Internet Appendix to “Understanding FX Liquidity”

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The Internet Appendix discusses details, additional results and robustness checks on the paper *"Understanding FX Liquidity"* by Karnaukh, Ranaldo, and Söderlind (forthcoming in *The Review of Financial Studies*).

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1 Cleaning procedure of EBS data

We run the algorithm proposed by Brownlees and Gallo (2006) to clean the EBS data. This filtering procedure removed only very few and obvious outliers.

The observation at time t_i is removed from the sample if both bid and ask price are zero or if the price p_{t_i} is such that

$$|p_{t_i} - \bar{p}_i(\alpha, k)| > 3s_i(\alpha, k) + \nu \tag{1}$$

where $\bar{p}_i(\alpha, k)$ and $s_i(\alpha, k)$ denote the α-trimmed sample mean and standard deviation based on k observations in the neighborhood of t_i, respectively. To avoid zero variance for a sequence of equal prices, ν is added on the right hand side of the inequality. As the purpose of the filtering is to remove only the most obvious outliers, we choose ν equal to five pips (for JPY the smallest price change is 0.01, for all other currencies it is 0.0001). We set $\alpha = 5\%$ and $k = 100$. Hence the 100 prices closest to p_{t_i} are chosen as the neighborhood, and the largest and smallest 2.5% of these prices are discarded for the computation of mean and standard deviation.

2 Details on the High-frequency Measures

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

$$EC = \begin{cases} (P^T - P)/P, & \text{for buyer-initiated trades,} \\ (P - P^T)/P, & \text{for seller-initiated trades,} \end{cases} \tag{2}$$

where P^T denotes the transaction price, superscripts A and B indicate the ask and bid quotes, and $P = (P^A + P^B)/2$ is the mid-quote price.

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

$$BA = (P^A - P^B)/P. \tag{3}$$

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

$$\Delta p_t = \vartheta + PI \times (\upsilon_{b,t} - \upsilon_{s,t}) + \sum_{k=1}^{5} \gamma_k (\upsilon_{b,t-k} - \upsilon_{s,t-k}) + \varepsilon_t, \tag{4}$$

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

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

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

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

[Table IA.1 about here.]

[Table IA.2 about here.]

[Figure IA.1 about here.]

The full descriptive statistics are found in Table IA.1, but the following are worth mentioning. First, average effective costs are smaller than average bid-ask spreads, reflecting within-quote trading. Second, the average return reversal (temporary price change accompanying order flow) is negative and the order flow price impact is positive for all exchange rates. Third, comparing liquidity estimates across currencies, we observe a substantial cross-sectional variation in which EUR/USD is the most liquid exchange rate, while AUD/USD is the least liquid. Figure IA.1 depicts the average (across currencies) HF measures, Table IA.2 shows the correlations between the average HF measures. To construct this figure and table, we first average liquidity across the FX rates for each out of five measures, and then compute the correlations between the five average liquidity measures.

3 Details on the Low-frequency Measures

For each currency pair, we compute *four low-frequency (LF) liquidity measures* which are widely used in the literature on stocks and bond liquidity: bid-ask spread, Corwin-Schultz measure, Roll spread, and Gibbs estimate.

3.1 Main LF measures

3.1.1 Bid-ask spread

Our first low-frequency liquidity measure is the relative *bid-ask spread* (*BA*) defined as in (3). We get the monthly *BA* estimates by averaging the daily bid-ask estimates over the month.

[Table IA.3 about here.]

Table IA.3 compares the HF and LF proportional bid-ask spreads, looking at the correlations of the changes. Table IA.3 shows correlations between (1) daily HF EBS transactable bid-ask spreads and effective cost, when the one-second data is averaged over one day, (2) snaps of EBS bid-ask spreads at the same time when the LF data from various sources is provided (22:00 GMT and 16:00 GMT), (3) LF bid-ask spreads from three alternative data providers: Bloomberg (17:00 EST), Thomson Reuters (TR, 22:00 GMT), and WM/Reuters (WMR, 16:00 GMT).

Table IA.3 shows that (1) daily averages of the HF transactable EBS quotes are more correlated with the LF quotes (Bloomberg, TR, WMR) than the EBS snaps at the same time when daily LF quotes are taken, (2) among the LF sources, Bloomberg daily indicative quotes have the highest correlations with the EBS transactable quotes, while TR and WMR have weak correlations.

3.1.2 Corwin-Schultz high-low estimate

Our second low-frequency liquidity measure is the *CS*, the simple closed-form bid-ask estimator from daily high and low prices from Corwin and Schultz (2012). The daily high prices are almost always buyer-initiated trades and daily low prices are almost always seller-initiated trades. The ratio of high-to-low prices for a day therefore reflects both the fundamental volatility of the asset and its bid-ask spread. Although the variance component of the high-low ratio is proportional to the return interval, the spread component is not. This implies that the sum of the price ranges over 2 consecutive single days reflects 2 days' volatility and twice the spread, while the price range over one 2-day period reflects 2 days' volatility and one spread. Corwin and Schultz derive a spread estimator as a function of high-low ratios over 1-day and 2-day intervals. The high-low estimator may capture other forms of transitory volatility, and therefore liquidity costs, that are not reflected in the effective spread (see Corwin and Schultz 2012).

The CS (high–low spread estimate) is calculated as

$$CS = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}} \approx \alpha, \text{ for small values of } \alpha \in [-0.25, 0.25], \tag{5}$$

$$\text{where } \alpha = \left(1 + \sqrt{2}\right)(\sqrt{\beta} - \sqrt{\gamma}), \tag{6}$$

$$\beta = \left[\ln\left(\frac{H_t}{L_t}\right)\right]^2 + \left[\ln\left(\frac{H_{t+1}}{L_{t+1}}\right)\right]^2, \text{ and } \gamma = \left[\ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2,$$

where H_t and L_t denote the observed high and low prices on day t (similarly for day $t + 1$), while $H_{t,t+1}$ and $L_{t,t+1}$ are the high and low over two days (t to $t + 1$).

[Table IA.4 about here.]

We use an adjusted version of the *CS* measure, which excludes all negative two-day spreads and divides the monthly *CS* by number of positive 2-day estimates. Table IA.4 shows the performance of two different versions of the *CS* measure: (1) removing negative 2-day estimates, divide the monthly *CS* by total number of days, (2) removing negative 2-day estimates, divide the monthly *CS* by number of positive 2-day estimates. The changes of average (across currencies) *CS* measure computed as in (2) provides the highest (average) correlation with the changes of the EC (0.53). This correlation is much higher than the one obtained when using the approach as in (2), 0.39.

Before applying the estimator, we correct for the overnight returns, as described by Corwin and Schultz (see p.726). Specifically, if the day $t + 1$ low is above the day t close, we assume that the price rose overnight from the close to the day $t + 1$ low and decrease both the high and low for day $t + 1$ by the amount of the overnight change when calculating spreads. Similarly, if the day $t + 1$ high is below the day t close, we assume the price fell overnight from the close to the day $t + 1$ high and increase the day $t + 1$

high and low prices by the amount of this overnight decrease. We use Thomson Reuters daily high and low prices to compute the monthly CS spread estimates. Using the high and low prices from Bloomberg leads to very similar results (not tabulated). The higher is the *CS*, the lower is the liquidity.

3.2 Alternative LF Measures

3.2.1 Roll measure

Our third low-frequency liquidity measure is the *Roll* estimator of transaction costs from Roll (1984). The Roll model is formulated for trade prices, so as to measure the bid-ask bounce by the autocovariance of price changes. Trade prices are not provided by common LF data sources, so we instead use mid-quotes. For this reason, the results cannot capture the essence of the Roll model (the bid ask bounce), but they may still be of interest. Roll suggests a simple model of security prices in the market with transaction costs

$$\begin{cases} m_t = m_{t-1} + u_t \\ p_t^T = m_t + cq_t, \end{cases} \tag{7}$$

where m_t is the log quote midpoint prevailing prior to the t^{th} trade ("efficient price"), p_t^T is the log trade price, and q_t are direction indicators, which take the values +1 (for a buy) or -1 (for a sell) with equal probability. The disturbance, u_t, reflects public information and is assumed to be uncorrelated with q_t. The Roll model (7) implies

$$\Delta p_t^T = c\Delta q_t + u_t, \tag{8}$$

where Δ is a change operator. Given this setup, Roll shows that the effective (transaction) cost c is the square root of minus auto-covariance of consecutive price changes. The Roll model is designed for the trade data and implies an MA(1) process for log price changes. Using time-aggregated (lower frequency) data in the Roll model does not change the MA(1) property for log price changes.

We use the daily log mid quotes to compute the (monthly) Roll estimate

$$Roll = \sqrt{-\text{Cov}(\Delta p_t^T, \Delta p_{t-1}^T)} \tag{9}$$

where Δp_t is the change of the log mid-quote price between day t and $t-1$ (using bid or ask prices instead gives very similar results). The *Roll* estimate is feasible only if the first-order sample autocovariance is negative. In samples of daily frequency this is often not the case. For instance, Roll (1984) finds positive autocovariances in roughly half the cases in annual samples of daily returns. Harris (1990) shows that positive autocovariances are more likely for low values of the spread. Another problem arises when using the mid-quote prices instead of the trade prices to compute the *Roll* estimate. The estimated cost will generally be biased downward, because midpoint realizations do not include the cost.

3.2.2 Gibbs estimate

Our fourth low-frequency liquidity measure is the *Gibbs* effective cost estimate based on a Bayesian approach to the Roll model (7), see Hasbrouck (2009). In particular, Hasbrouck assumes that the disturbance u_t is normally distributed with zero mean and standard deviation σ_t. The transaction cost, c, standard deviation of the disturbance, σ_u^2, and trade direction indicators q are unknown parameters in the Roll model. The unknown parameters are estimated with a Bayesian approach using a Gibbs procedure.[1] Hasbrouck corrects for possible negative transaction cost estimates in the Roll model by restricting them to be positive in the Bayesian approach.

We compute the *Gibbs* estimates for each month from the daily log mid-quote prices. We run each Gibbs sampler for 1000 sweeps and discard the first 200 draws.

[Table IA.5 about here.]

Joel Hasbrouck generously provides the programming code for 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 $(\overline{p^A} - \overline{p^B})^{1/2}$, where $\overline{p^A}$ and $\overline{p^B}$ are the monthly averages of log ask and log bid quotes, respectively. The estimates are robust to this choice, unless we choose a very small value. Using a higher number of sweeps (up to 10000) or changing the prior of the transaction cost does not affect the mean parameter estimates materially. Table IA.5 shows the results for calibrating the prior for the standard deviation of transaction cost. *Panel A* of the table shows time-series correlations of the

[1] See Hasbrouck (2009) for detailed description of the estimation procedure.

monthly *Gibbs* estimates based on different priors for the standard deviation of transaction cost (σ_c) with the effective cost for each exchange rate. Setting the standard deviation of the prior to a very small value (eg. 0.001) gives estimates that are much less correlated with the HF benchmark. Starting from the values of the standard deviation of the prior above 0.01 the correlations of the Gibbs estimates with the EC stabilize and stay at the same level. *Panel B* of the table shows that the sample mean values of our prior specification, $(\overline{p^A} - \overline{p^B})^{1/2}$, are above 0.01, that is well inside the range giving good estimates. However, when we estimate liquidity on a weekly instead of the monthly frequency, the prior becomes more important. (See Hasbrouck 2009 for the further details.)

3.3 Finding the most accurate LF measures

3.3.1 Evidence for individual currency liquidity

[Table IA.6 about here.]

Table IA.6 reports the time-series correlations of levels of each LF liquidity measure for each exchange rate with the levels of their effective cost benchmarks. The *BA* measure has the highest average correlation (0.82), followed by *CS* and *Gibbs* measures (0.78 and 0.70). The *Roll* has a mild average correlation (0.30). The bid ask spread and the Corwin-Schultz measures are highly correlated with the EC benchmark. For the rest of our analysis, we choose to focus on an average between the BA (from Bloomberg, 5 p.m. EST) and the CS measure (Thomson Reuters, 9 p.m. GMT) for two main reasons: both methods perform well and they are well-suited for the kind of data that is available. In practice, this means using only CS before 1996 (since there is little BA data then) and an average of the two methods afterwards. Averaging is a simple way to extract the common component and to reduce the noise.

3.3.2 Evidence for systematic (average) liquidity

[Table IA.7 about here.]

[Figure IA.2 about here.]

To construct measures of systematic FX liquidity, we first standardize all liquidity measures (for each currency) by subtracting the time-series mean and dividing by the standard deviation. After the standardization process, we calculate an average across all nine currency pairs. Table IA.7 shows the average correlations between the FX rate LF measures. Figure IA.2 depicts the average (across currencies) liquidity measures versus effective cost benchmark for 2007–2012.

In our analysis, we rely on the simple average across FX pairs to construct the average liquidity measure based on the straightforwardness and simplicity of this approach. Since all measures are standardized and have similar correlations, the simple average is very similar to the first principal component (when constructing the systematic LF liquidity the first principal component accounts for 60% of total variation).

[Table IA.8 about here.]

We considered different weighting schemes to construct a systematic liquidity measure. First, we collect the data on FX trading volume (from Bank of International Settlements 2013) for the nine FX rates as well as bilateral trade and GDP (both from Datastream) of the countries with the quoted and base currency. Second, for each indicator (FX trading volume, bilateral trade, and overall GDP), we scale the value for each FX pair by the sum across all FX pairs to get the weights (see *Panel A* of Table IA.8 for the details on the data and weighting schemes). Third, we use these weights to construct the average (across currencies) LF liquidity measures. Finally, we compare the performance of these LF measures with the base-case approach used in the paper (i.e. equal weighting of the measures, see *Panel B* of Table 1 in the main paper). *Panel B* of Table IA.8 shows the correlations of the changes in average LF measures with the changes in average EC benchmark, where each measure is constructed from using four weighting schemes (equal, FX trading volume, bilateral trade, and overall GDP weighted averages). Overall, the alternative weighting schemes do not lead to any marked differences.

3.3.3 Different frequencies

[Table IA.9 about here.]

Instead of using months, we consider shorted timeframes for constructing the LF measures. Table IA.9 shows the correlations of the average LF measures based on different number of days to construct the proxy (1, 2, 3, 5, 10, 15, 1 month) with the effective cost. *Panel A* of Table IA.9 shows the average (across currencies) correlations between the changes in the most accurate LF liquidity measures and FX rate effective cost. *Panel B* of Table IA.9 of the table shows the correlations between the changes in the average (across currencies) LF liquidity measures and average effective cost.

Looking at Table IA.9 we conclude the following: (1) performance deteriorates at higher frequencies: the correlations with the HF benchmark are 0.72–0.82 (for changes in average measures, *Panel B*) on the 20 trading days frequency and only 0.33–0.58 on the 5-day frequency, (2) daily bid-ask (which uses Bloomberg at 5 p.m. EST) performs reasonably well (0.33) even at the daily frequency, while the CS measure needs at least 3 days of data to show a good performance, (3) averaging across the two most accurate measures (BA and CS) increases the correlation with the effective cost at each frequency.

3.3.4 Quote-based measures

As a robustness check, we extend the set of LF liquidity measures to three price impact proxies, namely the liquidity measures proposed by Amihud (2002), Pàstor and Stambaugh (2003) and the so-called Amivest proxy from Cooper, Groth, and Avera (1985) and Amihud, Mendelson, and Lauterbach (1997). Trading volume data are not readily available for FX markets. A method to approximate trading volume proposed in FX literature is the quote frequency: the number of quote revisions over a given period (e.g., Melvin and Yin 2000). The quote revisions data is available for all nine currencies from 17 January 2007.

The *Amihud* proxy proposed by Amihud (2002) measures the absolute price changes per unit of dollar volume

$$Amihud = \frac{|\, r_t|}{\nu_t}, \tag{10}$$

where r_t is the currency return on day t and ν_t is the dollar volume on day t. We use the daily number quote revisions from Thomson Reuters as a proxy for trading volume.

The higher is the *Amihud*, the less liquid is the FX rate (larger price impact). We get the monthly *Amihud* estimates by averaging the daily *Amihud* estimates over the month.

Pàstor and Stambaugh (2003) introduce a price impact measure called gamma (γ), which is estimated from the regression

$$r^e_{t+1} = \theta + \phi r_t + \gamma \,\text{sign}(r^e_t)\nu_t + \varepsilon_t, \tag{11}$$

where r_t is the daily log currency return; r^e_t is the daily excess currency return on day t, computed as $r^e_{t+1} \approx f_t - s_{t+1}$, where f_t is the log forward rate at day t and s_{t+1} is the spot rate at day $t+1$; sign(r^e_t) is one if r^e_t is positive, and zero otherwise. Since daily excess currency returns are almost perfectly (above 0.99) correlated with the daily log currency returns, we use the latter in the regression. We estimate the regression for each month to get monthly γ (*Pastor-Stambaugh*) estimates. The gamma measure should have a negative sign. The larger is the γ in absolute terms, the lower is liquidity (larger price impact).

The *Amivest* proxy is a measure of price impact, used by Cooper, Groth, and Avera (1985) and Amihud, Mendelson, and Lauterbach (1997), and others. The *Amivest* proxy is defined as

$$Amivest = \frac{v_t}{|r_t|} \tag{12}$$

and calculated over all non-zero-return days. The larger is the *Amivest*, the higher is liquidity (lower price impact).

[Table IA.10 about here.]

Table IA.10 shows the correlations of the changes of quote-based measures with the changes of HF EC benchmark. The Amihud measure performs relatively well, the Amivest measure does somewhat worse, while the Pastor-Stambaugh measure appears almost uncorrelated with the HF effective cost.

3.3.5 Using the most accurate LF measures in a larger sample

[Table IA.11 about here.]

[Figure IA.3 about here.]

Using the data on 30 (floating) currency pairs over 1991–2012, we compute monthly time series for the *CS* and BA measure for each exchange rate. The bid-ask spreads in Bloomberg are available from 1996–1999 depending on the exchange rate. The full descriptive statistics and details on start of *BA* availability for each exchange rate are found in Table IA.11. Figure IA.3 depicts the average (across currencies) and systematic liquidity measures for 1991–2012.

4 Additional results and robustness checks for the section 3 "Explaining FX liquidity"

Table IA.12 shows the results from simple panel regressions in which monthly changes of the liquidity of 30 currency pairs are regressed on one factor at a time $\Delta L_{ij,t} = \alpha + \beta' f_t + \varepsilon_{ij,t}$, where $\Delta L_{ij,t}$ is, for the FX rate between currencies i and j, the change in liquidity from month $t-1$ to t, f_t denotes the demand-side, supply-side factor or market conditions. Table IA.13 shows the correlations between the main liquidity drivers, used as regressors in Table 3 of the main paper.

[Table IA.12 about here.]

[Table IA.13 about here.]

[Figure IA.4 about here.]

Figure IA.4 depicts systematic liquidity on the FX market (average across 30 FX pairs and across standardized BA and CS measures), stock market (Amihud measure), and bond market (on-off-the run 10-year spread).

5 Additional results and robustness checks for the section 4 "Explaining commonality in FX liquidity"

Panel A of table IA.14 shows the results from running commonality regression (3) of the main paper, i.e. each FX rate liquidity is regressed on the systematic FX liquidity, based on the average across 29 FX rates excluding the left hand side variable. Regressing the FX rate liquidity on the systematic FX liquidity computed as the average across those FX pairs which exclude two currencies forming the regressed currency pair[2] gives similar results (not tabulated). Including one lead and one lag of the systematic liquidity as additional regressors also does not affect the results materially–see R^2 in *Panel B* of table IA.14.

[Table IA.14 about here.]

[2]For example, systematic liquidity used for AUD/USD is based only on 15 FX pairs out of 30, since there are 3 FX pairs containing AUD and 13 FX pairs containing USD, the regressed FX rate is an overlapping one

[Table IA.15 about here.]

[Table IA.16 about here.]

Table IA.15 shows the results from single panel time-series regressions of logit transformation of commonality $R^2_{ij,t}$ on 30 FX rates on the stress factors $\ln[R^2_{ij,t}/(1-R^2_{ij,t})] = \alpha + \beta' f_t + u_{ij,t}$. The commonality $R^2_{ij,t}$ is calculated by running recursive commonality regressions on expanding data windows, but where old data is weighted with exponentially declining weights (the weight on lag s is 0.7^s). All the stress factors (VIX, TED spread, FX volatility, MSCI volatility, and carry trade losses) are significant in explaining the time-series variation of commonality $R^2_{ij,t}$.

Table IA.16 shows the results from regressing logit transformations of commonality R^2_{ij} (from equation (4) of the main paper) for 30 exchange rates on one of the fundamental factors (demand-side, supply-side or controls) at a time, $\ln[R^2_{ij}/(1-R^2_{ij})] = \alpha+\beta z_{ij}+\varepsilon_{ij}$. The fundamental factors z_{ij} refer to the country representing the quoted currency (unless specified otherwise). Higher central bank transparency, sovereign credit rating (both institutional variables), lower local money market interest rate (funding conditions variable) and higher GDP per capita (a control variable) are positively related with commonality and show the highest explanatory power.

References

Aït-Sahalia, Y., P. A. Mykland, and L. Zhang, 2005, "How often to sample a continuous-time process in the presence of market microstructure noise," *Review of Financial Studies*, 18(2), 351–416.

Amihud, Y., 2002, "Illiquidity and stock returns: cross-section and time-series effects," *Journal of Financial Markets*, 5, 31–56.

Amihud, Y., H. Mendelson, and B. Lauterbach, 1997, "Market microstructure and securitites values: evidence from Tel Aviv stock exchange," *Journal of Financial Economics*, 45, 365–390.

Bank of International Settlements, 2013, "Foreign exchange and derivatives market activity in April 2013," Triennial Central Bank Survey.

Brownlees, C., and G. Gallo, 2006, "Financial econometric analysis at ultra-high frequency: Data handling concerns," *Computational Statistics & Data Analysis*, 51(4), 2232–2245.

Campbell, J. Y., S. J. Grossman, and J. Wang, 1993, "Trading volume and serial correlation in stock returns," *Quarterly Journal of Economics*, 108(4), 905–39.

Chordia, T., R. Roll, and A. Subrahmanyam, 2001, "Market liquidity and trading activity," *Journal of Finance*, 56, 501–530.

Cooper, K. S., J. C. Groth, and W. E. Avera, 1985, "Liquidity, exchange listing and common stock performance," *Journal of Economics and Business*, 37, 19–33.

Corwin, S. A., and P. H. Schultz, 2012, "A simple way to estimate bid-ask spreads from daily high and low prices," *Journal of Finance*, 67, 719–759.

Driscoll, J. C., and A. C. Kraay, 1998, "Consistent covariance matrix estimation with spatially dependent panel data," *Review of Economics and Statistics*, 80, 549–560.

Harris, L. E., 1990, "Statistical properties of the Roll serial covariance bid/ask spread estimator," *Journal of Finance*, 45, 579–590.

Hasbrouck, J., 2009, "Trading costs and returns for us equities: estimating effective costs from daily data," *Journal of Finance*, 64, 1445–1477.

Kyle, A. S., 1985, "Continuous auctions and insider trading," *Econometrica*, 53, 1315–1335.

Melvin, M., and X. Yin, 2000, "Public information arrival, exchange rate volatility, and quote frequency," *Economic Journal*, 110, 644–661.

Newey, W. K., and K. D. West, 1987, "A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix," *Econometrica*, 55, 703–708.

Pàstor, L., and R. F. Stambaugh, 2003, "Liquidity risk and expected stock returns," *Journal of Political Economy*, 111, 642–685.

Roll, R., 1984, "A simple implicit measure of the effective bid-ask spread in an efficient market," *Journal of Finance*, 39, 1127–1139.

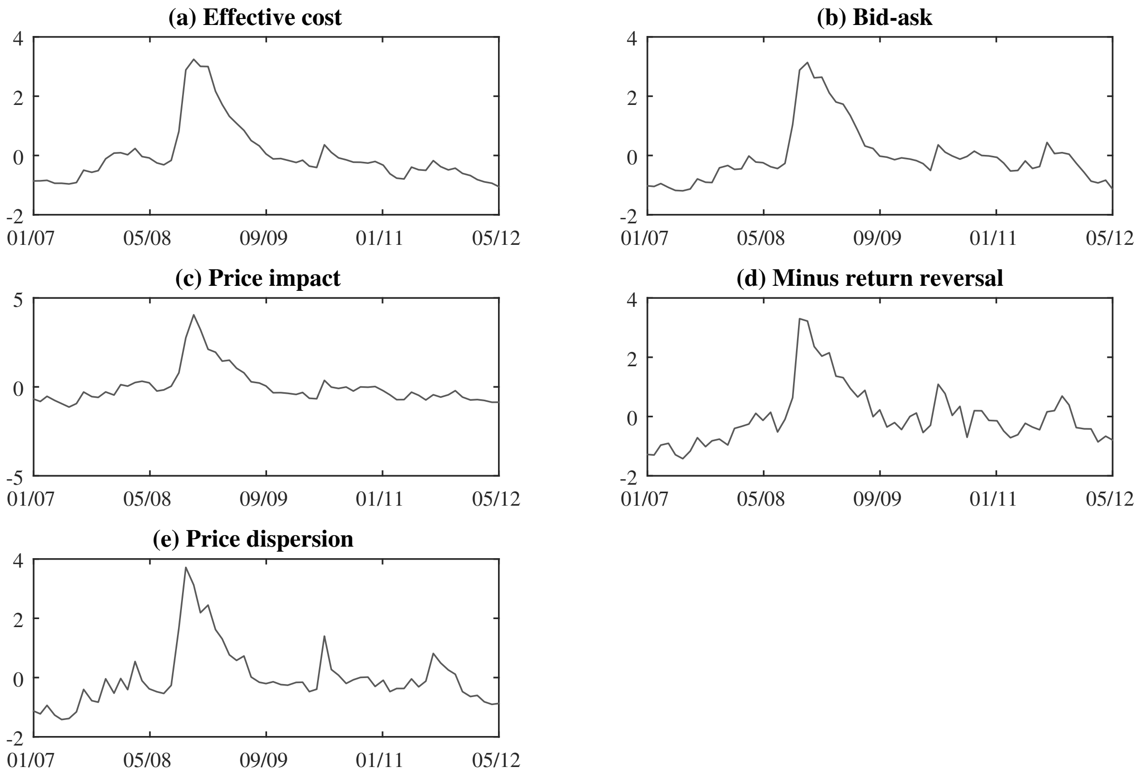

Figure IA.1 **Average HF illiquidity measures, 2007–2012.**
The figure shows the monthly standardized average (across currencies) levels of HF liquidity measures. The sign of each measure is adjusted such that the measure represents illiquidity rather than liquidity: Price impact (Panel (a)), minus return reversal (Panel (b)), bid-ask (Panel (c)), effective cost (Panel (d)), price dispersion (Panel(e)). The sample is January 2007 – May 2012.

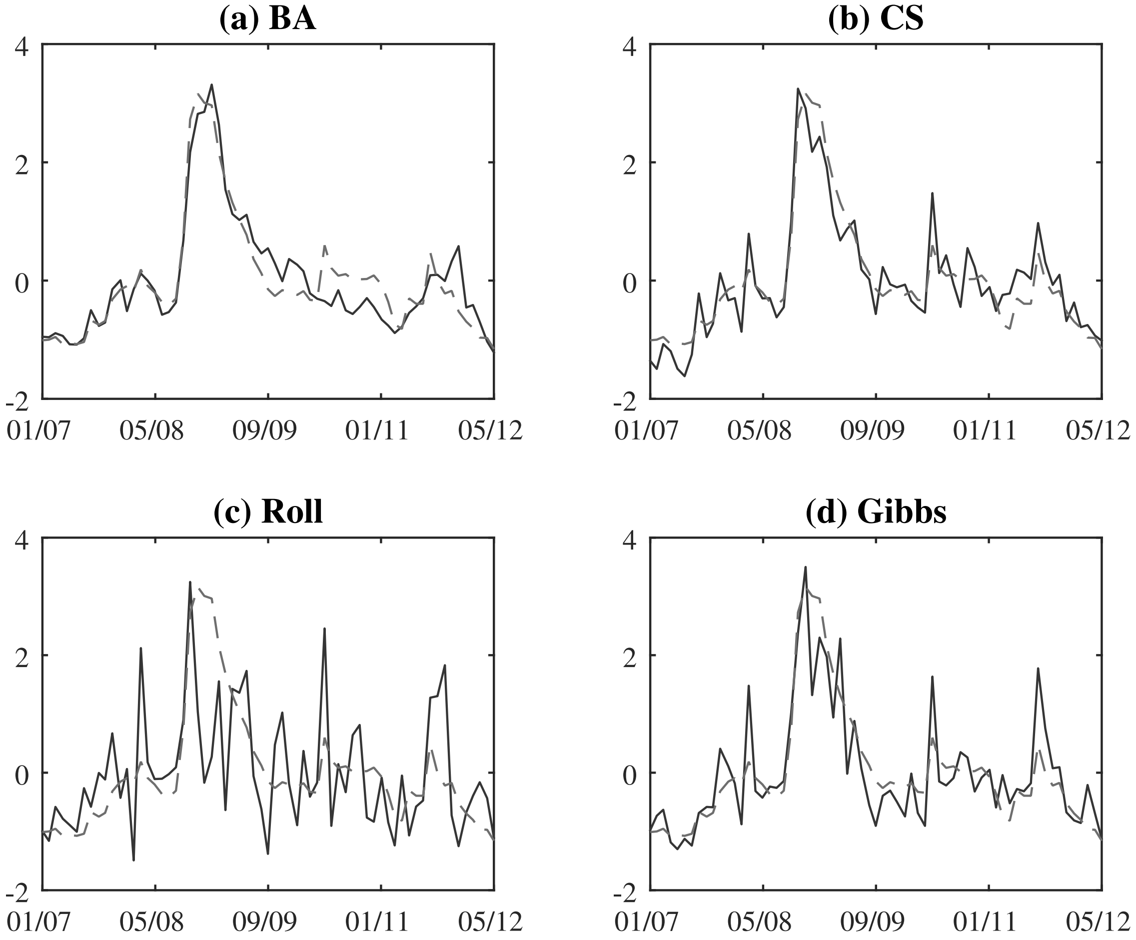

Figure IA.2 **Average illiquidity measures vs effective cost, 2007–2012.**
Panels (a)–(d) depict levels of average (across currencies) standardized LF illiquidity measures (solid line) and levels of average (across currencies) effective cost (dotted). The sample is January 2007 – May 2012, 65 months.

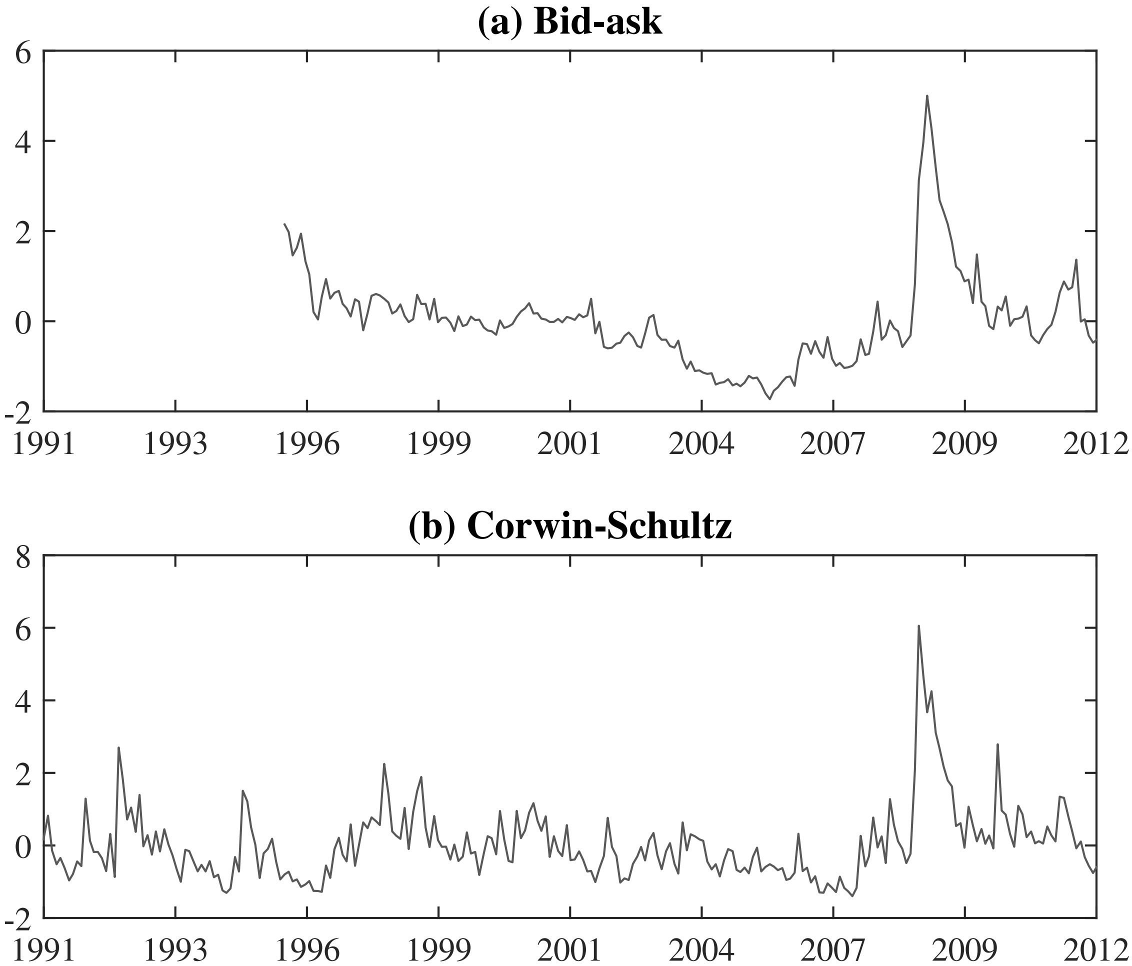

Figure IA.3 **Average LF illiquidity measures, 1991–2012.**
Panels (a)–(b) depict levels of average (across currencies) standardized LF illiquidity measures. The full sample is January 1991 – May 2012, 257 months.

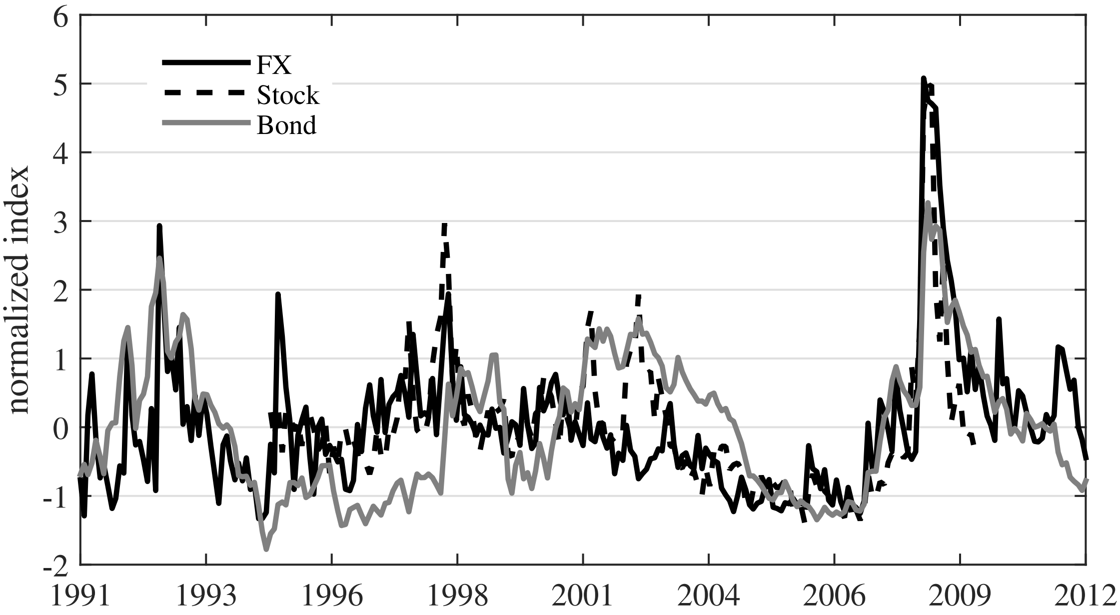

Figure IA.4 **Illiquidity in FX, stock, and bond markets.**
The figure depicts levels of systematic illiquidity on the FX market (average across 30 FX pairs and across standardized BA and CS measures), stock market (Amihud measure), and bond market (on-off-the run 10-year spread). All measures are standardized. The full sample is January 1991 – May 2012, the stock market liquidity is from January 1995 to December 2009.

	AUD/USD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	USD/CAD	USD/CHF	USD/JPY
Effective cost (in bps)									
Mean	1.119	0.388	0.760	0.460	0.292	0.693	1.074	0.473	0.401
Std. dev.	0.652	0.125	0.260	0.132	0.053	0.381	0.406	0.094	0.091
Bid-ask spread (in bps)									
Mean	4.693	2.331	4.019	2.418	1.057	4.480	6.050	2.539	1.501
Std. dev.	2.982	1.015	1.645	0.717	0.227	3.603	3.328	0.812	0.364
Price impact									
Mean	0.804	0.128	0.432	0.242	0.070	0.383	0.689	0.172	0.099
Std. dev.	0.533	0.068	0.175	0.113	0.029	0.199	0.248	0.061	0.041
Return reversal									
Mean	-0.153	-0.024	-0.092	-0.053	-0.013	-0.093	-0.131	-0.024	-0.020
Std. dev.	0.117	0.015	0.044	0.025	0.005	0.059	0.066	0.013	0.009
Price dispersion (TSRV, five minutes, in %, annualized)									
Mean	15.00	6.87	8.70	13.26	9.89	11.18	11.91	10.87	10.23
Std. dev.	7.84	4.01	3.36	6.06	3.64	6.09	4.28	3.49	3.83

Table IA.1 **Monthly illiquidity measures from high-frequency (HF) data.**
The table shows summary statistics for FX illiquidity measures computed from one-second data. Effective cost spread denotes the monthly average of daily effective cost estimates. The effective cost is measured as in Equation (1), in bps. Bid-ask spread denotes the monthly average of daily proportional bid-ask spreads. The proportional bid-ask spread is measured as in Equation (2), in bps. Price impact is monthly average of daily estimated coefficients of contemporaneous order flow in a regression of one-minute returns on the contemporaneous and lagged order flow (Equation (3)). Return reversal is monthly average of daily sum of estimated coefficients of lagged order flow (1-5 lags) in the same regression. Price dispersion is estimated using two-scale realized volatility (TSRV). It is expressed in a percentage on an annual basis. The sample covers 65 months, January 2007 – May 2012.

	EC	BA	PI	RR	PD
Bid-ask	**0.939**	**1**			
Price impact	**0.782**	**0.761**	**1**		
Return reversal	**-0.683**	**-0.657**	**-0.708**	**1**	
Price dispersion	**0.830**	**0.842**	**0.633**	**-0.622**	**1**

Table IA.2 **Correlations between the changes of average high-frequency (HF) illiquidity measures.**
The table shows correlations between the changes of average (across currencies) effective cost (*EC*), bid-ask spread (*BA*), price impact (*PI*), return reversal (*RR*), and price dispersion (*PD*). Bold numbers are statistically significant at the 5% level. The significance test is the GMM based test using a Newey and West (1987) covariance estimator with 4 lags. Correlations are computed using 65 non-overlapping monthly observations. The sample is January 2007 – May 2012.

	EBS BA	EBS EC	EBS BA 22:00 GMT	EBS BA 16:00 GMT	Bloomberg 17:00 EST	TR 22:00 GMT	WMR 16:00 GMT
EBS BA	1						
EBS EC	0.75	1					
EBS BA 22:00 GMT	0.51	0.45	1				
EBS BA 16:00 GMT	0.57	0.68	0.38	1			
Bloomberg 17:00 EST	0.43	0.44	0.22	0.30	1		
TR 22:00 GMT	0.20	0.22	0.08	0.15	0.14	1	
WMR 16:00 GMT	0.27	0.24	0.11	0.22	0.10	0.12	1

Table IA.3 **Correlation matrix between daily and monthly changes of illiqudity measures based on data from EBS, Bloomberg, TR, and WMR.**
This table shows the mean (across 9 FX rates) correlations between the changes of mean EBS bid-ask spreads (BA), EBS effective cost (EC), EBS bid-ask spread snap at 22:00 GMT, EBS bid-ask spread snap at 16:00 GMT, Bloomberg bid-ask spread collected at 17:00 EST, Thomson Reuters (TR) bid-ask spread collected at 22:00 GMT, and WM/Reuters (WMR) bid-ask spread collected at 16:00 GMT. The sample is January 2007 – May 2012.

	[1]	[2]
	Removing negative 2-day estimates, divide the monthly CS by total number of days	Removing negative 2-day estimates, divide the monthly CS by number of positive 2-day estimates
AUD/USD	0.490	0.593
EUR/CHF	0.635	0.699
EUR/GBP	0.315	0.484
EUR/JPY	0.533	0.614
EUR/USD	0.336	0.372
GBP/USD	0.424	0.63
USD/CAD	0.094	0.406
USD/CHF	0.335	0.528
USD/JPY	0.421	0.411
Mean	0.398	0.526

Table IA.4 **Correlations between the changes of effective cost and changes of CS measure.** Table shows (for each exchange rate) the correlations between the changes of monthly effective cost and changes of CS measure (two versions). Last row shows the mean correlations across the exchange rates. The sample is January 2007 – May 2012, 65 months.

Prior for σ_c	AUD/USD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	USD/CAD	USD/CHF	USD/JPY
Panel A. Correlations of the Gibbs estimates with the EC									
0.00013	**-0.0624**	**0.0414**	**-0.1507**	**-0.1494**	-0.0060	**-0.1328**	**-0.0961**	**-0.0676**	-0.0183
0.00063	**-0.1439**	**0.3627**	-0.0086	**0.0805**	**-0.0522**	**-0.1374**	**-0.2114**	**-0.1156**	**0.0796**
0.00125	**-0.0824**	**0.5624**	**0.2144**	**0.2452**	**-0.0204**	-0.0022	**-0.1344**	**0.1213**	**0.2544**
0.00313	**0.3279**	**0.7303**	**0.4558**	**0.4418**	**0.3414**	**0.4649**	**0.3919**	**0.5875**	**0.5186**
0.00626	**0.6484**	**0.7851**	**0.5588**	**0.6041**	**0.5432**	**0.6685**	**0.5617**	**0.7211**	**0.6208**
0.00940	**0.7604**	**0.7892**	**0.5908**	**0.6495**	**0.5768**	**0.7101**	**0.5983**	**0.7454**	**0.6347**
0.01253	**0.7947**	**0.7925**	**0.6025**	**0.6640**	**0.5868**	**0.7280**	**0.6081**	**0.7526**	**0.6378**
0.03132	**0.8152**	**0.7903**	**0.6233**	**0.6706**	**0.6003**	**0.7492**	**0.6167**	**0.7556**	**0.6397**
0.06265	**0.8140**	**0.7901**	**0.6279**	**0.6725**	**0.6016**	**0.7515**	**0.6182**	**0.7457**	**0.6428**
0.12530	**0.8145**	**0.7900**	**0.6283**	**0.6725**	**0.6017**	**0.7522**	**0.6193**	**0.7456**	**0.6428**
1.25300	**0.8148**	**0.7899**	**0.6285**	**0.6728**	**0.6018**	**0.7523**	**0.6193**	**0.7452**	**0.6429**
Panel B. Mean values of the prior for σ_c									
$(\overline{p^A} - \overline{p^B})^{1/2}$	0.02136	0.02695	0.02184	0.02470	0.01537	0.01551	0.02038	0.02189	0.01911

Table IA.5 **Calibrating the prior for the standard deviation of transaction cost in the *Gibbs* procedure.**
Panel A of the table shows time-series correlations of the (levels of) monthly *Gibbs* estimates (from Hasbrouck 2009) based on different priors for the standard deviation of transaction cost (σ_c) with the (levels of) effective cost for each exchange rate. The half-normal distribution implies $\sigma_c = \sqrt{\pi/2}Ec$, where Ec is the mean of the transaction cost. Effective cost is estimated by averaging the HF data over the month. Bold numbers are statistically significant at the 5% level (GMM based test using a Newey-West covariance estimator with 4 lags). Panel B of the table shows the mean values of the prior specification, used in the Gibbs estimation, for each exchange rate. $\overline{p^A}$ and $\overline{p^B}$ denote the monthly averages of log ask and log bid prices, respectively. The sample covers 65 months, January 2007 - May 2012.

	BA	CS	Roll	Gibbs
AUD/USD	0.887	0.851	0.678	0.815
EUR/CHF	0.833	0.809	0.425	0.790
EUR/GBP	0.881	0.796	0.156	0.628
EUR/JPY	0.759	0.751	0.543	0.673
EUR/USD	0.806	0.550	0.234	0.602
GBP/USD	0.901	0.905	-0.013	0.752
USD/CAD	0.891	0.745	-0.008	0.619
USD/CHF	0.781	0.825	0.280	0.746
USD/JPY	0.640	0.775	0.423	0.643
Average	0.820	0.779	0.302	0.696

Table IA.6 **Correlations between the levels of effective cost and levels of four LF liquidity measures.**

Table shows (for each exchange rate) the correlations of levels in four low-frequency (LF) liquidity measures with levels of effective cost. The monthly low-frequency spread proxies are: *BA* is the relative bid-ask spread, *CS* from Corwin and Schultz (2012), *Roll* from Roll (1984), and *Gibbs* from Hasbrouck (2009). The *BA* is from Bloomberg at 5 p.m. EST, while the other LF measures use Thomson Reuters at 10 p.m. GMT. Effective cost (EC) is estimated by averaging the HF data over the month. The sample is January 2007 – May 2012, 65 months.

	BA	CS	Roll	Gibbs
BA	**1**			
CS	**0.505**	**1**		
Roll	**0.122**	**0.636**	**1**	
Gibbs	**0.355**	**0.689**	**0.654**	**1**

Table IA.7 **Correlations between the changes in LF liquidity measures, 2007–2012.**
The table shows correlations between changes in average (across currencies) low-frequency liquidity measures for the FX market. The LF liquidity measures are: *BA* is the relative bid-ask spread, *CS* from Corwin and Schultz (2012), *Roll* from Roll (1984), and *Gibbs* from Hasbrouck (2009). Bold numbers are statistically significant at the 5% level. The *BA* is from Bloomberg at 5 p.m. EST, while the other LF measures use Thomson Reuters at 10 p.m. GMT. The significance test is the GMM based test using a Newey and West (1987) covariance estimator with 4 lags. The sample is January 2007 – May 2012, 65 months.

	Equal weighting	FX trading volume	Bileteral trade	Overall GDP
Panel A. Weights to construct systematic liquidity				
AUD/USD	11.11%	8.57%	1.43%	8.96%
EUR/CHF	11.11%	2.45%	31.60%	10.09%
EUR/GBP	11.11%	3.67%	16.54%	11.20%
EUR/JPY	11.11%	3.81%	2.99%	12.78%
EUR/USD	11.11%	37.69%	5.35%	18.08%
GBP/USD	11.11%	12.38%	3.55%	9.73%
USD/CAD	11.11%	6.26%	29.09%	9.22%
USD/CHF	11.11%	5.71%	5.26%	8.62%
USD/JPY	11.11%	19.46%	4.20%	11.32%
Panel B. Correlations of changes of systematic liquidity with the changes of EC				
	0.734	**0.691**	**0.726**	**0.723**

Table IA.8 **Different weighting schemes to construct the systematic FX liquidity.**
Panel A of the table shows the weights of the FX pairs for the weighted-average approach to construct LF liquidity for each measure. The FX trading volume weights are based on the data from Bank of International Settlements (2013). Bilateral trade weights are based on the data from Datastream. Bilateral trade is the sum of the export from country with quoted currency to the country with base currency scaled by the GDP of country with quoted currency and the export from country with base currency to the country with quoted currency scaled by the GDP of country with base currency. We take the time-series mean over 2007–2012 to get the bilateral trade value for each FX pair. Overall GDP weights are based on the data from Datastream. Overall GDP is the sum of GDP of the country with the base currency and GDP of the country with the quote currency. For each indicator (FX trading volume, bilateral trade, and overall GDP), we scale the value for each FX pair by the sum across all FX pairs to get the weights. Panel B of the table shows correlations between the changes of average (across currencies) effective cost and changes of systematic LF liquidity, based on four different weighting schemes for currencies. To construct systematic LF liquidity we proceed in two steps. First, for each weighting scheme (equal, FX trading volume, bilateral trade, and overall GDP) we construct average (across currencies) bid-ask and CS liquidity measures. Then, we take the equally-weighted average across the resulting average bid-ask and CS to get the systematic liquidity. The bold correlations are statistically significant at the 5% level (GMM based test using a Newey-West covariance estimator with 4 lags). The sample is January 2007 – May 2012, 65 months.

	Panel A			*Panel B*		
N days	Average FX rate correlations			Correlations of average measures		
	BA	CS	Average of BA, CS	BA	CS	Average of BA, CS
1	0.138	-	0.138	0.335	-	0.335
2	0.188	0.076	0.182	0.378	0.131	0.377
3	0.158	0.153	0.218	0.336	0.306	0.453
5	0.131	0.214	0.240	0.326	0.498	0.575
10	0.306	0.226	0.346	0.595	0.502	0.681
15	0.423	0.413	0.523	0.723	0.738	0.827
1 month	0.442	0.526	0.602	0.730	0.742	0.850

TableIA.9 **Correlations between the changes in LF measures and EC at different frequencies.** Panel A of the table shows the average (across currencies) correlations between the changes in the most accurate LF liquidity measures and FX rate effective cost. Panel B of the table shows the correlations between the changes in the average (across currencies) LF liquidity measures and average effective cost. The correlations are based on different frequencies. Whenever it is possible, each liquidity measure is computed for 1, 2, 3, 5, 10, 15, and 1 month (around 22 trading days). The *BA* is the relative bid-ask spread and uses Bloomberg at 5 p.m. EST, *CS* is from Corwin and Schultz (2012) and uses Thomson Reuters at 10 p.m GMT. The sample is January 2007 – May 2012, 65 months.

	Amihud	Amivest	Pastor-Stambaugh
AUD/USD	0.817	-0.087	-0.012
EUR/CHF	0.545	-0.351	0.054
EUR/GBP	0.382	-0.123	0.043
EUR/JPY	0.365	-0.072	-0.023
EUR/USD	0.581	-0.068	-0.148
GBP/USD	0.634	-0.076	-0.023
USD/CAD	0.453	-0.217	-0.167
USD/CHF	0.373	0.006	-0.098
USD/JPY	0.480	-0.065	-0.298
Average	0.515	-0.117	-0.075

Table IA.10 **Correlations between the changes of three quote-based LF measures and the changes of EC.**
The table shows the time-series correlations of the changes of three quote-based low-frequency measures for each exchange rate with the changes of effective cost for the same exchange rate. Effective cost is estimated by averaging the HF data over the month. The monthly quote-based low-frequency 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). Bold numbers are statistically significant at the 5% level. The sample covers 65 months, January 2007 - May 2012.

Bid-ask spread/2 (LF), bps										
	AUD/USD	CAD/USD	INR/USD	JPY/USD	MXN/USD	NZD/USD	NOK/USD	SGD/USD	ZAR/USD	SEK/USD
Mean	1.583	1.098	5.460	1.020	3.032	2.561	2.632	1.688	6.617	2.361
Std. dev.	0.655	0.369	9.117	0.429	2.102	0.915	1.853	0.786	3.581	1.334
Start of av.	Jan/1996	Jan/1996	Jan/1996	Jan/1996	Jan/1996	Jan/1996	Jan/1996	Jan/1996	Jan/1996	Jan/1996
	CHF/USD	GBP/USD	AUD/EUR	CAD/EUR	JPY/EUR	NZD/EUR	NOK/EUR	SGD/EUR	CHF/EUR	GBP/EUR
Mean	1.158	0.890	1.730	1.660	1.149	2.601	1.848	1.997	1.016	1.619
Std. dev.	0.558	0.407	0.783	0.592	0.605	1.982	1.554	1.023	0.524	0.913
Start of av.	Jan/1996	Jan/1996	Jan/1999	Jan/1999	Jan/1999	Jan/1999	Jan/1999	Jan/1999	Jan/1999	Jan/1999
	AUD/GBP	CAD/GBP	JPY/GBP	NZD/GBP	NOK/GBP	SGD/GBP	ZAR/GBP	SEK/GBP	CHF/GBP	EUR/USD
Mean	1.652	1.381	1.414	2.140	4.035	2.399	5.308	3.197	1.505	0.790
Std. dev.	0.963	0.977	0.751	1.562	1.775	0.810	4.520	1.679	0.949	0.525
Start of av.	Nov/1996	Jan/1996	Jan/1996	Nov/1996	Jan/1996	Jan/1996	Nov/1996	Nov/1996	Nov/1996	Jan/1999
Corwin-Schultz high-low estimate/2 (LF), bps										
	AUD/USD	CAD/USD	INR/USD	JPY/USD	MXN/USD	NZD/USD	NOK/USD	SGD/USD	ZAR/USD	SEK/USD
Mean	0.235	0.158	0.138	0.218	0.198	0.237	0.265	0.116	0.321	0.275
Std. dev.	0.123	0.087	0.090	0.077	0.168	0.121	0.098	0.068	0.235	0.100
	CHF/USD	GBP/USD	AUD/EUR	CAD/EUR	JPY/EUR	NZD/EUR	NOK/EUR	SGD/EUR	CHF/EUR	GBP/EUR
Mean	0.239	0.195	0.275	0.243	0.273	0.304	0.208	0.222	0.162	0.204
Std. dev.	0.078	0.081	0.105	0.072	0.107	0.115	0.079	0.089	0.074	0.071
	AUD/GBP	CAD/GBP	JPY/GBP	NZD/GBP	NOK/GBP	SGD/GBP	ZAR/GBP	SEK/GBP	CHF/GBP	EUR/USD
Mean	0.275	0.227	0.267	0.305	0.254	0.214	0.382	0.257	0.221	0.221
Std. dev.	0.109	0.078	0.107	0.116	0.086	0.092	0.185	0.089	0.080	0.080

Table IA.11 **LF illiquidity measures: descriptive statistics over Jan 1991 - May 2012.**
This table shows summary statistics for the two most accurate low-frequency (LF) measures of illiquidity. The *BA* is the relative bid-ask spread and is from Bloomberg at 5 p.m. EST. The Corwin-Schultz (*CS*) measure is from Corwin and Schultz (2012) and use Thomson Reuters at 10 p.m. GMT. The start of data availability for the bid-ask quotes is shown in the table. For all series, the sample period ends in May 2012.

	beta	tstat	R^2	N
Demand-side factors				
a) Current account				
Δ U.S. (Export+Import)/GDP	0.076	[1.751]	0.006	255
Δ U.S. Export/GDP	0.078	[1.768]	0.006	255
b) Portfolio balances				
Δ U.S. CB reserves / GDP	0.035	[0.891]	0.001	255
Δ U.S. Gross capital flow / GDP	**-0.106**	[-3.100]	0.011	255
Δ Gross foreigners purchases of the U.S. treasuries / GDP	**-0.082**	[-2.069]	0.007	255
Δ Gross U.S. citizens purchases of the foreign stocks and bonds / GDP	**-0.061**	[-2.166]	0.004	255
c) Sentiments				
Δ U.S. investor sentiment index	0.014	[0.486]	0.000	238
Δ VIX	**-0.227**	[-3.938]	0.051	255
Supply-side factors				
a) Funding conditions				
Δ TED spread	**-0.102**	[-2.613]	0.010	255
Δ U.S. commercial paper spread	-0.061	[-1.202]	0.004	247
Return on the 10 biggest FX dealers	**0.119**	[2.049]	0.014	255
b) Monetary conditions				
Δ U.S. Monetary aggregates	-0.054	[-0.829]	0.003	255
Inflation in the U.S.	0.052	[1.055]	0.003	255
c) Banking				
Δ U.S. Bank deposits / GDP	0.036	[0.831]	0.001	255
Δ Financial commercial paper rate	-0.019	[-0.483]	0.000	184
Market conditions				
USD appreciation	**-0.124**	[-2.000]	0.015	255
MSCI return	**0.140**	[2.154]	0.020	255
Δ AAA bond rates	-0.057	[-0.788]	0.003	254
Δ FX volatility	**-0.332**	[-7.466]	0.110	241
Δ MSCI volatility	**-0.232**	[-3.715]	0.054	255
Δ Bond volatility	**-0.132**	[-3.342]	0.017	255
Δ Stock liquidity	0.182	[1.832]	0.033	179
Δ Bond liquidity	**0.204**	[3.366]	0.042	255
Δ FX liqudity lagged	**-0.097**	[-1.733]	0.009	255

Table IA.12 **Explaining liquidity with single factors.**
The table shows the results from single panel regressions of liquidity on FX rates on its drivers, $\Delta L_{ij,t} = \alpha + \beta' f_t + \varepsilon_{ij,t}$, where $\Delta L_{ij,t}$ is, for the FX rate between currencies i and j, the change in liquidity from month $t-1$ to t, f_t denotes the demand-side and supply-side factors as well as market conditions. The liquidity of each currency pair is the average across standardized *BA* and *CS* measures. . The t-statistics are reported in brackets. They are based on the standard errors robust to conditional heteroscedasticity, cross-sectional and serial (up to one lag) correlation as in Driscoll and Kraay (1998). Bold numbers are statistically significant at the 5% level. The sample is Jan 1991 – May 2012, except for the U.S. sentiment index (Jan 1991 – Dec 2012), U.S. commercial paper spread (Nov 1991 – May 2012), Financial commercial paper rate (Jan 1997 – May 2012), FX volatility (Apr 1992 – May 2012), and stock liquidity (Jan 1995 – Dec 2012).

	Δ U.S. Gross capital flow / GDP	Δ VIX	Δ TED spread	Return on the 10 biggest FX dealers	USD appreciation	MSCI return	Δ AAA bond rates	Δ FX volatility	Δ MSCI volatility	Δ Bond volatility	Δ Stock liquidity	Δ Bond liquidity	Δ FX liqudity lagged
Δ U.S. Gross capital flow / GDP	1												
Δ VIX	0.205	1											
Δ TED spread	0.250	0.260	1										
Return on the 10 biggest FX dealers	-0.063	-0.539	-0.101	1									
USD appreciation	0.028	0.345	0.094	-0.481	1								
MSCI return	-0.086	-0.600	-0.142	0.813	-0.586	1							
Δ AAA bond rates	-0.082	0.070	0.058	-0.082	0.177	-0.083	1						
Δ FX volatility	0.123	0.561	0.190	-0.429	0.297	-0.441	0.060	1					
Δ MSCI volatility	0.326	0.696	0.281	-0.387	0.297	-0.450	0.187	0.490	1				
Δ Bond volatility	0.273	0.319	0.328	-0.246	0.157	-0.295	0.087	0.303	0.269	1			
Δ Stock liquidity	-0.178	-0.588	-0.156	0.264	-0.152	0.294	0.077	-0.473	-0.416	-0.217	1		
Δ Bond liquidity	0.076	-0.343	-0.077	0.193	-0.022	0.140	-0.156	-0.356	-0.242	-0.163	0.314	1	
Δ FX liqudity lagged	0.215	-0.159	0.000	0.086	-0.111	0.131	-0.012	-0.018	0.080	0.012	0.127	0.179	1

Table IA.13 **Correlations between the main FX liquidity drivers.**
This table shows the correlations between the main liquidity drivers (demand-side, supply-side or market conditions), used as regressors in Table 4 of the main paper. The full sample is January 1991 – May 2012, 257 months. See caption to Table IA.12 for the exceptions on data availability.

			Panel A			Panel B
FX pair	Country	Type	beta	tstat	R^2	R^2
AUD/USD	Australia	developed	**0.507**	[4.639]	0.257	0.274
CAD/USD	Canada	developed	**0.516**	[4.552]	0.266	0.284
INR/USD	India	emerging	0.158	[1.762]	0.025	0.041
JPY/USD	Japan	developed	**0.524**	[7.426]	0.275	0.271
MXN/USD	Mexico	emerging	**0.262**	[2.334]	0.069	0.076
NZD/USD	New Zealand	developed	**0.529**	[6.575]	0.280	0.288
NOK/USD	Norway	developed	**0.472**	[5.627]	0.223	0.227
SGD/USD	Singapore	emerging	**0.362**	[4.336]	0.131	0.137
ZAR/USD	South Africa	emerging	**0.382**	[2.694]	0.146	0.155
SEK/USD	Sweden	developed	**0.576**	[11.623]	0.332	0.336
CHF/USD	Switzerland	developed	**0.660**	[6.486]	0.435	0.439
GBP/USD	UK	developed	**0.677**	[7.344]	0.458	0.474
AUD/EUR	Australia	developed	**0.538**	[9.459]	0.290	0.325
CAD/EUR	Canada	developed	**0.628**	[8.198]	0.394	0.411
JPY/EUR	Japan	developed	**0.648**	[9.302]	0.420	0.458
NZD/EUR	New Zealand	developed	**0.561**	[8.514]	0.315	0.320
NOK/EUR	Norway	developed	**0.663**	[12.896]	0.440	0.432
SGD/EUR	Singapore	emerging	**0.625**	[9.046]	0.391	0.410
CHF/EUR	Switzerland	developed	**0.622**	[6.110]	0.387	0.385
GBP/EUR	UK	developed	**0.617**	[7.928]	0.381	0.378
AUD/GBP	Australia	developed	**0.622**	[8.644]	0.386	0.400
CAD/GBP	Canada	developed	**0.674**	[11.218]	0.455	0.455
JPY/GBP	Japan	developed	**0.536**	[10.049]	0.287	0.301
NZD/GBP	New Zealand	developed	**0.656**	[6.835]	0.430	0.430
NOK/GBP	Norway	developed	**0.611**	[10.362]	0.374	0.362
SGD/GBP	Singapore	emerging	**0.684**	[11.967]	0.468	0.468
ZAR/GBP	South Africa	emerging	**0.558**	[6.753]	0.311	0.305
SEK/GBP	Sweden	developed	**0.504**	[10.044]	0.254	0.252
CHF/GBP	Switzerland	developed	**0.666**	[12.029]	0.443	0.446
EUR/USD	Eurozone	developed	**0.715**	[8.283]	0.512	0.534

Table IA.14 **Commonality regressions for each currency pair.**
Panel A of the table shows the output from regressing (changes of) individual FX rate liquidities on the (changes of) systematic LF liquidity, see equation (4) of the main paper, i.e. each FX rate liquidity is regressed on the systematic FX liquidity, based on the average across 29 FX rates excluding the left hand side variable. Panel B of the table shows the R^2 from regressing the (changes of) individual FX rate liquidities on the (changes of) lagged, comtemporaneous, and leading systematic LF liquidity. The individual FX rate liquidities are based on the average across two most accurate liquidity measures (*BA* and *CS*). The t-statistics are reported in brackets. Bold numbers are statistically at the 5% level. The R^2 in Panel A are equal to the squared betas (all variables are standardized to have zero mean and unit variance). The sample is January 1991 – May 2012, 257 months.

	beta	tstat	R^2	N months
VIX	**0.227**	[2.708]	0.011	255
TED spread	**0.373**	[7.431]	0.029	255
FX volatility	**0.369**	[5.468]	0.029	241
MSCI volatility	**0.319**	[5.238]	0.022	255
Carry trade losses	**0.206**	[2.572]	0.009	254

Table IA.15 **Explaining time-series variation in commonality: single regressions.**
This table shows the results from single panel regressions of logit transformation of commonality $R^2_{ij,t}$ on 30 FX rates on the stress factors $\ln[R^2_{ij,t}/(1-R^2_{ij,t})] = \alpha + \beta' f_t + u_{ij,t}$. The commonality $R^2_{ij,t}$ is calculated by running recursive commonality regressions on expanding data windows, but where old data is weighted with exponentially declining weights (the weight on lag s is 0.7^s). The t-statistics are reported in brackets. They are based on standard errors, robust to conditional heteroscedasticity, spatial, and serial (up to one lag) correlations as in Driscoll and Kraay (1998). Bold numbers are statistically significant at the 5% level. The sample for the regression on FX volatility is April 1992 – May 2012. The sample all the other regressions is January 1991 – May 2012.

	beta	tstat	R^2
Demand-side factors			
a) Current account			
(Export + Import)/GDP	0.048	[0.321]	0.003
Export QC to BC / GDP QC	-0.105	[-0.586]	0.015
Export BC to QC / GDP BC	**0.169**	[3.319]	0.038
Trade flow (gravity model)	0.056	[0.530]	0.004
b) Portfolio balances			
International debt issues / GDP	**0.392**	[2.438]	0.206
CB reserves / GDP	0.008	[0.061]	0.000
Net foreign assets / GDP	-0.003	[-0.022]	0.000
Gross capital flow / GDP	0.251	[1.521]	0.085
c) Institutional setting			
Central bank transparency	**0.435**	**[2.011]**	**0.255**
Central bank independence	0.056	[0.288]	0.004
Sovereign credit ratings	**0.676**	**[4.733]**	**0.614**
Supply-side factors			
a) Funding conditions			
Volatility of the FX rate return	0.264	[1.207]	0.094
Local money market interest rate	**-0.543**	[-3.949]	0.395
b) Monetary conditions			
Money supply/GDP	**0.255**	[2.125]	0.087
c) Banking			
Bank deposits / GDP	**0.282**	[2.367]	0.107
Controls			
ln (GDP pro capita)	**0.644**	[4.371]	0.557
GDP growth volatility	-0.153	[-0.983]	0.032
ln GEO size	-0.144	[-1.527]	0.028
Stock market cap / GDP	**0.254**	[2.160]	0.086

Table IA.16 **Explaining cross-sectional variation in commonality: single regressions.** This table shows the results from regressing logit transformations of commonality R^2_{ij} for 30 exchange rates on the fundamental factors, $\ln[R^2_{ij}/(1-R^2_{ij})] = \alpha + \beta z_{ij} + \varepsilon_{ij}$. The commonality R^2_{ij} is from regression (4) of the main paper. The table uses the following abbreviations: QC and BC denote Quotes and Base Currency forming the currency pair. Unless specified otherwise, the fundamental factors z_{ij} refer to the country representing the QC. The t-statistics are in brackets. They are based on the standard errors, robust to conditional heteroscedasticity and serial correlation up to one lag as in Newey and West (1987). Bold numbers are statistically significant at the 5% level. The number of exchange rates used in each regression is 30. The only exception is regression on central bank independence variable, which uses data on 27 exchange rates.