Understanding FX Liquidity

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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 the first comprehensive study of FX liquidity and commonality over more than two decades and a cross-section of forty exchange rates. We show that FX liquidity deteriorates with risk in FX, stock, bond, and money markets, and it comoves with liquidity in bond and stock markets. We also show that commonality in FX liquidities increases in distressed markets and it is stronger for countries with high-quality institutions, financial integration, and price stability. (*JEL* C15, F31, G12, G15)

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Market liquidity is an important feature for all financial markets, yet very little is known about market liquidity of the foreign exchange (FX) market. This paper provides the first comprehensive study of FX liquidity and commonality in FX liquidities over more than two decades and forty currency pairs. Having found the most accurate liquidity measures for FX liquidity, this paper shows the main determinants of commonality in FX liquidities 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, the FX market has unique characteristics, such as limited transparency, heterogeneity of participants, and market fragmentation (Lyons 2001). The very nature of FX liquidity is also exceptional, and thus it is not obvious a priori why liquidity patterns documented for the stock market should apply to the FX market. For instance, whereas a typical financial transaction entails some maturity transformation (i.e., cash for securities), a spot FX trade converts cash (in one currency) into cash (in another one). Contrary to stocks, an FX rate does not pay any dividend and it can be closely connected to central banks' operations. Moreover, a spot FX transaction generally demands little or no margin requirements (also called haircuts), allowing FX traders to take highly leveraged positions. Given these fundamental reasons, we should expect FX and stock liquidity to show different patterns. Second, 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; Acharya and Pedersen 2005) and on other assets but only recently on foreign exchange (Christiansen, Ranaldo, and Söderlind 2011; Banti, Phylaktis, and Sarno 2012; Mancini, Ranaldo, and Wrampelmeyer 2013). However, a clear understanding of why and how FX illiquidity materializes is still missing. Third, a new strand of theoretical models (hereafter called "liquidity spirals theories") tries to shed light on the intricate link between market liquidity, funding liquidity, and risk (e.g., Brunnermeier and Pedersen 2009; Vayanos and Gromb 2002). Empirically, Brunnermeier, Nagel, and Pedersen (2009) show that financial crises are typically associated with unwinding carry trade and liquidity drops, and Mancini, Ranaldo, and Wrampelmeyer (2013) 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.

This paper contributes to the literature in three respects. First, it documents and then explains the significant temporal and cross-sectional variation in currency liquidities. 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). The FX market is not only big but it also facilitates essential activities, such as the determination of the relative values of currencies and any related assets. The liquidity in the FX market is crucial in guaranteeing efficiency and arbitrage conditions in many other markets, including bonds and derivatives. Despite its size and 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 (2013) provide an accurate measurement of FX liquidity. However, none of the previous studies performs a comprehensive analysis of FX liquidity 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). Some clear results emerge. First, FX liquidity is strongly related to risk arising not only from the FX market but also from the stock, bond, and money markets. This interconnection between FX liquidity and market risk of other markets adds a new dimension to flight-to-quality and flight-to-liquidity dynamics. Our findings suggest that the FX market is involved in cross-market spillovers and that propagations are channeled not only via volatility (Fleming, Kirby, and Ostdiek 1998) but also via illiquidity. Moreover, we add to the extant literature on the interconnections between stock-bond illiquidity (Goyenko and Ukhov 2009) by showing that FX liquidity is also tied to stock and bond liquidities. These common liquidity patterns imply that when risk increases, liquidity evaporates at the same time in FX, stock, and bond markets. Because the FX market is an important source of funding liquidity, this result provides empirical support to the liquidity spirals theories suggesting that risk can spill over across markets, creating contagion and commonality in illiquidity (e.g., Kyle and Xiong 2001). Another novel result is the detection of groups of currencies more exposed to liquidity drops. More specifically, the liquidity of developed currencies is more exposed to risk, whereas that of emerging currencies follows more idiosyncratic movements. Furthermore, the liquidity of those currencies bearing larger exposure to the systematic risk factors highlighted in the recent FX asset pricing liter-

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

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

ature (e.g., Lustig, Roussanov, and Verdelhan 2011; Menkhoff, Sarno, Schmeling, and Schrimpf 2012a) tends to react more negatively to our risk measures.

The second contribution of this paper is an original analysis of commonality in FX liquidities. Mancini, Ranaldo, and Wrampelmeyer (2013) find that commonality of the FX market during the 2007–2009 financial crisis was strong. We extend this finding by showing that this is a systematic characteristic of the FX market; that is, comovements of FX rate liquidities have always been strong in the last two decades and stronger than that found in the stock market literature. Additionally, we find that commonality systematically increases in distressed markets similarly to what Hameed, Kang, and Viswanathan (2010) and Karolyi, Lee, and Dijk (2012) find for the stock market. More precisely, we show that the common component in liquidity across currencies is stronger when volatility in stock and FX markets is high, when the short-term funding market is tight, and when FX carry trade returns are most negative. Another novelty of this study is to bring to light the cross-sectional determinants of commonality in FX liquidities. Our results indicate that the liquidity of a currency pair comoves more strongly with that of the whole FX market when the two countries forming the currency pair have a higher degree of quality of their institutions (Morck, Yeung, and Wu 2000; La Porta, de Silanes, Shleifer, and Vishny 1998), financial integration and price stability. These results are consistent with the extant literature on capital market segmentation (e.g., Bekaert 1995) and global liquidity risk (e.g., Lee 2011).

The third contribution of this paper is methodological. To answer the two key questions addressed in this study, that is what explains FX liquidity and what explains its commonality, we first need to accurately measure FX liquidity over a long period and a large and representative panel of currencies. Using the same precise high-frequency measures as Mancini, Ranaldo, and Wrampelmeyer (2013) as benchmarks, we show that it is possible to gauge FX market liquidity from price data that are readily available on a daily frequency. The possibility to use a low-frequency measure circumvents a number of severe limits related to high-frequency data, for instance, a very limited access only to recent data, a restricted and delayed use, and the need of time consuming data handling and filtering techniques. We use two main sources of data: First, we use low-frequency data from Thomson Reuters (a very common data provider), from which we measure low-frequency liquidity, applying the main methods proposed in the equity and bond literature.[3] Second, we use a unique dataset of high-frequency and sophisticated data from Electronic Broking Services (EBS)—the leading platform for FX spot inter-dealer 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. 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). But, to our knowledge, there is no such study of FX liquidity. We fill this gap in the literature by showing that the best low-frequency FX liquidity measures are *Corwin-Schultz* (Corwin and Schultz 2012), the *Gibbs sampler estimate of Roll's model* (Hasbrouck 2009), and *Volatility*. In the same vein as Korajczyk and Sadka (2008), we then construct a systematic low-frequency measure as the first principal component across the best low-frequency measures and across all currencies. From January 2007 to May 2012, this measure has a 0.93 correlation with an effective cost liquidity measure constructed from the EBS data. We then provide monthly estimates of the low-frequency FX liquidity measure based on forty currencies from January 1991 to May 2012.

[Figure 1 about here.]

The availability of reliable LF measures of FX liquidity is important in practice. For instance, our results can be used to estimate FX trading costs for historical episodes, when little (or no) high-frequency data is available. As an illustration, Figure 1 illustrates two historical cases, that is "the Black Wednesday" and "Lehman collapse" in September 1992 and 2008, respectively. In the earlier episode the British government was forced to withdraw the pound sterling from the European Exchange Rate Mechanism (ERM). The estimated effective spread on GBP/USD increased approximately by three times (from 0.5 to 1.5 basis points) from end of August to September 1992. Similarly, by the end of October 2008 after the Lehman bust, the effective spread measure on AUD/USD increased

[3]Because of the limited datasets with high-quality trade and quote data, for decades starting with Roll (1984) several scholars have for decades been looking for reliable low-frequency measures of market liquidity. Low-frequency proxies applied to the stock market are proposed by Lesmond, Ogden, and Trzcinka (1999), Amihud (2002), Pàstor and Stambaugh (2003), Hasbrouck (2009), Holden (2009), and Corwin and Schultz (2012). Bao, Pan, and Wang (2011) and Dick-Nielsen, Feldhütter, and Lando (2012) analyze market liquidity on the corporate bonds market. Hu, Pan, and Wang (2012) and Deuskar, Gupta, and Subrahmanyam (2011) focus on government bond and OTC markets, respectively.

by four times (i.e., from 0.9 to 4.1 bp). Both FX rates would have been involved in typical carry trade strategies.[4] Because any international portfolio position involves FX trading costs and eventually liquidity risk, our paper provides new insights for asset allocation and risk management.

1. Measurement of FX Liquidity

1.1 High-frequency benchmark

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

Hereafter, we will use the abbreviations *LF* and *HF* to refer to low-frequency and high-frequency. We obtain HF data from ICAP that runs the leading interdealer electronic FX platform called Electronic Broking Services (EBS). The EBS dataset spans January 2007 to May 2012, and it is organized on a one-second basis (i.e., 86,400 observations per day). 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., whether 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.[5] Dealers on the EBS platform are prescreened for credit and bilateral credit lines, which together with the continuous monitoring by the system, makes the potential counterparty risk virtually negligible.[6]

We use HF data on nine currency pairs, namely the AUD/USD, EUR/CHF, EUR/GBP, EUR/JPY, EUR/USD, GBP/USD, USD/CAD, USD/CHF, and USD/JPY. These exchange rates accounted for 71% of daily average trading volume in April 2013 (see Bank of International Settlements 2013). Observations between Friday 10 p.m. and Sunday 10 p.m. GMT are excluded, because only minimal trading activity is observed during these

[4]The money market rates in GBP and AUD were the highest (across the panel), whereas the USD money market rate was lowest in August 1992, and the second-lowest rate in August 2008.

[5]In 2013, a few articles appeared in the media about the perception that interdealer electronic brokers, such as EBS, apparently been losing market share. This is a minor concern for our study because our liquidity measures do not rely on transaction volume and our sample period for HF data spans from 2007 to May 2012.

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

nonstandard hours.[7]

Following the previous literature, our benchmark measure of (the negative of) liquidity is the effective cost (*EC*), which 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

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

P^T denotes the transaction price, $P = (P^A + P^B)/2$ is the midquote price, and superscripts *A* and *B* are the ask and bid quotes.

We estimate effective cost for each month and each exchange rate by averaging the HF data on EC over the month. For comparison, we also estimate four alternative HF liquidity measures: bid-ask spread, price impact (Kyle 1985), return reversal (Campbell, Grossman, and Wang 1993), and price dispersion (Chordia, Roll, and Subrahmanyam 2001). They are very highly correlated with the effective cost (see the Internet Appendix for details), so the choice of HF benchmark is not important for our main findings.

[Figure 2 about here.]

For the subsequent analysis, we standardize the monthly effective cost 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 an across-currencies effective cost. This data series is represented by the dotted line in Figure 2. Liquidity was quite stable from January 2007 to mid-2008, followed by a substantial drop in September 2008 to November 2008. The decline reflects 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 precrisis level at the end of 2009. We also observe a contraction of liquidity when the European sovereign debt crisis intensified in early 2010. During the first half of 2012, liquidity visibly improved and returned close to the precrisis level.

[7]We drop U.S. holidays and other days with unusually light trading activity from the dataset. We also remove a few obvious outlying observations. The Internet Appendix for Mancini, Ranaldo, and Wrampelmeyer (2013) discusses in detail the filtering procedure for the data.

1.2 Finding the best low-frequency measures

Following the previous literature, in this section we identify the *best low-frequency FX liquidity measures*—defined as those with the consistently highest correlations with the high-frequency effective cost.[8] The aim is to find the most-accurate measures of FX liquidity over a long time span and a large number of currencies (where only daily data are available), thus circumventing various other limitations imposed by high-frequency data.

The LF data is daily high, low, bid, ask, and midquote prices, as well as quote frequencies from Datastream Thomson Reuters. Daily close bid, ask, and midquote prices are snapped at 22:00 GMT based on the indicative data from the latest contributor. To guarantee a consistent comparison, the dataset covers the same nine currency pairs and the same time period (trading days) as that of the HF data. For one of our LF measures (*LOT*, see below), we also use the daily effective exchange rate computed by the U.S. Federal Reserve.

For each exchange rate, we compute *eight LF liquidity measures* that are widely used in the literature on stock and bond liquidity. Below we summarize these measures, and more detailed information can be found in the Internet Appendix. We compute the LF measures for each month and each exchange rate, using daily data.

Roll (1984) shows that the transaction cost induces a bid-ask bounce. This leads to a negative autocovariance for price changes—even if sampled at a low frequency, so the transaction cost can be estimated from the (negative of the) autocovariance of the return process. Following the previous literature, when the autocovariance is positive,[9] we substitute the transaction cost estimator with zero

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

where Δp_t is the change of the log midquote price between t and $t-1$. As for all LF measures considered in this section, a higher value means lower liquidity.

The second LF liquidity measure is the gamma (*BPW*) measure put forward by Bao,

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

[9] 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.

Pan, and Wang (2011) to measure liquidity in the corporate bond market, defined as

$$BPW = -\mathrm{Cov}(\Delta p_t, \Delta p_{t-1}). \tag{3}$$

By construction, this is very similar to the Roll measure.

The third LF liquidity measure is the Bayesian *Gibbs* sampler estimate of the effective cost in the Roll model (Hasbrouck 2009). We run each Gibbs sampler for 1,000 sweeps and discard the first 200 draws, calibrating the prior for the transaction cost to get a good proxy of the HF benchmark.[10]

The fourth LF liquidity measure is the relative bid-ask spread (*BA*).

The fifth LF liquidity measure is the high-low cost estimate *CS* from Corwin and Schultz (2012). The CS is calculated as

$$CS = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}}, \text{ with } \alpha = (1 + \sqrt{2})(\sqrt{\beta} - \sqrt{\gamma}), \tag{4}$$

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. (The expression for α looks different from the original Corwin and Schultz (2012) formulation but is equivalent.) The basic idea is that the bid-ask spread is unaffected by the horizon, whereas the variance is proportional to the horizon. We estimate spreads for each two-day period and calculate the average across all overlapping two-day periods in the month. 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.

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 ex-

[10] 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.

pected 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.[11] 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.[12]

Finally, the eighth LF liquidity measure is an estimate of realized *Volatility*, calculated as monthly averages of the daily absolute returns (see French, Schwert, and Stambaugh 1987 for a discussion). The microstructure theory relates transaction costs to volatility in various ways,[13] so volatility is an indirect measure of FX liquidity, and it has been commonly used in the literature (e.g., Chordia, Roll, and Subrahmanyam 2001).

[Table 1 about here.]

Table 1 reports the times-series correlations of each LF liquidity measure for each exchange rate with their HF effective cost benchmarks. Boldfaced numbers are different from zero at the 5% significance level.[14] 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 are 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. Further results are reported in the Internet Appendix.

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 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 2 about here.]

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

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

[13] For instance, directly as in Roll (1984), through inventory risk as in Stoll (1978), or by the probability of informed trading as in Glosten and Milgrom (1985)

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

Table 2 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 subperiods in the rest of Table 2. Specifically, we study three subperiods: the pre-Lehman period, the turmoil after the Lehman bankruptcy, 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. First, the *CS*, *Gibbs* and *Volatility* measures (once again) perform well in all three subperiods (the correlation with the HF benchmark is always above 0.76). Second, *BPW*, *BA*, and *LOT* show very inconsistent performance across the subsamples.

To summarize, Tables 1 and 2 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 (Harris 1990 points to a significant deterioration of the *Roll* estimator performance when the spread gets smaller). Another problem could be due to the use of indicative quotes rather than of actual transaction prices, as it is the case for FX data. The *BPW* measure may suffer for the same reasons. The poor performance of the *EffTick* measure is probably driven by the fact that there is little clustering of FX rates to some “round” numbers.

The weak and unstable performance of the bid-ask spread is both disappointing and surprising. A closer look reveals the following. The daily Thomson Reuters (TR) bid-ask spreads, snapped at 22.00 GMT, are only weakly correlated with the HF *BA* (0.02–0.27 for the nine FX rates) at 22.00 GMT or with the daily average HF *BA* (0.05–0.35). The correlations with HF *EC* are similar. It is only when we average over a month that the correlations increase to moderate levels. Results for the bid-ask spread from an alternative data provider, WM/Reuters, based on the fixings at 16:00 GMT, are even worse. See the Internet Appendix for details. This suggests that the information content in the bid-ask spreads from the daily indicative snaps is limited.

In sum, the analysis shows that the *CS*, *Gibbs*, and *Volatility* measures give the best proxies of the HF liquidity benchmark on the FX market and they work fairly well. To illustrate this, we 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.[15] This is the solid line in Figure 2, whereas 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.

1.3 Finding the best LF measures: Other measures and horizons

In the previous section we have shown that it is possible to measure systematic liquidity by combining the best LF measures by a *principal component approach*. Using straight or trimmed averages gives very similar results, because the first principal component typically loads more or less equally on the currencies/measures.[16]

However, it is not obvious that principal components or averaging 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 3, Column 1, shows the regression of the monthly HF effective cost on the systematic LF liquidity. The coefficient is 0.93 and highly significant, and the coefficient of determination (R^2) is 0.86. In Column 2, we use instead only LF volatility as the regressor, and it works equally well.

In addition to volatility, Columns 3 and 4 include the other good LF measures (*Gibbs* and *CS*), and doing so 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*, whereas the second factor is 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

[15] The first principal component explains 59% of the total variation. For details, see the Internet Appendix.

[16] There is one exception to this finding: some of the across-currencies LF measures (for instance, in Table 2) 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.

second). The results suggest that both *CS* and *Gibbs* are useful in providing additional explanatory ability. Column (5) includes only the volatility and its absolute value. The latter has a small and insignificant coefficient, which suggests that a linear equation is a reasonable specification.

Overall, the regression results demonstrate that all three of the best HF measures (*Volatility*, *CS*, and *Gibbs*) are important for proxying the HF effective cost and that a regression can improve the fit somewhat. However, it also shows that the principal components approach is almost as good as the regression based "optimal" weights. Because the principal component approach is already well established in the literature (see, e.g., Korajczyk and Sadka 2008), we will henceforth rely on it.

[Table 3 about here.]

Trading volume data are not readily available for FX markets. A method to approximate trading volume proposed in FX literature is the quote frequency, that is the number of quote revisions over a given period (e.g., Melvin and Yin 2000). 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) and Pàstor and Stambaugh (2003) and the so-called Amivest measure from Cooper, Groth, and Avera (1985) and Amihud, Mendelson, and Lauterbach (1997). Data on quote revisions are available only from January 2007, so these measures are not helpful in calculating LF measures for a long sample period (which is our main goal). However, they are of independent interest.

Table 4 shows correlations of the across-currencies quote based LF measures with the HF effective cost benchmark. The Amihud measure 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 subperiods. In contrast, the Amivest measure 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—probably because it uses the lagged (instead of the contemporaneous) quote revisions.[17]

[Table 4 about here.]

[17]We also analyzed the Zeros measure from Lesmond, Ogden, and Trzcinka (1999) and the FHT measure from Fong, Holden, and Trzcinka (2011). However, we discarded them because of the nearly complete absence of daily zero returns.

The previous analysis shows that some LF measures provide good proxies of the HF effective cost on the *monthly frequency*. Here, we explore what happens at frequencies higher than a month. We do this for the three best LF measures, as well as for the *BA*, which is commonly used in the literature. We compute the LF *Volatility* and *BA* on frequencies of 1 to 5 days, as well as for 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 for 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.

1.4 Finding the best LF measures: Robustness analysis

Below we briefly describe additional robustness checks. Further details are reported in the Internet Appendix.

First, we replicated our analysis by using HF benchmarks (bid-ask, price impact, and return reversal) other than the HF effective cost. Overall, we obtain very similar results, probably because of the very high correlation between the HF liquidity measures.

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 10,000) or changing the prior of the transaction cost did not affect the mean parameter estimates materially. However, there are two exceptions to this finding: (1) setting the standard deviation of the prior to a very small value (e.g., 0.001) gives estimates that are much less correlated with the HF benchmark, and (2) when we study liquidity on a weekly, instead of a monthly frequency, then the prior becomes more important (consistent with 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 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.

1.5 Using the best LF liquidity measures on a larger sample

High-frequency data are available only for a small number of exchange rates and for very recent time periods. This severely restricts the possibility of calculating HF liquidity measures outside the major currencies and back in time. However, our previous analysis shows that it is possible to construct accurate liquidity proxies from low-frequency (daily) data. We now demonstrate the usefulness of 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 includes fourty exchange rates (over 84% of daily average trading volume in April 2013) and encompasses more than twenty years (from January 1991 to May 2012).[18]

We compute monthly times series 1991–2012 of the *CS*, *Gibbs*, and *Volatility* measures for each exchange rate. To create a measure of systematic FX liquidity, we calculate the first principal component across the 120 data series (forty currency pairs, three measures). We also investigated the effect of using just the nine main currencies, instead of the full cross-section of forty currencies. The results are very similar. For instance, the systematic liquidity measures from the nine and the forty currencies have a correlation of 0.97. See the Internet Appendix for further details.

Figure 4 shows the time series of the systematic liquidity measure. It also indicates some major (financial and geopolitical) crises. Although the turmoil around the Lehman bankruptcy caused the largest drop in systematic liquidity, our FX liquidity measure allows us to spot a number of other significant events, for instance, the ERM crisis (1992), the peso crisis (1994), the Russian default (1998), and 9/11 (2001). On the other hand,

[18] The EUR/USD is replaced with the DEM/USD prior to 1999. The other FX rates against the EUR are replaced with the quotes against the ECU prior to 1999 due to data availability in Thomson Reuters.

the reaction of FX liquidity to more stock-specific events, such as the dotcom bubble burst (spring 2000) or the Enron scandal (2001), are less discernable. The prima facie evidence suggests that systematic FX liquidity correlates with global risk indicators. For instance, its correlation with the VIX and TED spread is 0.67 and only 0.51, respectively. An in-depth inspection of the main drivers of FX liquidity will be conducted in the next sessions.

[Figure 4 about here.]

2. Explaining FX Liquidity

In the previous section, we showed that it is possible to accurately measure FX liquidity using low-frequency data. We can therefore create a long and large sample of FX liquidity.

In this section, we try to understand FX liquidity by analyzing commonality of FX liquidities and by relating FX liquidity to its possible drivers. We proceed in three steps: First, we measure commonality in FX liquidity. Second, we explain the cross-sectional variation in FX commonality by proxies for market integration and development. Third, we regress liquidity on its key drivers: returns, risk proxies, and liquidities of the main asset classes. We focus on floating currencies because a pegged exchange rate implies that the central bank steps in as a liquidity provider.

2.1 Measuring 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; Karolyi, Lee, and Dijk 2012). However, to our knowledge only two papers investigate commonality of FX liquidity. Mancini, Ranaldo, and Wrampelmeyer (2013) use HF data to study FX commonality of nine exchange rates during the recent financial crisis of 2007–2009. Banti, Phylaktis, and Sarno (2012) use institutional customer data to approximate the Pastor-Stambaugh liquidity proxy for twenty exchange rates over a period of fourteen years. Here, we extend the FX literature by investigating FX commonality across a long period (1991–2012), across a large cross-section (forty currencies), and after making sure to use the most accurate FX liquidity measures. This allows us to identify different patterns for developed and emerging currencies as well as the asymmetries in normal and distressed markets.

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

$$\triangle L_{ij,t} = \alpha_{ij} + \beta_{ij} \triangle L_{M,t} + \varepsilon_{ij,t}, \tag{5}$$

where $\triangle L_{ij,t}$ is, for the FX rate between currencies i and j, the change from month $t-1$ to t in FX 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, that is, from January 1991 to May 2012. All estimated slope coefficients are positive and statistically significant at any conventional level.[19]

[Figure 5 about here.]

As in Karolyi, Lee, and Dijk (2012), we use the R^2 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 taken from the Bank of International Settlements (2013) ordered from the most to the least traded); (2) developed, but less-traded exchange rates; and (3) emerging currencies. Solid black bars are for currencies that were not pegged at any time during our sample, and gray 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^2 across our sample of forty currencies is 36%. Only seven exchange rates have an R^2 lower than 10% (four of which involve pegged currencies), suggesting that liquidity comoves 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. For instance, Korajczyk and Sadka (2008) find adjusted R^2 values ranging from 4% to 26%.[20]

[19]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. Also, excluding both currencies in the FX pair from the computation of $\triangle L_{M,t}$ does not affect qualitatively our results, suggesting that the strength of commonality in FX liquidity cannot be explained by the triangular construction of FX rates. See the Internet Appendix for details. With 257 data points and one regressor, the R^2 and the adjusted R^2 are very similar.

[20]Several papers find significant comovement of liquidity in cross-sections of U.S. stocks (e.g., Datar,

Third, FX commonality is stronger for developed currencies (R^2 values of around 45% compared with around 20% for emerging currencies). This is in line with earlier findings that developed markets are more integrated and have higher exposure to common factors (Korajczyk 1996; Bekaert and Harvey 1995). This finding holds 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). In addition, within the group of developed and liquid currencies (first group) there seems to be no relation between trading volume (according to which the exchange rate are sorted) and commonality.

[Figure 6 about here.]

Figure 6 illustrates how the degree of commonality (for floating currencies) has changed across different time periods. We use a GMM-based method that accounts for serial and cross-sectional correlations to test the difference between the mean commonality R^2 for developed and emerging currencies. We find that the difference is statistically significant at any conventional level for the whole period (the t-statistic is 11.9) and for the three sub-periods (the t-statistic is 8.3, 9.0, 5.5). Though emerging currencies have lower commonality than do developed currencies in all subperiods, they seem to be catching up—consistent with a recent study by Bekaert and Harvey (2013), who find a low, but increasing, degree of integration of emerging markets in the global economy over the last twenty-five years.

[Table 5 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 higher volatility and tighter funding constraints. Specifically, we run the regressions of individual (floating) FX rate liquidities on the FX systematic liquidity as well as of the FX systematic liquidity interacted with a dummy for severely distressed markets

$$\triangle L_{ij,t} = \alpha_{ij} + \beta_{ij} \Delta L_{M,t} + \gamma_{ij} \Delta L_{M,t} \cdot D_t + \varepsilon_{ij,t}, \tag{6}$$

Naik, and Radcliffe 1998; Chordia, Roll, and Subrahmanyam 2000; Chordia, Roll, and Subrahmanyam 2001; Hasbrouck and Seppi 2001; Huberman and Halka 2001; Lesmond 2005). Karolyi, Lee, and Dijk 2012 show that commonality is also discernible across international stock markets.

where the dummy D_t is one in periods of market distress. The regressor $\Delta L_{M,t}$ is based on the first principal component across 39 out of 40 liquidities (excluding the FX rate liquidity on the left hand side of the regression, $\triangle L_{ij,t}$).

The results in Table 5 provide evidence of significantly stronger commonality in periods of market stress—as indicated by high FX and stock market volatility, tight funding constraints (high TED spread), and losses of carry trade portfolios. More precisely, in Panel A of Table 5 the dummy variables are equal to one when the risk factors are 1.5 standard deviations above their average values indicating that the cross-sectional (across the 31 exchange rates) average of the γ_{ij} coefficient is significantly positive for all risk factors. This means that liquidity of exchange rate ij is more strongly correlated with the systematic liquidity in periods of market stress. For instance, for the TED spread the average R^2 is around 0.33 in calm periods and 0.47 in distressed periods. Panel B of Table 5 shows the same results except that the dummy variables are equal to one when the risk factors are one standard deviation above the mean.

The stronger liquidity commonality in the times of high TED spread is consistent with the theory of decreasing supply of liquidity in times when market makers and other intermediaries are constrained by their capital base (Hameed, Kang, and Viswanathan 2010). The depreciation of investment currencies rather than the appreciation of funding currencies of carry trade strategies is particularly important to explain the strengthening of commonality in liquidity (the results for funding currencies are not tabulated).

2.2 Explaining commonality in FX liquidity

This section investigates the determinants of cross-sectional differences in commonality FX liquidity. To build an empirical framework, we rely on the previous literature on market segmentation—briefly summarized below.

Commonality of a currency's liquidity might be related to a country's level of global integration (Bekaert and Harvey 2000). For instance, Korajczyk (1996) finds that deviations of stock returns from an equilibrium model are much larger for emerging markets than for developed markets, which is consistent with larger barriers to capital flows. Similarly, Demirguc-Kunt and Levine (1996) find that mispricing correlates negatively with the market capitalization and positively with market volatility. Global integration would also mean a high covariance with a common world factor (Bekaert and Harvey 1995), and it has been found that less-integrated countries tend to have higher and more idiosyncratic equity volatility (Bekaert and Harvey 1997).

Low quality of institutions and of legal environment also contributes to financial market segmentation (La Porta, de Silanes, Shleifer, and Vishny 1998). Poor institutions, political instability, and high inflation may affect risk assessments of foreign investors, thus reducing capital market integration (Bekaert 1995). Lee (2011) finds that the global liquidity risk is more important than local liquidity risk in countries in which more global investors are present: specifically, in developed countries and in countries with high transparency, low political risk, and large cross-border investment flows. Poorly developed financial systems is another factor driving market segmentation (Bekaert, Harvey, Lundblad, and Siegel 2011).

Based on these findings, we regress commonality of a currency pair's liquidity on factors that capture the level of economic and financial market integration. We consider five groups of factors: trade, portfolio positions and capital flows, macroeconomic variables, institutional framework, and asset markets (other than FX).

First, we use the commonality regression (5) with the systematic liquidity based on the floating currencies on the right-hand side to obtain commonality R^2_{ij} for each of the thirty floating FX pairs.[21] Second, following Karolyi, Lee, and Dijk (2012),[22] we make a logistic transformation of the R^2 measures. Third, we run cross-sectional simple regressions of commonality on a potential determinant

$$\ln[R^2_{ij}/(1 - R^2_{ij})] = a + bz_{ij} + u_{ij}, \tag{7}$$

where z_{ij} is a single characteristic of the currency pair. Fourth, we run multiple (cross-sectional) regressions, where z_{ij} includes several variables (discussed below).

Table 6 shows the results from simple regressions. The first panel investigates five different trade variables. The first two variables measure foreign trade as a fraction of GDP: as a sum of country i and j (to measure overall foreign trade importance) or as the difference (to measure the economic "distance" of the countries). The third variable instead focuses on bilateral trade between i and j; the fourth variable focuses on the geographical distance between the capitals; and the fifth variable focuses on the trade flows as measured by a gravity model (Tinbergen 1962). See the Internet Appendix for

[21] Excluding Taiwan, for which we do not have the most of fundamental data.

[22] Studying commonality on stock markets, Karolyi, Lee, and Dijk (2012) find that commonality (of individual stocks with the national stock market) is greater in countries with higher average market volatility, more correlated trading activity, greater equity inflows, and weaker protection laws.

the detailed data descriptions and sources of the data. The empirical results suggest that none of these trade variables is important for understanding commonality in FX liquidity.

[Table 6 about here.]

The second panel of Table 6 uses portfolio positions and capital flows, more specifically international debt issues, stock market capitalizations, and net foreign assets—all expressed as fractions of GDP. Again we allow for either the overall level (sum across country i and j) or the differences to enter the regression. The empirical results suggest that only the total debt issue is significantly related to commonality—and the coefficient is positive.

The third panel uses macro variables such as GDP/capita, inflation, money supply, and changes in PPP. There are several significant variables. In particular, inflation is negatively related to FX commonality. The fourth panel focuses on institutional variables, and the results suggest that a high "good government" index (Morck, Yeung, and Wu 2000; La Porta, de Silanes, Shleifer, and Vishny 1998) is strongly positively correlated with commonality. The fifth panel studies asset market movements outside the FX market, more specifically stock returns, interest rates, and stock volatility. We find that both stock returns and interest rates are significantly negatively related to FX commonality, meaning that higher (excess) stock returns and interest rates (differential) correlate negatively with commonality in FX liquidity. The sixth panel includes just a dummy for being an emerging market (following the classification in Figure 5), which we will use as a control variable in the multiple regressions. As expected, it has a significantly negative coefficient.

[Table 7 about here.]

The variables within each of the groups (panels in Table 6) tend to be correlated. It is therefore necessary to select some of the variables for the multiple regressions. To do that, we follow a simple rule: from each category, we pick the best (see the highest R^2 marked in bold italic in Table 6). This allows each group (which broadly correspond to a set of related theories) to have its best chance. Clearly, this two-step procedure means that we have to apply conservative critical values in the second step (the multiple regressions). Table 7 shows the findings from the multiple regressions.

We consider several combinations of the factors to deal with the remaining collinearity between some of the regressors.[23] Model (1), which includes all five variables, gives a high cross-sectional fit of 71%, suggesting that the chosen factors do a good job in explaining commonality. The good government index appears to be the most important driver. It is significant (compared to standard critical values) in all specifications—also when we include the emerging market dummy in model (5). When we exclude some of the other regressors (inflation and interest rates, see models (2) and (3)) to avoid multicollinearity, the good government index is significant even when compared with very conservative critical values. Excluding it from the model still gives an R^2 of 63% (see Column (4)) and makes international debt issues and inflation the key determinants of commonality.

Overall, our findings suggest that good governance, international debt issues, and inflation of the two countries forming the currency pair are key determinants of commonality in liquidity of the exchange rate. These factors apparently capture the level of market integration and development of the countries and explain the large portion of the cross-sectional variation in commonality.

2.3 Drivers of FX liquidity

In this section, we try to identify the main drivers of FX liquidity. To motivate our empirical approach we first discuss the theoretical literature.

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 (covered and uncovered interest rate parity) and stocks (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 link between asset returns and FX trading are likely to arise. Therefore, this class of models suggests that FX liquidity could be related to returns of FX and other assets, such as bonds and stocks.

Market liquidity also relates 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

[23] In particular, the inflation and good government index variables have a correlation of -0.88; inflation and interest rates 0.86; the government index and interest rates -0.82.

sheds light on the intricate dynamics between market liquidity, funding constraints and risk (e.g., Vayanos and Gromb 2002; Morris and Shin 2004; Brunnermeier and Pedersen 2009; Acharya and Viswanathan 2011). Although the exact mechanisms in the theoretical models differ, they all predict that funding constraints and market illiquidity can generate spirals through fire-sales and increased risk. This mechanism can spill over across markets, creating contagion and commonality in illiquidity (e.g., Kyle and Xiong 2001). In short, this class of models implies a link between market illiquidity, risk, and funding constraints.

Inspired by the models discussed above, we analyze whether FX liquidity is linked to returns, liquidity, and risk variables of the main asset classes, that is, FX, stocks, and bonds (including government and corporate as well as money markets). We make no attempts to control endogeneity and reverse causality, but (as will be seen later) the correlation patterns are strong enough to tell which theories are consistent with data and which are not. We perform panel regressions in which (changes of) the monthly liquidities of 31 floating individual exchange rates are regressed on global factors. Because all liquidity variables are standardized (zero mean, unit variance) these panel regressions are effectively fixed-effects estimates.

We proceed in two steps. First, we regress (changes of) liquidity on one variable at a time: monthly FX returns (IMF return, FX return, and AER factor), stock returns (MSCI World index return), interest rate return (changes in yields of U.S. Financial commercial paper, FED funds rates, U.S. corporate bonds yields rated AAA and BAA by Moody's), risk variables of FX markets (changes in FX implied volatility and HML factor), stock markets (changes in VIX and MSCI return realized volatility), the bond market (changes in MOVE index, TED spread, and default spread for U.S. companies). We also use liquidity measures of the stock and Treasury bond markets. An exact description of these variables is available on the Internet Appendix. With few exceptions, our sample period spans from January 1991 to May 2012.[24] Second, we run multiple regressions.

Table 8 presents the findings from the simple (panel) regressions. The t-statistics (in brackets) are robust to cross-sectional and serial correlations, using the Driscoll and Kraay (1998) covariance estimator. The only *return variables* that are significant are FX returns (an appreciating USD is associated with lower liquidity) or stock returns (high

[24]The sample period is January 1991–May 2012, except for the Mean IMF return (Jan 1995–May 2012), FX implied volatility (Apr 1992–May 2012), and Financial commercial paper (Jan 1998–May 2012).

MSCI World index returns are associated with higher liquidity). The other return variables (on money and bond market instruments) are far from significant. In contrast, most *risk variables* are strongly significant, and more risk is consistently associated with lower FX liquidity. The risk variables include implied and realized volatilities of stock, bond and FX returns, as well as spreads on the FX, money, and stock markets—and also a spread on the corporate bond market.

[Table 8 about here.]

The variables within each category tend to be highly correlated, so we select one (with the highest R^2, marked in bold italic)[25] from each category to enter the multiple panel regressions

$$\triangle L_{ij,t} = \alpha + \beta' x_t + \gamma \triangle L_{M,t-1} + \varepsilon_{ij,t}, \tag{8}$$

where x_t are the global drivers that we are interested in.[26] We include the lagged systematic liquidity to control for possible persistence in liquidity. The procedure to select the variables for the multiple regressions has the advantage of giving each category of variables its best chance but it also suggests that we should apply conservative critical values in tests of the coefficients.

Table 9 summarizes the results from the multiple (panel) regressions. Regression model (1) includes risk and return variables from the money, bond and stock markets. As in the simple regressions, the risk variables are more important than the return variables. A Wald test rejects the null hypothesis that the estimated coefficients of all risk variables are equal to zero (the test statistic is 81.7, which can be compared with the 0.1% critical value from a χ^2_3 distribution, 16.3). The strength of the rejection is comforting, especially in the light of our variable selection procedure. The coefficients of the risk variables have

[25]The only exception is the mean IMF return because a shorter sample period is available.

[26]The variables that we use in the multiple regressions are as follows. The return measures are mean USD return (average return across the USD-based currencies in our sample), Federal funds rate, Moody's long-term BAA corporate bond yield, and return on the MSCI World index. The risk measures are JP Morgan Global FX implied volatility index, TED spread, U.S. default spread (difference between Moody's BAA and AAA corporate bond yield), and MSCI volatility (monthly volatility of daily returns on the MSCI World index). The stock market liquidity is based on the PCA across price impact proxies of the monthly Amihud (2002) measure (from Karolyi, Lee, and Dijk 2012), calculated as the value-weighted average of all individual stock in each country. The bond market liquidity is the off-the-run liquidity premium 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). Further details are available in the Internet Appendix.

negative signs, indicating that FX liquidity decreases with an increase of risk in each asset classes. These results continue to hold in model (2), which includes also return and risk variables for the FX market itself.

Model (3) drops the return and risk variables to instead include only stock and bond market liquidity. Both coefficients are positive and strongly significant, suggesting important commonality in liquidity between FX, stock, and bond markets. (The sample for this specification is only 1995–2009 due to availability of the stock liquidity data.) Model (4) includes all variables to show that the importance of the stock liquidity is overshadowed by the other variables and that the risk factors remain significant when we control for stock and bond liquidity. Model (5) drops the stock market liquidity (because it is not significant in model (4) and because it is only available for a shorter sample) to arrive at our preferred specification. We also validate the results from the panel data by running OLS regressions with the systematic FX liquidity as the dependent variable; see model (6).[27] The results are similar: the same signs and the same degree of statistical significance as for the panel. However, the R^2 is much higher (0.54 instead of 0.19), because the systematic liquidity averages out much of the idiosyncratic noise in the panel.

In sum, the results in Table 9 suggest that risk arising from the main asset classes (stocks, bonds, money market, and FX) is important in explaining FX liquidity patterns—consistent with the flight-to-liquidity dynamics and liquidity spirals theories. In contrast, the parity condition theory, at least in its original risk-neutral framework, is not supported by our results. There is also evidence of commonality between liquidity of FX, bond, and stock markets (to a lesser extent for the stock market).

[Table 9 about here.]

Table 10 extends the analysis by interacting the global drivers with dummy variables that capture different characteristics of the currencies. The global drivers are the same as in model (5) in Table 9: all variables, except the stock market liquidity (which was insignificant and available only for a shorter sample).

In model (1) of Table 10, the dummy variable is equal to one for emerging currencies (and zero otherwise). The upper panel of coefficients reports the estimates for developed

[27]Systematic FX liquidity based on 40 FX pairs has 0.996 correlation with the systematic liquidity based on 31 floating FX pairs. Using only USD-, EUR-, or GBP-based liquidities in models (1)–(5) gives similar results, see the Internet Appendix.

currencies. They are similar to the results (in Table 9) for the entire cross-section. The lower panel of coefficients shows the difference between the emerging and developed currencies. The main results are that emerging currencies are much less related to the interest rate risk (summing the coefficients in the two panels gives a value close to zero) and to the bond market liquidity. It can also be shown that the R^2 within the group of the emerging currencies is 0.117, compared with 0.226 within the group of developed currencies. This is in line with our earlier findings that emerging countries experience weaker commonality in FX liquidity.

Inspired by the recent FX asset pricing literature, models (2)–(4) use different time-varying dummies, indicating "riskier" currencies. For instance, Lustig, Roussanov, and Verdelhan (2011) find that the return on the USD and on a carry trade portfolio are pricing factors for carry trade returns, and Menkhoff, Sarno, Schmeling, and Schrimpf (2012a) demonstrate the importance of volatility. Verdelhan (2013) shows that the USD return and carry trade risk factors also explain excess returns on individual exchange rates.

[Table 10 about here.]

The dummy variable in model (2) of Table 10 is equal to one if a currency pair underperforms the cross-sectional average U.S. dollar return in that month.[28] In model (3), we instead use a carry trade 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. In model (4), we use a volatility dummy, which is equal to one if a currency pair has a higher realized volatility than the cross-sectional average in that month. Overall, few of the interaction terms are significant. However, there are indications that risk currencies are more (negatively) exposed to corporate bond market returns and risk, as well as the FX risk.

Finally, in model (5), we use a commonality dummy, which is equal to one if an exchange rate has stronger commonality in FX liquidity than the cross-sectional average (in terms of the R^2 from Figure 5). As expected, the results are the flip side of those for the emerging currency dummy in model (1)—because commonality is lower for the emerging currencies.

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

In sum, the results in this section suggest that *(1)* FX liquidity is strongly related to risk measures for different asset markets, *(2)* there is substantial commonality in liquidity between FX and bond markets, and *(3)* the liquidity of emerging currencies are less exposed to the risk measures and show more idiosyncratic movements in FX liquidity.

3. Concluding Remarks

This paper provides the first comprehensive study of FX liquidity and commonality in FX liquidities over more than two decades and forty currency pairs. Having found the most-accurate liquidity measures for FX liquidity, this paper shows the main determinants of commonality in FX liquidities and which factors that explain the time-series and cross-sectional variation of FX liquidity.

We access a unique dataset of high-frequency (HF) data from the beginning of 2007 to May 2012 that has been provided by the leading platform for FX spot interdealer trading. We are able to form precise benchmark measures of FX liquidity based on HF data and find the low-frequency (LF) methods that most accurately measure FX liquidity. Combining the best LF measures across currency pairs, we construct an index of systematic FX liquidity that tracks very closely the HF effective cost benchmark.

We find several new results. The first contribution of this paper is the analysis of commonality in FX liquidities. We find that strong commonality of the FX liquidities has been a systematic characteristic over the last two decades, and it systematically increases in distressed markets, that is, when volatility in stock and FX markets is high, when the short-term funding market is tight, and when the currency carry trade incurs substantial losses. Another novelty of this study is to highlight the cross-sectional determinants of commonality in FX liquidities. Commonality increases with the degree of quality of institutions, financial integration, and price stability.

Second, FX liquidity is strongly related to risk arising from the FX market but also from the stock, bond, and money markets. We also find commonality in liquidities across these markets, indicating that when risk increases, liquidity evaporates at the same time in the stock, bond, and FX markets. All of this adds a new dimension to flight-to-quality or flight-to-liquidity dynamics, that is cross-markets spillovers of risk and illiquidity impair FX liquidity. Another novel result is the identification of groups of currencies that are more exposed to liquidity drops, namely, (1) developed currencies, (2) currencies traded at a forward premium, and (3) those that experienced a recent depreciation against the U.S. dollar.

Our findings are relevant for investors, policy makers, 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, the recent financial crisis has proved that liquidity can suddenly evaporate even on the FX market that was commonly regarded as extremely liquid. More generally, our results suggest another channel of risk spillovers, that is, from risk intensification in stock, bond, and money markets to illiquidity in another (the FX market, in this case). Third, liquidity issues dominate the agenda of policy makers, see, for example, 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 an in-depth understanding of liquidity issues on currency markets.

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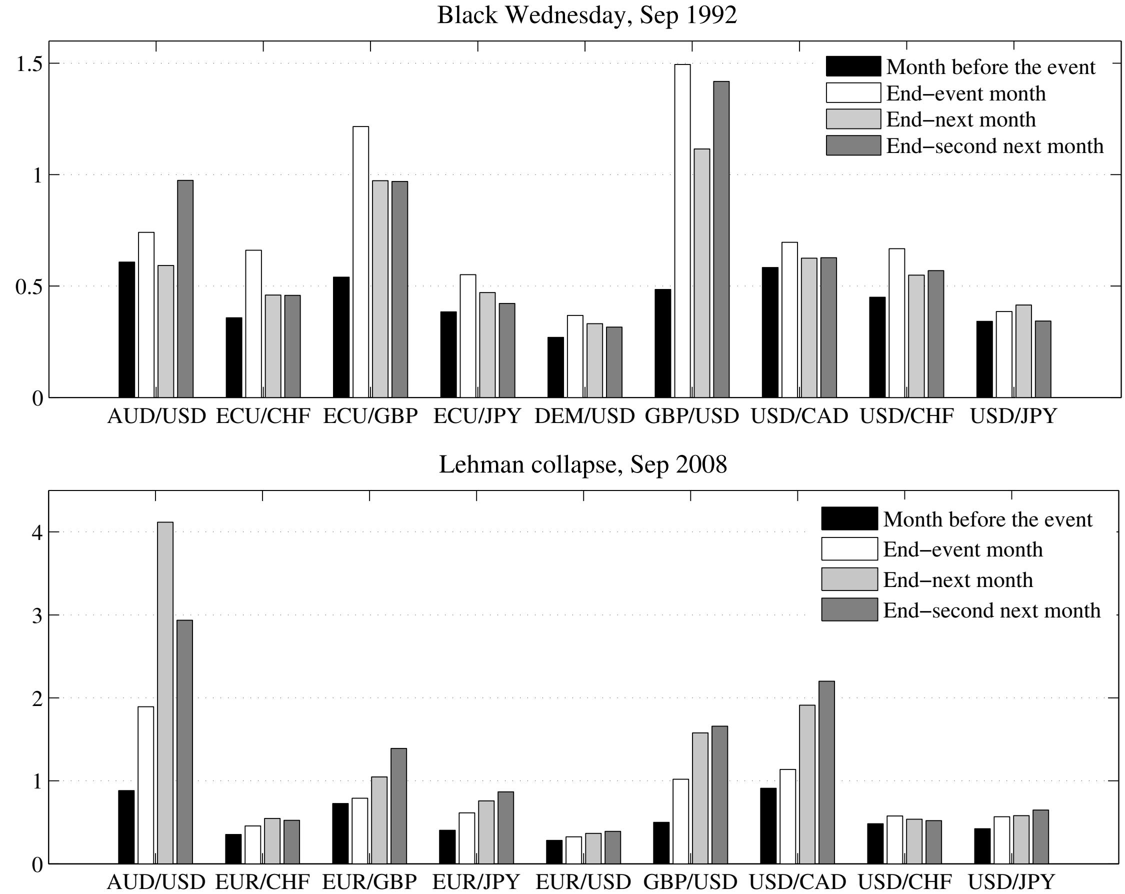

Figure 1: **Effect of the crisis events on the estimated effective cost (EC).** Figure depicts the monthly estimated EC (in basis points) for 9 exchange rates before and after two crisis events: "the Black Wednesday" on 16 September 1992 and "Lehman collapse" on 15 September 2008. The estimated EC for 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*).

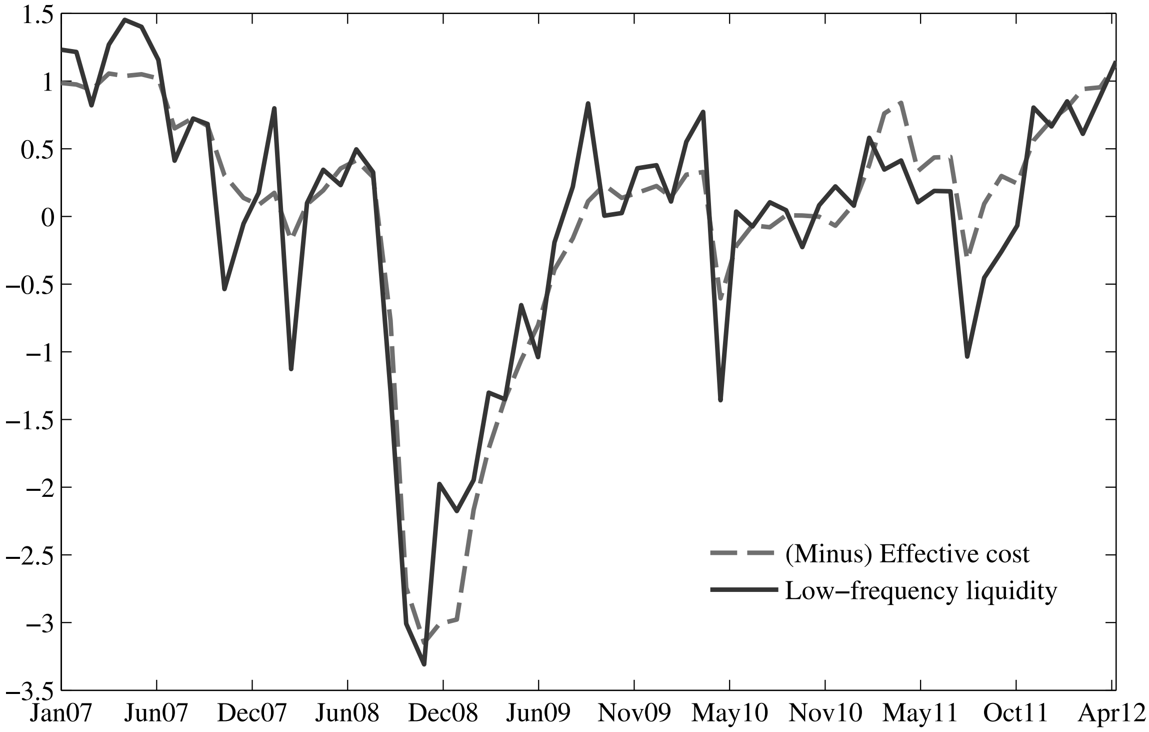

Figure 2: **Across-currencies effective cost (HF) vs. systematic low-frequency (LF) liquidity.** The across-currencies effective cost liquidity is obtained from the PCA across exchange rates (dotted line). The systematic LF liquidity is obtained from the PCA across exchange rates as well as three best 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.

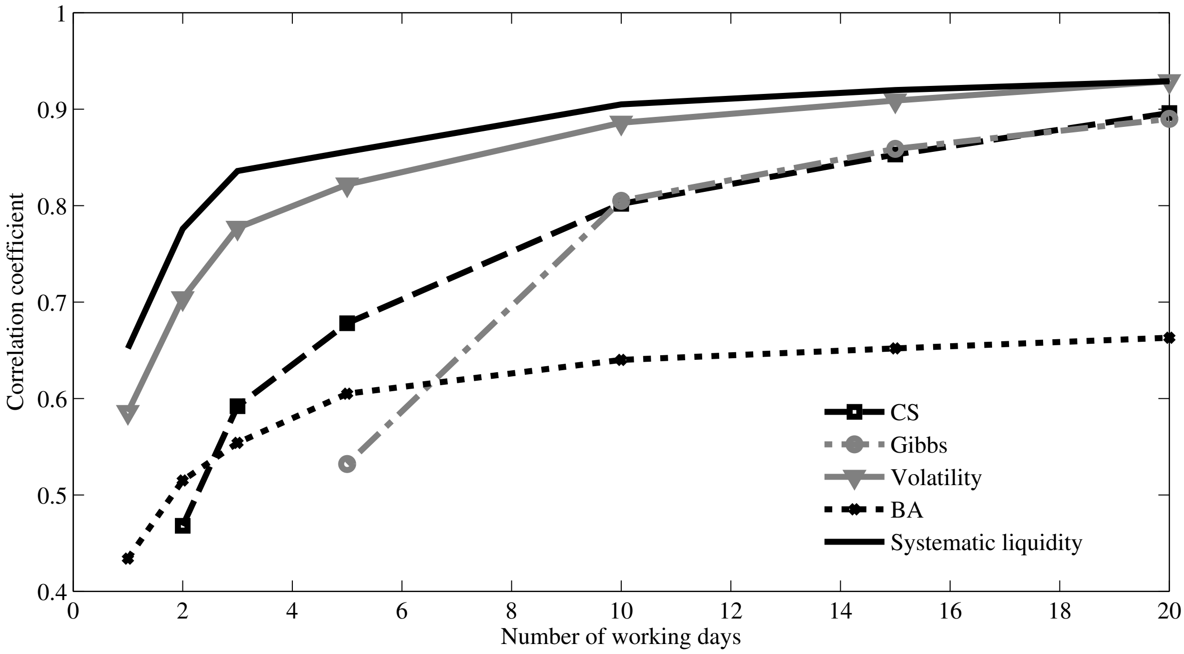

Figure 3: **Low-frequency (LF) liquidity measures based on different frequencies vs effective cost liquidity.** Each line represents the correlations of the LF liquidity measures based on different frequencies with the effective cost benchmark. Whenever it is possible, each liquidity measure is computed 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.

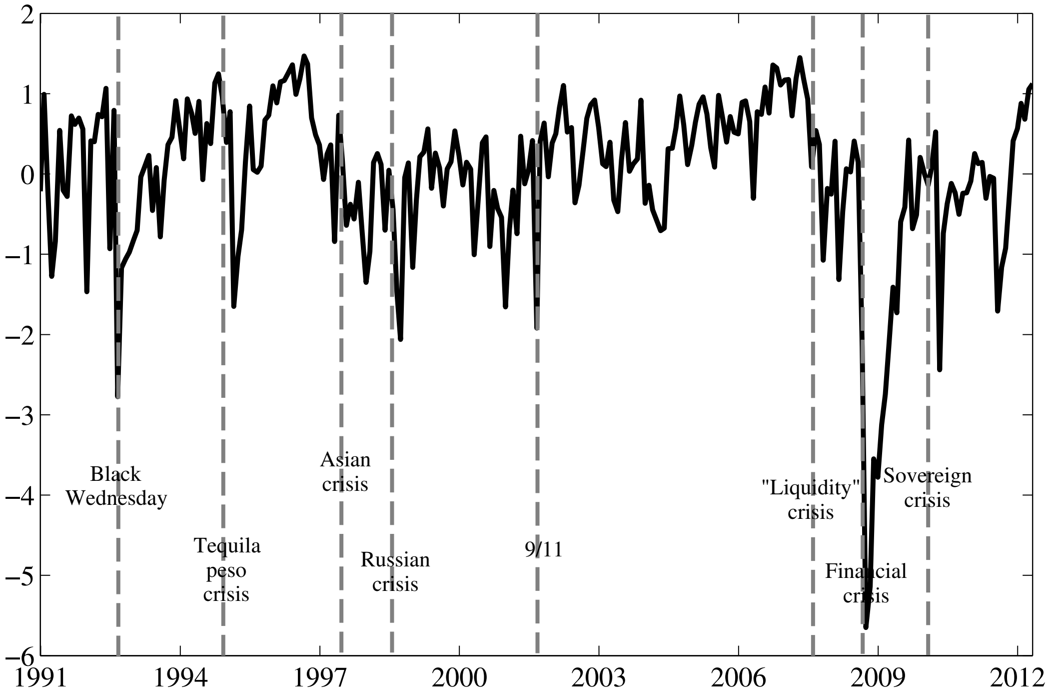

Figure 4: **Systematic low-frequency (LF) FX liquidity over 1991–2012.** Figure depicts the monthly standardized systematic LF liquidity obtained from the PCA across the 40 exchange rates as well as three best LF liquidity proxies (*CS*, *Gibbs* and *Volatility*). The sign of each liquidity measure is 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.

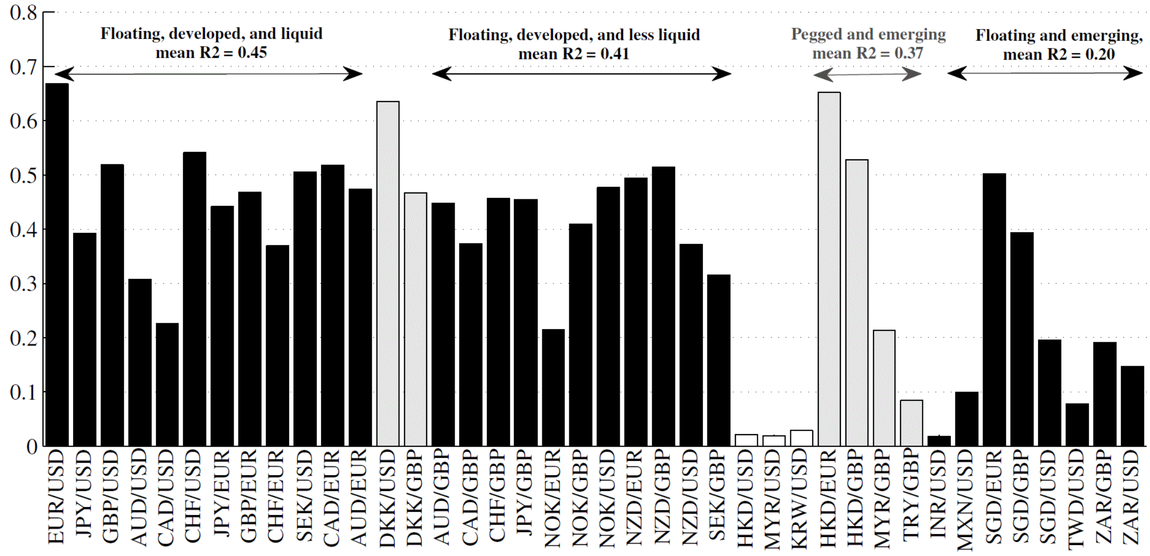

Figure 5: **Commonality in the FX liquidity for each currency pair.** The Figure shows the R^2 from regressing individual FX liquidities on the systematic LF liquidity. The individual FX rate liquidities are obtained from the PCA across the three best LF liquidity proxies (*CS*, *Gibbs* and *Volatility*) for each currency pair. The systematic LF liquidity is obtained from the PCA across the forty 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 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. White bars denote the pegged currency pairs over some period in our sample (HKD/USD, MYR/USD, KRW/USD). Grey bars denote the currency pairs, where one currency in a pair is pegged to the other currency outside the pair (liquidity on these currencies replicate liquidity of the floating rate of the base currency to the currency outside the pair: for example, liquidity of the HKD/EUR replicates liquidity of the EUR/USD). The sample is January 1991 – May 2012, 257 months.

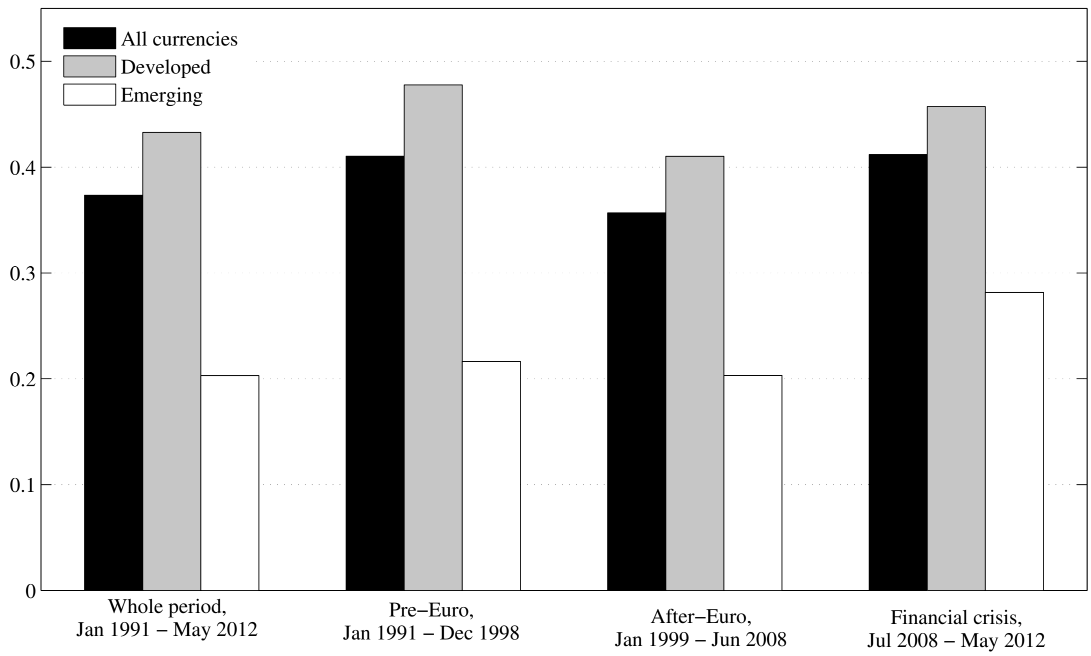

Figure 6: **Commonality in the FX liquidity by groups and sub-periods.** The Figure shows the average R^2 from regressing individual FX liquidities on the systematic LF liquidity for different groups of floating currencies and for different periods. The groups of (floating) currencies are: all 31 currencies, 23 developed and 8 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.

	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 1: **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 (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 2: **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.

	(1)	(2)	(3)	(4)	(5)
LF liquidity	**0.929**				
	[12.154]				
Volatility		**0.930**	**0.930**	**0.930**	**0.887**
		[10.160]	[12.150]	[12.150]	[12.581]
|Volatility|					-0.097
					[-0.997]
CS*			**0.253**		
			[2.076]		
Gibbs**			0.204		
			[1.787]		
Gibbs^{+}				**0.245**	
				[1.984]	
CS^{++}				0.206	
				[1.869]	
R^2	0.863	0.865	0.881	0.881	0.868

Table 3: **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 absolute value of the across-currencies volatility. 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 intercepts are omitted. 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 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.

	Implied FX volatility	TED spread	MSCI volatility	Losses on on 3 investment currencies	Losses on carry trade portfolio
	(1)	(2)	(3)	(4)	(5)
Panel A. Cut-off 1.5 std above the mean					
Mean(β_{ij})	**0.158**	**0.154**	**0.155**	**0.156**	**0.156**
Mean(γ_{ij}	**0.049**	**0.052**	**0.027**	**0.032**	**0.029**
t-stat of mean(γ_{ij})	[2.822]	[6.417]	[2.395]	[2.331]	[2.124]
Sum(D_t)	10	18	18	16	18
Number of obs.	239	255	255	255	255
Panel B. Cut-off 1 std above the mean					
Mean(β_{ij})	**0.159**	**0.155**	**0.154**	**0.155**	**0.153**
Mean(γ_{ij})	**0.023**	**0.041**	**0.027**	**0.022**	**0.023**
t-stat of mean(γ_{ij})	[2.504]	[3.859]	[2.593]	[2.042]	[2.541]
Sum(D_t)	22	27	25	32	38
Number of obs.	239	255	255	255	255

Table 5: **Commonality in FX liquidity in the distressed markets.** Changes in 31 (floating) FX rate liquidities $\triangle L_{ij,t}$ are regressed (one by one) on the changes in systematic FX liquidity $\triangle L_{M,t}$ and $\triangle L_{M,t}$, interacted with a dummy D_t for distressed market periods. D_t is equal to one if the risk factor is more than 1.5 (Panel A) or 1 (Panel B) standard deviations above its mean in period t. $\Delta L_{M,t}$ is based on the first principal component across 39 out of 40 liquidities (excluding the FX rate liquidity $\triangle L_{ij,t}$). The risk factors are the implied FX volatility, TED spread, MSCI volatility, losses on 3 investment currencies (minus mean return at time t on 3 currencies with the highest forward discounts at time $t-1$), and losses on carry trade portfolio (minus mean FX return at time t on 3 currencies with the highest forward discount at time $t-1$ plus mean FX return at time t on 3 currencies with the lowest forward discount at time $t-1$). The table shows the mean coefficients from the regressions $\triangle L_{ij,t} = \alpha_{ij} + \beta_{ij}\Delta L_{M,t} + \gamma_{ij}\Delta L_{M,t} \cdot D_t + \varepsilon_{ij,t}$. The intercepts are omitted. The t-statistics for testing the hypothesis of the cross-sectional mean coefficients being equal to zero are calculated using a GMM based method that accounts for serial and cross-sectional correlations and reported in brackets. Bold numbers are statistically significant at the 5% level. The sample for specifications (1) and (3)–(5) is January 1991 – May 2012, the sample for specification (2) is April 1992 – May 2012.

	beta	t-stat	R^2
I. Trade			
(Export i + Import i) / GDP i + (Export j + Import j) / GDP j	0.125	[0.915]	0.019
|(Export i + Import i) / GDP i - (Export j + Import j) / GDP j|	0.030	[0.232]	0.001
Export i to j / GDP i + Export j to i / GDP j	-0.160	[-1.171]	***0.031***
Geographical distance from i to j	0.006	[0.055]	0.000
Trade flow (gravity model)	-0.014	[-0.132]	0.000
II. Portfolio positions and capital flows			
International debt issues i / GDP i + International debt issues j / GDP j	**0.533**	[3.058]	***0.339***
|International debt issues i / GDP i - International debt issues j / GDP j|	0.087	[0.717]	0.009
Stock market cap i / GDP i + Stock market cap j / GDP j	0.003	[0.018]	0.000
|Stock market cap i / GDP i - Stock market cap j / GDP j	0.005	[0.041]	0.000
Net foreign assets i / GDP i + Net foreign assets j / GDP j	0.010	[0.093]	0.000
|Net foreign assets i / GDP i - Net foreign assets j / GDP j|	0.107	[0.795]	0.014
III. Macro			
GDP per capita i + GDP per capita j	**0.328**	[2.338]	0.128
|GDP per capita i - GDP per capita j|	**0.249**	[2.371]	0.074
Inflation i + Inflation j	**-0.663**	[-4.024]	***0.525***
|Inflation i - Inflation j	**-0.638**	[-3.780]	0.486
Money supply i / GDP i + Money supply j / GDP j	**0.308**	[2.323]	0.113
|Money supply i / GDP i - Money supply j / GDP j|	0.066	[0.546]	0.005
Change in PPP i + change in PPP j	**-0.572**	[-4.521]	0.391
|Change in PPP i - change in PPP j|	**-0.580**	[-4.540]	0.402
IV. Institutional			
Good government index i + good government index j	**0.739**	[4.995]	***0.651***
|Good government index i - good government index j|	**-0.731**	[-5.178]	0.637
Both i and j are in OECD	0.337	[1.443]	0.135
V. Asset markets			
Stock returns i + stock returns j	**-0.529**	[-3.720]	0.334
|Stock returns i - stock returns j|	**-0.328**	[-4.020]	0.128
Interest rate i + interest rate j	**-0.539**	[-4.019]	0.346
|Interest rate i - interest rate j|	**-0.604**	[-3.567]	***0.435***
Volatility of stock returns i + volatility of stock returns j	-0.011	[-0.085]	0.000
|Volatility of stock returns i - volatility of stock returns j|	-0.243	[-1.198]	0.071
VI. Emerging market dummy	**-0.570**	[-2.820]	***0.388***

Table 6: **Explaining commonality in FX liquidity with single factors.** The logistic transformation of commonality R^2 for 30 currency pairs (floating, excluding Taiwan) is regressed on the fundamental factors. The commonality R^2 are the taken from regression (5). The fundamental factors are based on the data on countries with currency i and j. 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.

		(1)	(2)	(3)	(4)	(5)
I	Export i to j / GDP i +	-0.154	-0.165	-0.161	-0.112	-0.161
	Export j to i / GDP j	[-1.823]	[-1.938]	[-1.793]	[-1.227]	[-1.749]
II	International debt issues i / GDP i +	0.201	0.179	0.171	**0.336**	0.198
	international debt issues j / GDP j	[1.876]	[1.723]	[1.627]	[2.434]	[1.849]
III	Inflation i + inflation j	-0.133			**-0.574**	-0.131
		[-1.122]			[-2.624]	[-1.125]
IV	Good government index i +	**0.610**	**0.693**	**0.638**		**0.651**
	good government index j	[2.140]	[2.612]	[3.768]		[2.151]
V	$\lvert$Interest rate i - interest rate $j\rvert$	0.129	0.071		0.077	0.135
		[0.623]	[0.354]		[0.393]	[0.653]
VI	Emerging dummy					0.042
						[0.287]
	R^2	0.707	0.704	0.702	0.634	0.708

Table 7: **Explaining commonality in FX liquidity.** The logistic transformation of commonality R^2 for 30 currency pairs (floating, excluding Taiwan) is regressed on the fundamental factors. The commonality R^2 are taken from regression (5). The fundamental factors are based on the data on countries with currency i and j (candidate with the highest R^2 within each category). Emerging dummy takes one for 7 emerging currency pairs. 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.

	beta	t-stat	R^2	N
FX return				
Mean IMF return	**-0.250**	[-3.969]	0.065	209
AER factor	0.095	[1.614]	0.009	255
Mean FX return	**-0.125**	[-2.125]	***0.016***	255
FX risk				
Δ HML	**0.163**	[3.622]	0.027	255
Δ FX implied volatility	**-0.324**	[-8.630]	***0.108***	241
Interest rate return				
Δ Fin commercial paper	-0.035	[-0.690]	0.001	184
Δ Fed funds rate	0.074	[1.234]	***0.005***	255
Interest rate risk				
Δ TED spread	**-0.136**	[-3.690]	***0.019***	255
Δ MOVE index	**-0.137**	[-3.125]	0.019	255
Corporate bond return				
Δi_{AAA} bonds	-0.023	[-0.372]	0.001	255
Δi_{BAA} bonds	-0.081	[-1.064]	***0.007***	255
Corporate bond risk				
Δ US default spread	-0.112	[-1.555]	***0.012***	255
Stock return				
MSCI return	**0.162**	[2.691]	***0.026***	255
Stock risk				
Δ VIX	**-0.286**	[-6.853]	0.082	255
Δ MSCI volatility	**-0.318**	[-6.894]	***0.101***	255

Table 8: **Explaining FX liquidity with single factors.** The table shows the output from single regressions of the panel of 31 (floating) FX rate liquidities on contemporaneous risk and return variables from FX, interest rate, corporate bonds and stock market. The t-statistics for the panel regressions (1)–(8) 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) and reported in brackets. Bold numbers are statistically significant at the 5% level. The sample is January 1991 – May 2012, except for the Mean IMF return (Jan 1995 – May 2012), JP FX implied volatility (Apr 1992 – May 2012), and Fin commercial paper (Jan 1998 – May 2012).

Group		(1)	(2)	(3)	(4)	(5)	(6)
FX ret	Mean FX return		-0.009		-0.010	-0.027	-0.037
			[-0.274]		[-0.282]	[-0.871]	[-0.714]
FX risk	Δ FX implied vol		**-0.204**		**-0.207**	**-0.171**	**-0.307**
			[-4.140]		[-3.426]	[-3.612]	[-3.702]
Int rate ret	Δ Fefunds rate	0.061	0.038		-0.010	-0.006	-0.014
		[1.664]	[1.044]		[-0.256]	[-0.187]	[-0.259]
Int rate risk	ΔTED	**-0.062**	**-0.058**		**-0.077**	**-0.053**	**-0.094**
		[-2.203]	[-2.539]		[-3.119]	[-2.522]	[-2.719]
Corp bond ret	Δi_{BAA}	0.037	0.023		0.015	0.036	0.054
		[1.054]	[0.731]		[0.360]	[1.010]	[0.955]
Corp bond risk	Δ US def spread	**-0.109**	**-0.071**		-0.053	**-0.065**	**-0.111**
		[-2.837]	[-2.005]		[-1.246]	[-2.057]	[-2.192]
Stock ret	MSCI return	0.028	-0.016		-0.004	-0.017	-0.029
		[0.774]	[-0.421]		[-0.096]	[-0.455]	[-0.483]
Stock risk	Δ MSCI volatility	**-0.262**	**-0.203**		**-0.167**	**-0.187**	**-0.295**
		[-6.541]	[-4.236]		[-2.992]	[-4.088]	[-3.927]
	$\Delta L_{M,t-1}$	**-0.174**	**-0.170**	**-0.172**	**-0.116**	**-0.186**	**-0.324**
		[-4.414]	[-4.186]	[-4.253]	[-3.403]	[-4.930]	[-4.828]
	Δ Stock liquidity			**0.129**	-0.034		
				[2.873]	[-0.883]		
	Δ Bond liquidity			**0.241**	**0.109**	**0.132**	**0.240**
				[4.290]	[2.244]	[3.324]	[3.432]
	R^2	0.139	0.178	0.099	0.182	0.191	0.535
	Number of obs.	255	241	179	179	241	241
	Start of the sample	01/1991	04/1992	01/1995	01/1995	04/1992	04/1992
	End of the sample	05/2012	05/2012	12/2009	12/2009	05/2012	05/2012

Table 9: **Explaining FX liquidity.** Table shows the results for the panel (specifications (1)–(5)) and non-panel (specification (6)) regressions of the FX liquidity. Panel of 31 (floating) FX rate liquidities is regressed on (1) non-FX contemporaneous risk and return variables and lagged systematic FX liquidity, (2) all contemporaneous risk and return variables, and lagged systematic FX liquidity, (3) lagged systematic FX liquidity, contemporaneous stock and bond liquidity, (4) all contemporaneous risk and return variables, lagged systematic FX liquidity, and contemporaneous stock and bond liquidity, (5) all contemporaneous risk and return variables, lagged systematic FX liquidity, and bond liquidity. In column (6) systematic FX liquidity (based on the PCA across 31 floating currencies) is regressed on all contemporaneous risk and return variables, lagged systematic FX liquidity, and bond liquidity. All variables except for the mean USD return and MSCI return are in changes. The t-statistics for the panel regressions (1)–(5) 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) and reported in brackets. The t-statistics for non-panel regression (6) are based on the standard errors, robust to conditional heteroscedasticity and serial (up to one lag) correlation as in Newey and West (1987) and reported in brackets. Bold numbers are statistically significant at the 5% level. The full sample is January 1991 – May 2012, 257 months.

	Dummy for:	Emerging market	High FX return	High forward premium	High FX volatility	High commonality in liquidity
Group		(1)	(2)	(3)	(4)	(5)
FX ret	Mean FX return	-0.010	-0.036	-0.006	-0.033	-0.053
		[-0.284]	[-1.068]	[-0.164]	[-1.220]	[-1.866]
FX risk	Δ FX implied vol	**-0.161**	**-0.139**	-0.108	**-0.089**	**-0.217**
		[-2.965]	[-1.990]	[-1.367]	[-1.494]	[-7.489]
Int rate ret	Δ Fefunds rate	-0.006	-0.006	-0.011	-0.037	0.013
		[-0.162]	[-0.174]	[-0.316]	[-1.380]	[0.570]
Int rate risk	ΔTED	**-0.077**	**-0.076**	**-0.074**	**-0.040**	0.004
		[-3.051]	[-2.889]	[-3.025]	[-2.115]	[0.149]
Corp bond ret	Δi_{BAA}	0.040	0.037	0.074	0.042	0.024
		[1.048]	[0.943]	[1.759]	[1.424]	[0.754]
Corp bond risk	Δ US def spread	-0.070	-0.027	**-0.090**	-0.052	-0.036
		[-1.932]	[-0.780]	[-2.147]	[-1.849]	[-1.078]
Stock ret	MSCI return	0.001	-0.018	0.006	0.003	-0.042
		[0.028]	[-0.425]	[0.123]	[0.084]	[-1.194]
Stock risk	Δ MSCI volatility	**-0.201**	**-0.160**	**-0.147**	**-0.156**	**-0.211**
		[-3.742]	[-3.251]	[-2.602]	[-4.460]	[-6.798]
	$\Delta L_{M,t-1}$	**-0.212**	**-0.217**	**-0.208**	**-0.111**	**-0.075**
		[-4.692]	[-4.953]	[-4.410]	[-3.643]	[-3.226]
	Δ Bond liquidity	**0.159**	**0.106**	**0.173**	**0.101**	0.036
		[3.426]	[2.387]	[3.549]	[2.986]	[1.230]
FX ret	Mean FX return	-0.064	0.022	-0.042	0.012	0.038
		[-1.641]	[0.555]	[-1.257]	[0.341]	[1.012]
FX risk	Δ FX implied vol $\cdot D$	-0.038	-0.047	-0.147	**-0.191**	0.068
		[-0.946]	[-0.803]	[-1.703]	[-2.931]	[1.196]
Int rate ret	Δ Fefunds rate $\cdot D$	0.000	0.004	0.011	0.065	-0.028
		[0.010]	[0.171]	[0.442]	[1.938]	[-0.956]
Int rate risk	$\Delta TED \cdot D$	**0.094**	0.039	0.038	-0.018	**-0.083**
		[2.982]	[1.248]	[1.054]	[-0.424]	[-2.701]
Corp bond ret	$\Delta i_{BAA} \cdot D$	-0.019	0.006	**-0.077**	-0.016	0.017
		[-0.564]	[0.165]	[-1.965]	[-0.365]	[0.548]
Corp bond risk	Δ US def spread $\cdot D$	0.019	**-0.075**	0.054	-0.041	-0.043
		[0.462]	[-1.982]	[1.157]	[-1.009]	[-1.031]
Stock ret	MSCI return $\cdot D$	-0.070	0.004	-0.054	-0.046	0.037
		[-1.514]	[0.132]	[-1.032]	[-1.076]	[0.991]
Stock risk	Δ MSCI volatility $\cdot D$	0.053	-0.054	-0.087	-0.069	0.035
		[1.158]	[-1.193]	[-1.902]	[-1.352]	[0.728]
	$\Delta L_{M,t-1} \cdot D$	**0.101**	0.059	0.036	**-0.145**	**-0.164**
		[2.439]	[1.863]	[0.996]	[-3.626]	[-3.503]
	Δ Bond liquidity $\cdot D$	**-0.106**	0.044	**-0.082**	0.056	**0.141**
		[-2.771]	[1.200]	[-1.960]	[1.353]	[3.517]
	R^2	0.198	0.199	0.208	0.230	0.200

Table 10: **Explaining FX liquidity for emerging and riskier currencies.** Panel of 31 (floating) FX rate liquidities is regressed on the contemporaneous FX, interest rates, and stocks risk variables, lagged systematic FX liquidity, bond liquidity, and these variables interacted with the dummy D, which takes one if and only if the condition holds. The dummy in column (1) is one if the currency pair is emerging. The dummy in column (2) is one if is one if currency i against the USD overperforms the average cross-sectional FX return (against the USD) 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 (mean of daily absolute returns) 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 dummy variables in specifications (1) and (5) are (in contrast to the other dummies) not time-varying. The t-statistics are based on standard errors, robust to conditional heteroscedasticity, spatial, and serial (up to one lag) correlations as in Driscoll and Kraay (1998) and reported in brackets. Bold numbers are statistically significant at the 5% level. The sample is April 1992 – May 2012, 241 months.