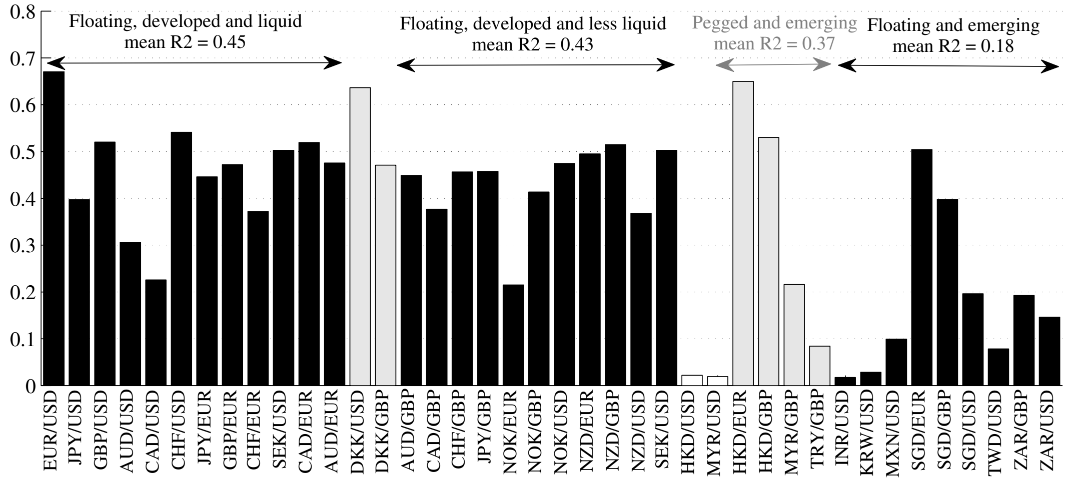

Figure 5: **Commonality in the FX liquidity for each currency pair.** The Figure shows the R^2 from regressing individual FX liquidities on the systematic LF liquidity. The individual FX rate liquidities are obtained from the PCA across the three best LF liquidity proxies (*CS*, *Gibbs* and *Volatility*) for each currency pair. The systematic LF liquidity is obtained from the PCA across the 40 exchange rates as well as the three best LF liquidity proxies. For each exchange rate, its liquidity is regressed on the systematic LF liquidity. Each bar represents the R^2 from these regressions. The exchange rates in the developed and liquid group are sorted according to their FX market turnover in April 2010 (Bank of International Settlements (2013)), starting from the highest turnover (on the left). The exchange rates in all the other groups are sorted alphabetically. White bars denote the pegged currency pairs. Grey bars denote the currency pairs, where one currency in a pair is pegged to the currency outside the pair. The sample is January 1991 – May 2012, 257 months.

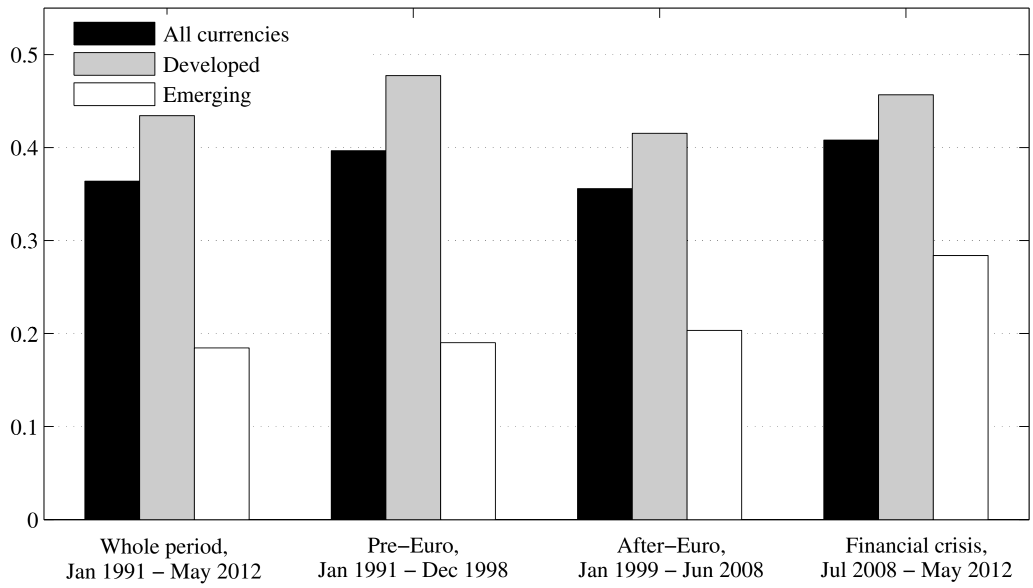

Figure 6: **Commonality in the FX liquidity by groups and sub-periods.** The Figure shows the average R^2 from regressing individual FX liquidities on the systematic LF liquidity for different groups of non-pegged currencies and for different periods. The groups of (floating) currencies are: all 32 currencies, 23 developed and 9 emerging. The periods are: whole period (Jan 1991 - May 2012), pre-Euro (Jan 1991 - Dec 1998), after-Euro (Jan 1999 - Jun 2008) and financial crisis (Jul 2008 - May 2012). The individual FX rate liquidities are obtained from the PCA across the three best LF liquidity proxies (*CS*, *Gibbs* and *Volatility*) for each currency pair. The systematic LF liquidity is obtained from the PCA across the 40 exchange rates as well as the three best LF liquidity proxies. The sample is January 1991 – May 2012, 257 months.

	EC	BA	PI	RR	PD
Effective cost	**1**				
Bid-ask	**0.985**	**1**			
Price impact	**0.963**	**0.946**	**1**		
Return reversal	**-0.939**	**-0.951**	**-0.917**	**1**	
Price dispersion	**0.940**	**0.947**	**0.898**	**-0.937**	**1**

Table 1: **Correlations between the across-currencies high-frequency (HF) liquidity measures.** The table shows correlations between the across-currencies effective cost (*EC*), bid-ask spread (*BA*), price impact (*PI*), return reversal (*RR*), and price dispersion (*PD*). The across-currencies *EC*, *BA*, *PI*, *RR*, and *PD* are computed from the PCA (within measures) across individual FX rate liquidities. Bold numbers are statistically significant at the 5% level. The significance test is the GMM based test using a Newey and West (1987) covariance estimator with 4 lags. Correlations are computed using 65 non-overlapping monthly observations. The sample is January 2007 – May 2012.

	Roll	BPW	BA	CS	Gibbs	Volatility	EffTick	LOT
AUD/USD	**0.678**	**0.597**	**0.540**	**0.852**	**0.812**	**0.851**	**0.284**	**0.629**
EUR/CHF	**0.425**	**0.170**	**0.505**	**0.780**	**0.790**	**0.848**	**0.199**	**0.381**
EUR/GBP	**0.156**	**-0.353**	**0.745**	**0.754**	**0.623**	**0.867**	**0.093**	**0.214**
EUR/JPY	**0.543**	**0.525**	**0.750**	**0.687**	**0.673**	**0.729**	**-0.034**	**0.581**
EUR/USD	**0.234**	**0.073**	**0.477**	**0.510**	**0.600**	**0.712**	**0.020**	**0.347**
GBP/USD	-0.013	**-0.501**	**0.725**	**0.818**	**0.747**	**0.929**	**0.142**	**0.595**
USD/CAD	-0.008	-0.017	**0.254**	**0.628**	**0.616**	**0.710**	**0.037**	**0.213**
USD/CHF	**0.280**	**0.035**	**0.520**	**0.609**	**0.756**	**0.874**	0.014	**0.443**
USD/JPY	**0.423**	**0.400**	**0.413**	**0.746**	**0.643**	**0.759**	**-0.224**	**0.431**
Average	0.302	0.103	0.548	0.709	0.695	0.809	0.059	0.426

Table 2: **Correlations between the FX rate LF liquidities and the EC.** The table shows the time-series correlations of the eight low-frequency liquidity measures for each exchange rate with the effective cost measure for the same exchange rate. Effective cost denotes the monthly average of daily effective cost estimates. The monthly low-frequency spread proxies are: *Roll* from Roll from Roll (1984), *BA* is the relative bid-ask spread, *BPW* from Bao, Pan, and Wang (2011), *CS* from Corwin and Schultz (2012), *Gibbs* from Hasbrouck (2009), *Volatility*, *EffTick* from Holden (2009), and *LOT* from Lesmond, Ogden, and Trzcinka (1999). Bold numbers are statistically significant at the 5% level (GMM based test using a Newey-West covariance estimator with 4 lags). The sample is January 2007 – May 2012, 65 months.

	Roll	BPW	BA	CS	Gibbs	Volatility	EffTick	LOT
Whole sample (Jan 2007 - May 2012), 65 months								
	0.584	**0.555**	**0.663**	**0.896**	**0.890**	**0.930**	0.023	**0.612**
Pre-crisis (Jan 2007 - Jun 2008), 18 months								
	0.493	**0.282**	**0.704**	**0.838**	**0.761**	**0.887**	**-0.156**	**0.066**
Financial crisis (Jul 2008 - Dec 2009), 18 months								
	0.568	**0.591**	**0.818**	**0.902**	**0.900**	**0.935**	**0.072**	**0.702**
European sovereign debt crisis (Jan 2010 - May 2012), 29 months								
	0.445	**0.110**	**0.390**	**0.826**	**0.763**	**0.783**	**0.086**	**0.139**

Table 3: **Correlations between the across-currencies LF liquidities and the EC.** The table shows times-series correlations between the across-currencies LF liquidities and the across-currencies effective cost over the whole period and over three subperiods: pre-crisis (Jan 2007 – June 2008), financial crisis (Jul 2008 – Dec 2009) and European sovereign debt crisis (Jan 2010 – May 2012). The monthly low-frequency spread proxies are: *Roll* from Roll (1984), *BA* is the relative bid-ask spread, *BPW* from Bao, Pan, and Wang (2011), *CS* from Corwin and Schultz (2012), *Gibbs* from Hasbrouck (2009), *Volatility*, *EffTick* from Holden (2009), and *LOT* from Lesmond, Ogden, and Trzcinka (1999). The across-currencies measures are based on the PCA (within measures) across individual FX rate liquidites. Bold numbers are statistically significant at the 5% level (GMM based test using a Newey and West (1987) covariance estimator with 4 lags). The sample is January 2007 – May 2012, 65 months.

	Amihud	Amivest	Pastor-Stambaugh
Whole sample (Jan 2007 - May 2012), 65 months			
	0.815	**-0.502**	**-0.144**
Pre-crisis (Jan 2007 - Jun 2008), 18 months			
	0.652	**-0.371**	0.001
Financial crisis (Jul 2008 - Dec 2009), 18 months			
	0.916	**-0.825**	**-0.297**
European sovereign debt crisis (Jan 2010 - May 2012), 29 months			
	0.797	**-0.770**	**-0.032**

Table 4: **Correlations between the across-currencies quote-based LF liquidities and the EC.** The table shows the time-series correlations of the across-currencies quote-based LF measures with the across-currencies effective cost over the whole period and over three subperiods: pre-crisis (Jan 2007 - Jun 2008), financial crisis (Jul 2008 - Dec 2009) and European sovereign debt crisis (Jan 2010 - May 2012). The monthly quote-based low-frequency spread proxies are: *Amihud* from Amihud (2002), *Amivest* from Cooper, Groth, and Avera (1985) and Amihud, Mendelson, and Lauterbach (1997), and *Pastor-Stambaugh* from Pàstor and Stambaugh (2003). The across-currencies measures are based on the PCA (within measures) across the individual FX rate liquiditites. Bold numbers are statistically significant at the 5% level. The sample is January 2007 - May 2012, 65 months.

	(1)	(2)	(3)	(4)	(5)
LF liquidity	**0.929**				
	[19.950]				
Volatility		**0.930**	**0.930**	**0.930**	**1.049**
		[20.092]	[21.059]	[21.059]	[15.124]
Volatility·dummy					**-0.207**
					[-2.214]
CS*			**0.253**		
			[2.187]		
Gibbs**			0.204		
			[1.851]		
Gibbs^{+}				**0.245**	
				[2.275]	
CS^{++}				0.206	
				[1.742]	
R^2	0.863	0.865	0.881	0.881	0.872

Table 5: **Regressions of the across-currencies EC on the LF liquidities.** The table shows the output of the regression of the across-currencies effective cost on (1) the systematic LF liquidity, obtained from the PCA across FX rates as well as best LF liquidities, (2) the across-currencies volatility, (3)-(4) the rotated best across-currencies low-frequency measures, (5) the across-currencies volatility and the latter interacted with the dummy, which takes 1, if there was an increase in volatility (illiquidity) one month before, zero otherwise. The best across-currencies low-frequency measures include: *Volatility*, *CS* (from Corwin and Schultz (2012)), *Gibbs* (Hasbrouck (2009)). All the across-currencies liquidity measures are obtained from the PCA (within measures) across individual FX rates liquidites and standardized. * denotes the second factor in the rotation [Volatility, CS, Gibbs]. ** denotes the third factor in the rotation [Volatility, CS, Gibbs]. $^{+}$ denotes the second factor in the rotation [Volatility, Gibbs, CS]. $^{++}$ denotes the third factor in the rotation [Volatility, Gibbs, CS]. The t-statistics is shown in the brackets. Bold numbers are statistically significant at the 5% level. The sample is January 2007 – May 2012, 65 months.

	CS	Gibbs	Volatility	Systematic
CS	**1**			
Gibbs	**0.812**	**1**		
Volatility	**0.861**	**0.877**	**1**	
Systematic	**0.931**	**0.935**	**0.973**	**1**

Table 6: **Correlation between the across-currencies low-frequency (LF) liquidities over 1991-2012.** The table shows correlations between the across-currencies LF liquidities and systematic LF liquidity based on 40 FX rates. The across-currencies *CS*, *Gibbs*, and *Volatility* liquidities are obtained from the PCA (within measures) across individual FX rate liquidites. The systematic liquidity measure is obtained from the PCA across FX rates as well as across *CS*, *Gibbs*, and *Volatility* liquidities. Bold numbers are statistically significant at the 5% level. The significance test is the GMM based test using a Newey and West (1987) covariance estimator with 4 lags. Correlations are computed using 257 non-overlapping monthly observations. The sample is January 1991 – May 2012.

	Simple panel	Systematic FX volatility	JP implied FX volatility	TED spread	MSCI volatility	VIX index	Mean USD return
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\triangle L_{M,t}$	**0.579**	**0.567**	**0.572**	**0.564**	**0.569**	**0.573**	**0.570**
	[55.415]	[62.974]	[62.282]	[66.052]	[62.889]	[51.205]	[63.163]
$\triangle L_{M,t} \cdot D_{DISTRESSEDMKT,t-1}$		**0.065**	**0.065**	**0.090**	**0.064**	**0.054**	**0.055**
		[3.020]	[3.595]	[5.916]	[2.875]	[2.118]	[2.124]
R^2	0.3347	0.3353	0.3361	0.3358	0.3352	0.3350	0.3351
Sum($D_{DISTRESSEDMKT,t-1}$)		14	10	18	18	18	16
Number of obs.	255	255	239	255	255	255	255

Table 7: **Commonality in FX liquidity in the distressed markets.** Panel of changes in FX rate liquidities is regressed on the changes in systematic FX liquidity and systematic FX liquidity $\triangle L_{M,t}$, interacted with a dummy $D_{DISTRESSEDMKT,t-1}$. $D_{DISTRESSEDMKT,t-1}$ is equal to one if the risk factor (systematic FX volatility, JP implied FX volatility, TED spread, MSCI volatility, VIX index or mean USD return) is more than 1.5 standard deviations above its unconditional mean. The intercepts are omitted. Standard errors, robust to conditional heteroscedasticity and spatial correlations as in Driscoll and Kraay (1998), are reported in brackets. Bold numbers are statistically significant at the 5% level. The sample for specifications (1), (2) and (4)-(7) is January 1991 – May 2012, the sample for specification (3) is April 1992 – May 2012.

	$\triangle L_{M,t}$ is based on...	32 currencies			23 developed currencies					11 emerging currencies			
Group	"Best" factor	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FX return	Mean USD return		-0.011		-0.020		0.016		0.012		-0.135		**-0.163**
			[-0.189]		[-0.338]		[0.282]		[0.207]		[-2.278]		[-2.165]
FX risk	$\triangle$ JP FX impl vol		**-0.372**		**-0.345**		**-0.341**		**-0.294**		**-0.428**		**-0.510**
			[-4.334]		[-3.837]		[-3.736]		[-3.075]		[-6.675]		[-6.721]
Int rates return	$\triangle$ Fefunds rate	0.103	0.063		-0.019	0.109	0.070		-0.019	0.050	0.013		0.006
		[1.662]	[1.038]		[-0.305]	[1.693]	[1.090]		[-0.299]	[1.013]	[0.284]		[0.104]
Int rates risk	$\triangle TED$	**-0.114**	**-0.104**		**-0.142**	**-0.128**	**-0.121**		**-0.160**	-0.005	0.018		-0.004
		[-2.439]	[-2.774]		[-3.440]	[-2.661]	[-2.994]		[-3.639]	[-0.100]	[0.475]		[-0.095]
Corp bonds return	$\triangle i_{BAA}$	0.062	0.035		0.019	0.063	0.034		0.011	0.062	0.053		0.074
		[1.068]	[0.682]		[0.282]	[1.116]	[0.666]		[0.169]	[1.001]	[0.933]		[0.905]
Corp bonds risk	$\triangle$ US def spread	**-0.188**	**-0.121**		-0.095	**-0.174**	**-0.113**		-0.085	**-0.196**	**-0.115**		-0.105
		[-2.930]	[-2.140]		[-1.368]	[-2.701]	[-1.960]		[-1.254]	[-2.980]	[-1.848]		[-1.150]
Stocks return	MSCI return	0.047	-0.029		-0.012	0.050	-0.004		0.020	0.027	-0.134		-0.159
		[0.776]	[-0.467]		[-0.184]	[0.834]	[-0.070]		[0.310]	[0.368]	[-1.569]		[-1.575]
Stocks risk	$\triangle$ MSCI vol	**-0.435**	**-0.325**		**-0.268**	**-0.428**	**-0.323**		**-0.264**	**-0.384**	**-0.281**		**-0.250**
		[-6.432]	[-4.169]		[-3.088]	[-6.272]	[-3.975]		[-2.944]	[-4.994]	[-4.490]		[-2.910]
	$\triangle L_{M,t-1}$	**-0.299**	**-0.289**	**-0.275**	**-0.185**	**-0.302**	**-0.291**	**-0.268**	**-0.182**	**-0.189**	**-0.185**	**-0.240**	**-0.143**
		[-4.382]	[-4.139]	[-4.272]	[-3.461]	[-4.266]	[-3.968]	[-3.956]	[-3.215]	[-3.123]	[-3.300]	[-3.268]	[-2.334]
	$\triangle$ Stock liquidity			**0.212**	-0.059			**0.200**	-0.057			**0.234**	-0.044
				[2.779]	[-0.952]			[2.807]	[-0.891]			[2.211]	[-0.487]
	$\triangle$ Bond liquidity			**0.392**	**0.172**			**0.394**	**0.192**			**0.251**	-0.008
				[4.137]	[2.150]			[4.330]	[2.296]			[2.283]	[-0.106]
	R^2	0.395	0.504	0.283	0.537	0.393	0.484	0.281	0.517	0.240	0.391	0.153	0.411
	Number of obs.	255	241	179	179	255	241	179	179	255	241	179	179
	Start of the sample	01/1991	04/1992	01/1995	01/1995	01/1991	04/1992	01/1995	01/1995	01/1991	04/1992	01/1995	01/1995
	End of the sample	05/2012	05/2012	12/2009	12/2009	05/2012	05/2012	12/2009	12/2009	05/2012	05/2012	12/2009	12/2009

Table 8: **Explaining FX systematic liquidity.** Systematic FX liquidity (based on the PCA for 32 floating currencies, 23 floating developed and 9 floating emerging currencies) is regressed on (a) non-FX contemporaneous risk and return variables, and lagged systematic FX liquidity–specifications (1), (5), and (9), correspondingly; (b) all contemporaneous risk and return variables, and lagged systematic FX liquidity–specifications (2), (6), and (10); (c) lagged systematic FX liquidity, contemporaneous stock and bond liquidity–specifications (3), (7), and (11); (d) all contemporaneous risk and return variables, lagged systematic FX liquidity, and contemporaneous stock and bond liquidity–specifications (4), (8), and (12). All variables except for mean USD return and MSCI stock return are in changes. Lagged systematic FX liquidity $\triangle L_{M,t-1}$ is based on the PCA for all 40 currencies. The t-statistics based on the standard errors, robust to conditional heteroscedasticity and serial correlation up to one lag as in Newey and West (1987), are reported in brackets. Bold numbers are statistically significant at the 5% level. The full sample is January 1991 – May 2012, 257 months.

		Basic setup	FX return risk	Carry trade risk	Volatility risk	Liquidity risk
		(1)	(2)	(3)	(4)	(5)
Int rates return	$\triangle$ Fefunds rate $\cdot D_{float}$	0.059	0.046	0.063	0.013	0.033
		[1.575]	[1.139]	[1.430]	[0.354]	[1.292]
Int rates risk	$\triangle$ TED $\cdot D_{float}$	**-0.056**	**-0.086**	**-0.087**	**-0.076**	-0.014
		[-2.088]	[-3.714]	[-3.600]	[-3.294]	[-0.458]
Corp bonds return	$\triangle i_{BAA} \cdot D_{float}$	0.042	0.040	**0.078**	0.054	0.037
		[1.260]	[1.300]	[2.264]	[1.857]	[1.131]
Corp bonds risk	$\triangle$ US def spread $\cdot D_{float}$	**-0.104**	-0.053	**-0.113**	-0.050	**-0.079**
		[-2.919]	[-1.685]	[-2.854]	[-1.774]	[-2.254]
Stocks return	MSCI return $\cdot D_{float}$	0.030	0.028	0.027	0.027	0.036
		[0.846]	[0.763]	[0.664]	[0.836]	[1.164]
Stocks risk	$\triangle$ US def spread $\cdot D_{float}$	**-0.252**	**-0.198**	**-0.216**	**-0.201**	**-0.231**
		[-6.675]	[-5.135]	[-4.798]	[-5.457]	[-6.793]
	$\triangle L_{M,t-1} \cdot D_{float}$	**-0.168**	**-0.198**	**-0.184**	**-0.146**	**-0.074**
		[-4.598]	[-4.726]	[-4.077]	[-3.953]	[-2.775]
Int rates return	$\triangle$ Fedfunds rate $\cdot D_{float\&cond}$		0.027	0.001	**0.133**	0.042
			[0.936]	[0.032]	[3.055]	[1.056]
Int rates risk	$\triangle$ TED $\cdot D_{float\&cond}$		0.058	0.064	0.051	**-0.069**
			[1.783]	[1.628]	[1.434]	[-2.263]
Corp bonds return	$\triangle i_{BAA} \cdot D_{float\&cond}$		0.012	**-0.082**	-0.019	0.008
			[0.321]	[-2.041]	[-0.512]	[0.282]
Corp bonds risk	$\triangle$ US def spread $\cdot D_{float\&cond}$		**-0.099**	0.007	**-0.156**	-0.041
			[-2.337]	[0.114]	[-3.774]	[-0.953]
Stocks return	MSCI return $\cdot D_{float\&cond}$		0.001	-0.004	-0.002	-0.011
			[0.027]	[-0.084]	[-0.049]	[-0.284]
Stocks risk	$\triangle$ MSCI volatility $\cdot D_{float\&cond}$		**-0.108**	-0.106	**-0.127**	-0.035
			[-2.286]	[-1.743]	[-3.019]	[-0.743]
	$\triangle L_{M,t-1} \cdot D_{float\&cond}$		0.057	0.017	**-0.094**	**-0.152**
			[1.806]	[0.399]	[-2.389]	[-3.375]
	R^2	0.121	0.128	0.139	0.137	0.127

Table 9: **Explaining FX currency-pair liquidities.** In column (1) panel of FX rate liquidities is regressed on non-FX contemporaneous risk and return variables and lagged systematic FX liquidity, interacted with the contemporaneous time-varying D_{float} dummy, which takes one if and only if the currency pair is floating. In columns (2)-(4) panel of FX rate liquidities is regressed on non-FX contemporaneous risk and return variables and lagged systematic FX liquidity, interacted with the dummy $D_{float\&cond}$, which takes one if and only if the currency pair is floating and the risk condition holds. The dummy in column (2) is one if a currency pair underperforms the cross-sectional average U.S. dollar return in that month (FX return risk). The dummy in column (3) is one if a currency pair has forward premium higher than the cross-sectional average in that month (carry trade risk). The dummy in column (4) is one if a currency pair has a higher realized volatility (monthly squared return) than the cross-sectional average in that month (volatility risk). The dummy in column (5) is one if a currency pair has a stronger commonality than the sample average (liquidity risk). The last dummy variable is (in contrast to the other dummies) not time-varying. All variables except for dummies and MSCI stock return are in changes. Standard errors, robust to conditional heteroscedasticity and spatial correlations as in Driscoll and Kraay (1998), are reported in brackets. Bold numbers are statistically significant at the 5% level. The sample is January 1991 – May 2012, 257 months.