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Liquidity in the Foreign Exchange Market: Measurement, Commonality, and Risk Premiums

LORIANO MANCINI, ANGELO RANALDO, and JAN WRAMPELMEYER*

ABSTRACT

We provide the first systematic study of liquidity in the foreign exchange market. We find significant variation in liquidity across exchange rates, substantial illiquidity costs, and strong commonality in liquidity across currencies and with equity and bond markets. Analyzing the impact of liquidity risk on carry trades, we show that funding (investment) currencies offer insurance against (exposure to) liquidity risk. A liquidity risk factor has a strong impact on carry trade returns from 2007 to 2009, suggesting that liquidity risk is priced. We present evidence that liquidity spirals may trigger these findings.

Over the last three decades, liquidity in equity and bond markets has been studied extensively in the finance literature.[1] By contrast, the literature has had little to say about liquidity in the foreign exchange (FX) market. This is

*Loriano Mancini is at EPFL and the Swiss Finance Institute. Angelo Ranaldo and Jan Wrampelmeyer are at the Swiss Institute of Banking and Finance, University of St. Gallen. The authors thank Campbell Harvey (the Editor), the Associate Editor, two anonymous referees, Viral Acharya, Francis Breedon, Michael Brennan, Pierre Collin-Dufresne, Rüdiger Fahlenbrach, Amit Goyal, Robert Hodrick, Antonio Mele, Lukas Menkhoff, Erwan Morellec, Ľuboš Pástor, Lasse Pedersen, Ronnie Sadka, René Stulz, Giorgio Valente, Adrien Verdelhan, Paolo Vitale, Christian Wiehenkamp, our discussants Alessandro Beber, Tarun Chordia, and Lucio Sarno, as well as participants at the 2012 American Economic Association meetings in Chicago, the 2010 Workshop on International Asset Pricing at the University of Leicester, the 2010 Eastern Finance Association Annual Meeting, the 2010 Midwest Finance Association Annual Meeting, the Warwick Business School FERC 2009 conference on Individual Decision Making, High Frequency Econometrics and Limit Order Book Dynamics, the 2009 CEPR/Study Center Gerzensee European Summer Symposium in Financial Markets, and the Eighth Swiss Doctoral Workshop in Finance for helpful comments. Financial support by the Swiss National Science Foundation—National Centre of Competence in Research "Financial Valuation and Risk Management"—is gratefully acknowledged.

[1] Based on the theoretical model of Amihud and Mendelson (1986), Chordia, Roll, and Subrahmanyam (2001), among others, use trading activity and transaction costs to study daily liquidity in equity markets. Amihud (2002) suggests the average ratio of absolute stock return to its trading volume as a measure of illiquidity. Hasbrouck (2009) estimates the effective cost of trades by relying on the spread model of Roll (1984). Chordia, Roll, and Subrahmanyam (2000) as well as Hasbrouck and Seppi (2001) document the fact that the liquidity of individual stocks comoves with industry and market-wide liquidity. Pástor and Stambaugh (2003) measure stock market liquidity using return reversal, and show that liquidity risk is priced in the cross-section of stock returns. Acharya and Pedersen (2005), Sadka (2006), and Korajczyk and Sadka (2008) lend further support to liquidity risk being a priced factor in stock returns. Goyenko, Holden, and Trzcinka (2009) compare various proxies of liquidity against high-frequency benchmarks. Fleming and Remolona (1999) and Chordia, Sarkar, and Subrahmanyam (2005), among others, provide related studies

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surprising since the FX market is the world's largest financial market with an estimated average daily trading volume of four trillion U.S. dollars (USD) in 2010 (Bank for International Settlements (2010)), corresponding to more than 10 times that of global equity markets (World Federation of Exchanges (2009)).

Due to its size, the FX market is commonly regarded as extremely liquid. However, given the market's limited transparency, heterogeneity of participants, and decentralized dealership structure (Lyons (2001)), FX liquidity is not well understood. The recent financial crisis and the study on currency crashes by Brunnermeier, Nagel, and Pedersen (2008) highlight the importance of liquidity in the FX market.[2] Short-term money market positions are extensively funded via FX markets. Thus, a decline in FX liquidity affects funding costs, increases rollover risks, and impairs hedging strategies. FX rates are also at the core of many arbitrage strategies such as triangular arbitrage, exploiting deviations from covered interest rate parity or price mismatching between multiple-listed equity shares and American depositary receipts. Consequently, FX market liquidity is crucial for arbitrage trading, which keeps prices tied to fundamental values and enables market efficiency (Shleifer and Vishny (1997)).

This paper provides the first systematic study of liquidity in the FX market. Using a novel and comprehensive data set of intraday data, we begin by analyzing FX liquidity from January 2007 to December 2009. We use data from Electronic Broking Services (EBS), the leading platform for spot FX interdealer trading.[3] We calculate a variety of liquidity measures covering the dimensions of price impact, return reversal, trading cost, and price dispersion. Contrary to common perceptions of the FX market being highly liquid at all times, we find significant temporal and cross-sectional variation in currency liquidities. To quantify illiquidity costs, we develop a carry trade example and show that FX illiquidity can aggravate losses during market turmoil by more than 25%.

Our analysis provides ample evidence of strong commonality in liquidity, that is, large comovements of FX rate liquidities over time. This suggests that FX liquidity is driven largely by shocks that affect the FX market as a whole, rather than individual FX rates. We also find that more liquid FX rates, like EUR/USD or USD/JPY, tend to have lower liquidity sensitivities to market-wide FX liquidity. The opposite is true for less liquid FX rates, such as AUD/USD or USD/CAD. We document strong contemporaneous comovements among FX, U.S. equity, and bond market-wide liquidities, suggesting that the efficacy of international and cross-asset class diversification may be impaired by liquidity risks.

for U.S. government bond markets, while Green, Li, and Schürhoff (2010) study municipal bond markets. Recently, Bao, Pan, and Wang (2011) and Dick-Nielsen, Feldhütter, and Lando (2012) study liquidity issues in corporate bond markets.

[2] Further recent studies of crash risk in currency markets include Jurek (2009), Farhi et al. (2009), and Plantin and Shin (2011).

[3] The Internet Appendix discusses the advantages of EBS data over other data sets provided by Datastream, Reuters, carry trade ETFs, and data from custodian banks.

Next, we study the impact of liquidity risk on the carry trade. This popular trading strategy consists of borrowing in low interest rate currencies and investing in high interest rate currencies. The high profitability of carry trades is a long-standing conundrum in the field of finance, fueling the search for risk factors driving these returns. Our main finding is that low interest rate currencies tend to exhibit negative liquidity betas, thus offering insurance against liquidity risk. On the other hand, liquidity betas for high interest rate currencies tend to be positive, providing exposure to liquidity risk.

Liquidity betas reflect the liquidity features of the various currencies. Low interest rate currencies tend to be more liquid and exhibit lower liquidity sensitivities. High interest rate currencies, by contrast, tend to be less liquid and have higher liquidity sensitivities. The following mechanism emerges from these findings. When FX liquidity improves, high interest rate currencies appreciate further because of positive liquidity betas, while low interest rate currencies depreciate further because of negative liquidity betas, increasing the deviation from the uncovered interest rate parity (UIP). During the unwinding of carry trades (i.e., when high interest currencies are being sold and low interest rate currencies are being bought), we find that market-wide FX liquidity drops, inducing a higher price impact of trades. Because FX liquidity drops and liquidity betas have opposite signs, high interest rate currencies depreciate further while low interest rate currencies appreciate further, exacerbating currency crashes. This finding is consistent with a "flight to liquidity." It also suggests that liquidity risk may be priced in currency returns. Carry traders seem to be aware of the liquidity features of various currencies and demand a liquidity premium accordingly.

To compute liquidity betas, we introduce a tradable liquidity risk factor constructed as a portfolio that is long in the most illiquid currencies and short in the most liquid currencies. When regressing daily carry trade returns on our liquidity risk factor and the "market" risk factor of Lustig, Roussanov, and Verdelhan (2011), we find that there are no more anomalous or unexplained returns during our sample period. This holds true even when the tradable liquidity factor is replaced by unexpected shocks to market-wide FX liquidity extracted via principal component analysis (PCA).

Some limitations of this analysis have to be highlighted. Our sample period spans only three years and includes a financial crisis, when liquidity issues are likely to be important. Previous studies document complementary or alternative factors driving carry trade returns, such as the volatility in global equity markets (Lustig, Roussanov, and Verdelhan (2011)), the volatility in FX markets (Menkhoff et al. (2012)), and aggregate consumption growth (Lustig and Verdelhan (2007)). It remains to be investigated whether and to what extent liquidity risk plays a role in explaining carry trade returns in "normal" times and over longer periods relative to other potential explanations.

Another contribution of this paper is to show that liquidity spirals may trigger our findings above. The theory of liquidity spirals is formalized by Brunnermeier and Pedersen (2009); Morris and Shin (2004) provide a related model for "liquidity black holes." These theoretical models imply that when traders' funding liquidity deteriorates, they are forced to liquidate positions. This reduces market-wide liquidity and triggers large price drops.[4]

We provide evidence that when traders' funding liquidity (proxied by the TED and the LIBOR-OIS spreads[5]) decreases, market-wide FX liquidity drops—a cross-market effect. The drop in FX liquidity then affects FX rates via their liquidity betas. As predicted by Brunnermeier and Pedersen (2009), funding liquidity has a strong impact on market-wide FX liquidity. This effect is more pronounced when the period following the bankruptcy of Lehman Brothers is included in the analysis. However, it is still significant when using data from January 2007 to mid-September 2008 only, when the FX market was relatively calmer. These findings support the conjecture in Burnside (2008) that liquidity frictions may explain the profitability of carry trades because liquidity spirals can aggravate currency crashes. Our contribution is to document the wedge in liquidity between high and low interest rate currencies, their different liquidity sensitivities to market-wide FX liquidity, and their liquidity betas of opposite signs. These features rationalize the impact of FX liquidity risk on carry trade returns.

The remainder of the paper is organized as follows. Section I discusses the related literature. Section II describes the data set and measures of liquidity. Section III presents an empirical investigation of liquidity in the FX market. Section IV introduces measures for market-wide liquidity and documents commonality in liquidity across FX rates. Section V relates FX liquidity to funding liquidity and liquidity of the U.S. equity and bond markets. Section VI analyzes the impact of liquidity risk on carry trade returns. Section VII concludes.

I. Related Literature

Despite its importance, very few studies exist on liquidity in the FX market. The existing literature mostly focuses on the contemporaneous correlation between order flow and exchange rate returns documented by Evans and Lyons (2002). Using a unique data set from a commercial bank, Marsh and O'Rourke (2005) investigate the effect of customer order flows on exchange rate returns. Breedon and Vitale (2010) argue that portfolio rebalancing can temporarily lead to liquidity risk premiums as long as dealers hold undesired inventories. Berger et al. (2008) document a prominent role of liquidity effects in the contemporaneous relation between order flow and exchange rate movements in their study of EBS data. However, none of these papers systematically measures benchmark liquidity or investigates commonality in liquidity as we do in this paper.

[4] It is even strategically optimal for traders to "run for the exit," that is, to liquidate their positions ahead of other traders, thereby avoiding distressed assets and buying the same assets back later before prices rebound to fundamental values; see Brunnermeier and Pedersen (2005).

[5] The TED spread is the difference between the one-month LIBOR interbank market interest rate and the risk-free T-Bill rate. The LIBOR-OIS spread is the difference between the London Interbank Offered Rate (LIBOR) and on overnight indexed swap (OIS) rate.

Extensive work documents the failure of UIP, beginning with the seminal studies by Hansen and Hodrick (1980), Fama (1984), and Hodrick and Srivastava (1986). This literature can be divided into two parts. The first approach endeavors to explain carry trade returns using standard asset pricing models based on systematic risk.[6] The second approach aims to provide non-risk based explanations.[7] Lustig, Roussanov, and Verdelhan (2011) provide a survey of both approaches. Recently, Burnside et al. (2011) find that traditional risk factors cannot explain the profitability of carry trades. Lustig, Roussanov, and Verdelhan (2011) develop a factor model in the spirit of Fama and French (1993) for FX returns. They find that a single carry trade risk factor, given by a currency portfolio that is long in high interest rate currencies and short in low interest rate currencies, can explain most of the variation in monthly carry trade returns. During our sample period, our liquidity risk factor is strongly correlated (0.92) with their carry trade factor. Menkhoff et al. (2012) illustrate the role of volatility risk for currency portfolios in Lustig and Verdelhan (2007). To the extent that liquidity spirals induce volatility increases (Brunnermeier and Pedersen (2009)), our asset pricing model suggests that the more fundamental explanation of liquidity risk can contribute to rationalizing carry trade returns.

II. Measuring FX Liquidity

A. Data Set

Apart from the fact that the FX market is more opaque and fragmented than stock markets, liquidity in FX markets has not been previously studied in more detail mostly due to the lack of available data. Through the Swiss National Bank, we gained access to a new data set from EBS that includes historical data for the most important currency pairs from January 2007 to December 2009 on a one-second basis. With a market share of more than 60%, EBS is the leading global marketplace for spot interdealer FX trading. For the two major currency pairs, EUR/USD and USD/JPY, the vast majority of spot trading is represented by the EBS data set (Chaboud, Chernenko, and Wright (2007)). EBS best bid and ask quotes as well as volume indicators are available and the direction of trades is known. This is crucial for an accurate estimation of liquidity, because it avoids using any Lee and Ready (1991)–type rule to infer trade directions. All EBS quotes are transactable, that is, they reliably represent the prevalent spot exchange rate. Moreover, all dealers on the EBS platform are prescreened for credit and bilateral credit lines, which are continuously monitored by the system, so counterparty risk is virtually

[6] This strand of literature includes, for example, Bekaert (1996), Brennan and Xia (2006), Bekaert and Hodrick (1992), Backus, Foresi, and Telmer (2001), Harvey, Solnik, and Zhou (2002), Lustig and Verdelhan (2007), Brunnermeier, Nagel, and Pedersen (2008), Verdelhan (2010), and Farhi and Gabaix (2011).

[7] This strand of literature includes, for example, Froot and Thaler (1990), Lyons (2001), Bacchetta and van Wincoop (2010), and Plantin and Shin (2011).

negligible when analyzing this data set.[8] This feature implies that all our findings pertain to liquidity issues and are not affected by potential counterparty risk. The Internet Appendix discusses further advantages of EBS data compared to data sets from Reuters and Datastream, compared to carry trade ETF data, and compared to customer order flow data from custodian banks.[9]

In this paper, we investigate nine currency pairs in detail, namely, the AUD/USD, EUR/CHF, EUR/GBP, EUR/JPY, EUR/USD, GBP/USD, USD/CAD, USD/CHF, and USD/JPY exchange rates. For each exchange rate, we process the irregularly spaced raw data to construct second-by-second price and volume series, each containing 86,400 observations per day. For every second, the midpoint of best bid and ask quotes or the transaction price of deals is used to construct one-second log-returns. For the sake of interpretability, we multiply these FX returns by 10,000 to obtain basis points (bps) as the unit of measurement. Observations between Friday 10 p.m. and Sunday 10 p.m. GMT[10] are excluded, since only minimal trading activity is observed during these nonstandard hours.[11]

This high-frequency data set allows for a very accurate estimation of liquidity in the FX market. Goyenko, Holden, and Trzcinka (2009) document the added value of intraday data when measuring liquidity. For portfolios of stocks, the time-series correlation between high-frequency liquidity benchmarks and lower frequency proxies (e.g., Roll (1984) or Amihud (2002)) can be as low as 0.018. Even the best proxy (Holden (2009)) achieves only a moderate correlation of 0.62 for certain portfolios. For individual assets these correlations are likely to be even smaller. Thus, when analyzing liquidity it is crucial to rely on high-quality data, as we do in this paper.

B. Liquidity Measures

This section presents the liquidity measures used in our study. Liquidity is a complex concept with different facets, and we thus break down our measures into three categories, namely, price impact and return reversal, trading cost, as well as price dispersion.[12]

[8] EBS keeps track of bilateral credit allocations between counterparties in real time. Moreover, the system relies on continuous linked settlement (CLS) to rule out settlement risk. This facility settles transactions on a payment versus payment (PVP) basis. When an FX trade is settled, each of the two parties to the trade pays out (sells) one currency and receives (buys) the other currency. PVP ensures that these payments and receipts occur simultaneously. Chaboud, Chernenko, and Wright (2007) provide a descriptive study of EBS. Further information can be found on the website of ICAP, http://www.icap.com/, the current owner of EBS.

[9] An Internet Appendix may be found in the online version of this article.

[10] GMT is used throughout the paper.

[11] We drop U.S. holidays and other days with unusually light trading activity from the data set. We also remove a few obvious outlying observations. The Internet Appendix discusses in detail the filtering procedure for the data.

[12] Measures of trading activity such as number of trades, trading volume, percentage of zero-return periods, or average trading interval are not used as proxies for FX liquidity in this paper. As more active markets tend to be more liquid, such measures are frequently used as an indirect

B.1. Price Impact and Return Reversal

Conceptually related to Kyle (1985), the price impact of a trade measures how much the exchange rate changes in response to a given order flow. The higher the price impact, the more the exchange rate moves following a trade, reflecting lower liquidity. Moreover, if a currency is illiquid, part of the price impact is temporary, as net buying (selling) pressure leads to excessive appreciation (depreciation) of the currency, followed by a reversal to the fundamental value (Campbell, Grossman, and Wang (1993)).

Our data set allows for an accurate estimation of price impact and return reversal, and thus we can avoid using proxies like those proposed by Amihud (2002) and Pástor and Stambaugh (2003). For each currency, let r_{t_i}, v_{b,t_i}, and v_{s,t_i} denote the log exchange rate return between t_{i-1} and t_i, the volume of buyer-initiated trades, and the volume of seller-initiated trades at time t_i during day t, respectively. Then, price impact and return reversal can be modeled as

$$r_{t_i} = \vartheta_t + \varphi_t(v_{b,t_i} - v_{s,t_i}) + \sum_{k=1}^{K} \gamma_{t,k}(v_{b,t_{i-k}} - v_{s,t_{i-k}}) + \varepsilon_{t_i}. \tag{1}$$

By estimating the parameter vector $\boldsymbol{\theta}_t = [\vartheta_t \quad \varphi_t \quad \gamma_{t,1} \ldots \gamma_{t,K}]$ on each day, we compute the liquidity dimensions of price impact and return reversal on a daily basis. To ensure that the estimates are not affected by potential outliers, we apply robust techniques to estimate the model parameters.[13] It is expected that the price impact of a trade $L^{(pi)} = \varphi_t$ is positive due to net buying pressure. The overall return reversal is measured by $L^{(rr)} = \gamma_t = \sum_{k=1}^{K} \gamma_{t,k}$, which is expected to be negative.

The intraday frequency for estimating model (1) should be low enough to distinguish return reversal from simple bid-ask bounce. Hence, one-second data need to be aggregated. A lower frequency or a longer lag length K also has the advantage of capturing delayed return reversal. On the other hand, the frequency should be sufficiently high to accurately measure contemporaneous impact and to obtain an adequate number of observations for each day. The results presented in this paper are mainly based on one-minute data and $K = 5$. Several robustness checks collected in the Internet Appendix largely confirm that our results are robust to the choice of sampling frequency and number of lags K.

We note that model (1) is consistent with recent theoretical models of limit order books. Rosu (2009) develops a dynamic model that predicts that more liquid assets should exhibit narrower spreads and lower price impact. In line with

measure of liquidity. Unfortunately, the relation between liquidity and trading activity is ambiguous. Jones, Kaul, and Lipson (1994) show that trading activity is positively related to volatility, which in turn implies lower liquidity. Melvin and Taylor (2009) document a strong increase in FX trading activity during the financial crisis, which they attribute to "hot potato trading" rather than an increase in market liquidity. Moreover, traders apply order splitting strategies to avoid a significant price impact of large trades.

[13] The robust estimation is described in detail in the Internet Appendix.

Foucault, Kadan, and Kandel (2005), prices recover quickly from overshooting following a market order if the market is resilient (i.e., liquid). By measuring the relation between returns and lagged order flow, model (1) captures delayed price adjustments due to lower liquidity.

B.2. Trading Cost

The second group of liquidity measures covers the cost aspect of illiquidity, that is, the cost of executing a trade. A market can be regarded as liquid if the proportional quoted bid-ask spread, $L^{(ba)}$, is low,

$$L^{(ba)} = (P^A - P^B)/P^M, \tag{2}$$

where the superscripts A, B, and M indicate the ask, bid, and mid quotes, respectively. The latter is defined as $P^M = (P^A + P^B)/2$.

In practice trades are not always executed at the posted bid or ask quotes.[14] Instead, deals frequently transact at better prices. Effective costs can be computed by comparing transaction prices with the quotes prevailing at the time of execution. The effective cost of a trade is defined as:

$$L^{(ec)} = \begin{cases} (P - P^M)/P^M, & \text{for buyer-initiated trades,} \\ (P^M - P)/P^M, & \text{for seller-initiated trades,} \end{cases} \tag{3}$$

with P denoting the transaction price. Since our data set includes quotes and trades we do not have to rely on proxies for the effective spread (see, for example, Roll (1984), Holden (2009), and Hasbrouck (2009)), but can compute it directly from observed data. Daily estimates of illiquidity are obtained by averaging the effective cost of all trades that occurred on day t.

B.3. Price Dispersion

When large dealers hold undesired inventories, the higher the volatility the more reluctant these dealers are to provide liquidity (see, for example, Stoll (1978)). Thus, if volatility is high, liquidity tends to be low, and intraday price dispersion, $L^{(pd)}$, can be used as a proxy for illiquidity (see, for example, Chordia, Roll, and Subrahmanyam (2000)). We estimate daily volatility from intraday data. Given the presence of market frictions, standard realized volatility (RV) is inappropriate (Aït-Sahalia, Mykland, and Zhang (2005)). Zhang, Mykland, and Aït-Sahalia (2005) develop a nonparametric estimator that corrects the bias of RV by relying on two time scales. This two-scale realized volatility (TSRV) estimator consistently recovers volatility even if the data are subject to microstructure noise.

[14] For instance, new traders may come in, executing orders at a better price, or the spread may widen if the size of an order is particularly large. Moreover, in some electronic markets traders may post hidden limit orders that are not reflected in quoted spreads.

B.4. Principal Component

All liquidity measures presented above capture different aspects of liquidity. A natural approach to extracting the common information across these measures is PCA. Principal components can be interpreted as liquidity factors for an individual exchange rate. For each FX rate j, all five liquidity measures, ($L^{(pi)}$, $L^{(rr)}$, $L^{(ba)}$, $L^{(ec)}$, $L^{(pd)}$), are demeaned, standardized, and collected in the $5 \times T$ matrix $\widetilde{\mathbf{L}}_j$, where T is the number of days in our sample. The usual eigenvector decomposition of the empirical covariance matrix is $\widetilde{\mathbf{L}}_j \widetilde{\mathbf{L}}'_j \mathbf{U}_j = \mathbf{U}_j \mathbf{D}_j$, where $\mathbf{U}_j$ is the 5×5 eigenvector matrix, $\mathbf{D}_j$ the 5×5 diagonal matrix of eigenvalues, and $'$ is the transpose operator. The time-series evolution of all five factors is given by $\mathbf{U}'_j \widetilde{\mathbf{L}}_j$, with, for instance, the first principal component corresponding to the largest eigenvalue. Such a decomposition is repeated for each exchange rate to capture the most salient features of liquidity with a few factors.

III. Liquidity in the FX Market

A. Liquidity of Exchange Rates during the Financial Crisis

Using the large data set described above, we estimate our six liquidity measures (price impact, return reversal, bid-ask spread, effective cost, price dispersion, and principal component) for each trading day and each exchange rate. Table I shows means and standard deviations for the liquidity measures.[15]

For all exchange rates, the average return reversal, that is, the temporary price change accompanying order flow, is negative and therefore captures illiquidity. Depending on the currency pair, one-minute returns are reduced by 0.013 to 0.172 bps on average, if there was an order flow of one to five million in the previous five minutes. This reduction is economically significant, given the fact that average five-minute returns are virtually zero. In line with the results of Evans and Lyons (2002) and Berger et al. (2008), the average trade impact coefficient is positive. Effective costs are less than half the bid-ask spread, implying significant within-quote trading. Annualized FX return volatility ranges between 5.4% and 14.3%.

Comparing liquidity estimates across currencies, EUR/USD is the most liquid exchange rate, which is in line with the perception of market participants and the fact that it has by far the largest market share in terms of turnover (Bank for International Settlements (2010)). The least liquid FX rates are USD/CAD and AUD/USD. Despite the fact that GBP/USD is one of the most important exchange rates, it is estimated to be relatively illiquid, which can be explained by the fact that GBP/USD is mostly traded on Reuters rather than on EBS (Chaboud, Chernenko, and Wright (2007)). The high liquidity of EUR/CHF and USD/CHF during our sample period may be related to "flight-to-quality" effects and the perceived safe haven properties of the Swiss franc (CHF; Ranaldo and Söderlind (2010)) during the crisis.

[15] Additional descriptive statistics are collected in the Internet Appendix along with statistics for exchange rate returns and order flow.

Table I

Daily Liquidity Measures

This table shows summary statistics for various daily measures of liquidity. Price impact is the robustly estimated coefficient of contemporaneous order flow, φ_t, in a regression of one-minute returns on contemporaneous and lagged order flow (equation (1)). Return reversal is the sum of the coefficients of lagged order flow, $\sum_{k=1}^{K} \gamma_{t,k}$, in the same regression. Bid-ask spread denotes the average relative bid-ask spread computed using intraday data for each trading day (equation (2)). Effective cost is the average relative difference between the transaction price and the bid/ask quote prevailing at the time of the trade (equation (3)). Price dispersion for each trading day is estimated using two-scale realized volatility (TSRV). It is expressed in percent on an annual basis. The sample is January 2, 2007 to December 30, 2009.

	AUD/USD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	USD/CAD	USD/CHF	USD/JPY
Price impact									
Mean	1.06	0.12	0.50	0.26	0.07	0.43	0.84	0.18	0.11
Std. dev.	0.77	0.07	0.29	0.15	0.08	0.31	0.47	0.08	0.05
Return reversal (number of lagged order flow $K = 5$)									
Mean	−0.17	−0.03	−0.09	−0.05	−0.01	−0.10	−0.16	−0.03	−0.02
Std. dev.	0.32	0.03	0.14	0.05	0.01	0.13	0.26	0.04	0.02
Bid-ask spread (in bps)									
Mean	5.75	2.07	4.75	2.21	1.05	6.16	8.27	2.50	1.50
Std. dev.	3.87	1.03	2.96	0.96	0.29	7.44	7.63	1.11	0.41
Effective cost (in bps)									
Mean	1.38	0.36	0.81	0.43	0.31	0.81	1.26	0.45	0.42
Std. dev.	0.78	0.11	0.33	0.17	0.06	0.48	0.46	0.11	0.10
Volume weighted effective cost (in bps)									
Mean	1.11	0.28	0.71	0.33	0.21	0.66	1.07	0.34	0.27
Std. dev.	0.64	0.10	0.30	0.14	0.04	0.41	0.41	0.10	0.07
Price dispersion (TSRV, five minutes, in %, annualized)									
Mean	14.25	5.36	8.28	12.26	8.91	11.31	11.84	9.81	10.41
Std. dev.	9.59	3.21	4.36	7.39	4.42	8.29	5.38	4.14	4.84

Figure 1 shows liquidities measured by minus the effective cost, as defined in equation (3), for all currencies in our sample over time. Most exchange rates were relatively liquid and stable at the beginning of the sample. Liquidity suddenly dropped during the major unwinding of carry trades in August 2007. In the following months liquidity rebounded slightly for most currency pairs before it entered on a downward trend at the end of 2007. The decrease in liquidity continued after the collapse of Bear Stearns in March 2008. A potential reason for the increase in liquidity during the second quarter of 2008 is that investors believed that the crisis might soon be over and began to invest in FX markets again. Moreover, central banks around the world supported the financial system by a variety of traditional as well as unconventional policy tools. However, in September and October 2008, liquidity plummeted following the collapse of Lehman Brothers. This decline reflected the turmoil and uncertainty in financial markets caused by the bankruptcy. During 2009, FX liquidity returned slowly but steadily.

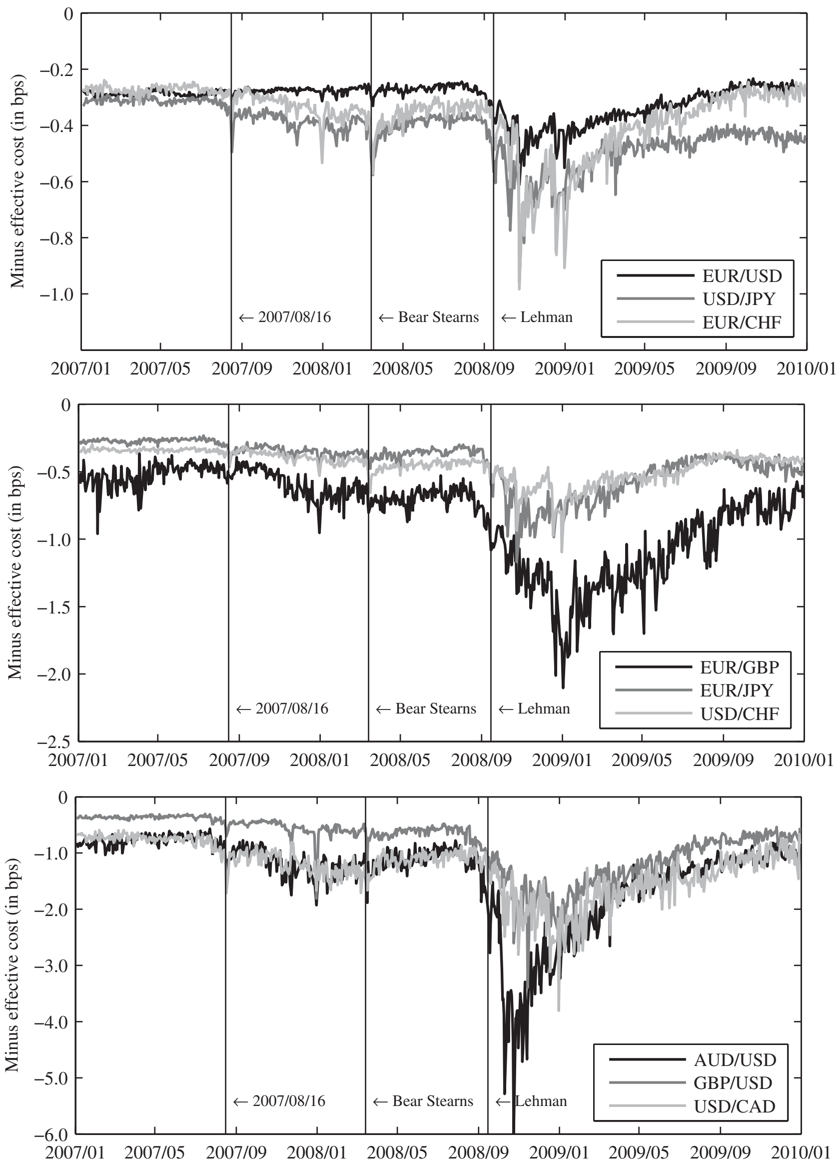

Figure 1. Effective cost. The figure plots daily liquidity estimates based on minus the effective cost. The upper graph shows minus the effective cost (in bps) for the most liquid exchange rates (EUR/USD, USD/JPY, EUR/CHF); the middle graph for intermediate liquidity exchange rates (EUR/GBP, EUR/JPY, USD/CHF); and the lower graph for the most illiquid exchange rates (AUD/USD, GBP/USD, USD/CAD). The effective cost is either $(P - P^M)/P^M$ for buyer-initiated trades or $(P^M - P)/P^M$ for seller-initiated trades, where P is the transaction price and P^M is the mid quote price. The sample is January 2, 2007 to December 30, 2009.

There were large cross-sectional differences in FX rate liquidities.[16] For instance, the decline in AUD/USD liquidity following the Lehman Brothers bankruptcy was quicker and more pronounced than that of other exchange rates. For all FX rates, levels of effective costs changed significantly over time but virtually never intersected over the entire sample period. While Figure 1 only shows effective cost, all other measures of liquidity share similar patterns. Indeed, PCA reveals that one single factor can explain up to 78.9% of variation in all liquidity measures for EUR/USD.[17]

To summarize, the level of liquidity varies significantly across FX rates and over time, liquidities comove strongly across FX rates, and liquidity-based ranking of FX rates is stable over time. Before analyzing all of these aspects in more detail, the next subsection highlights the economic relevance of illiquidity in the FX market by quantifying potential costs due to illiquidity for currency investors.

B. Impact of Illiquidity on a Currency Investor

To quantify the economic relevance of liquidity in the FX market we analyze the impact of illiquidity costs on a simple carry trade.[18] Pinning down FX illiquidity cost is a challenging task. We abstract from additional costs that may impact carry trade returns and focus on the direct effect of FX illiquidity on investors' profits. We keep exchange rates as well as interest rates constant and assume that the speculator is not leveraged. An extension of this example including leverage and additional costs is discussed later.

Consider a U.S. speculator who wants to engage in the AUD-JPY carry trade. She plans to fund this trade by borrowing the equivalent of USD one million at a low interest rate (1%) in Japan and invest at a higher interest rate (7%) in Australia. She institutes the trade by buying Australian dollars (AUD) and selling Japanese yen (JPY) versus USD to earn the interest rate differential. Suppose liquidity is high in the FX market, that is, bid-ask spreads are small and given by 2.64 bps for AUD/USD and 0.90 bps for USD/JPY (minimum precrisis level; see the Internet Appendix). If the U.S. speculator unwinds the

[16] Note that the vertical scale in Figure 1 differs considerably from one graph to another.

[17] The Internet Appendix reports loadings of the first three principle components for all currency pairs. The first two principle components have clear interpretation. The first component, which on average explains 70% of variation in liquidity measures, loads roughly equally on price impact, bid-ask spread, effective cost, and price dispersion. The loading on return reversal is consistently smaller for all exchange rates. In contrast, the second principle component is dominated by return reversal and accounts for an additional 15% of variation. These factor loadings are remarkably similar across exchange rates.

[18] Maturity mismatches (i.e., financing long-term lending with short-term borrowing) are frequently used to increase the carry trade performance. Moreover, investors have the choice between secured fixed income assets such as repos and more risky unsecured assets such as uncollateralized interbank loans. However, these aspects pertain to the fixed income markets and have no impact on the costs attributable to illiquidity in the FX market.

carry trade under these liquid conditions, the cost due to illiquidity is very small and amounts to 0.03% of the trading volume or 0.52% of the profit from the investment.[19]

Suppose now that the speculator is forced to unwind the carry trade when FX liquidity is low. For example, the speculator may face a liquidity shortage due to unexpected financial losses on other assets during a time of market turbulence. The turmoil triggers margin calls and the need to repatriate foreign capital to be invested in liquid USD-denominated assets. Low levels of liquidity in the Japanese fixed income market can also mean that it is impossible to roll over short-term positions. Such unfortunate circumstances are likely to occur when the investor's marginal utility is high due to additional losses. Thus, the carry trader (and any investor facing similar situations) is forced to unwind precisely when FX liquidity is low. Waiting for narrower bid-ask spreads is not feasible given the fact that movements in FX rates are also potentially harmful. If the bid-ask spread for AUD/USD is 54.03 bps, as it was at the peak of the crisis in October 2008, the cost due to illiquidity of unwinding the position is 10.70% of the profit! The cost of unwinding the trade is more than 20 times larger than under the liquid scenario. The 20-fold increase in the AUD/USD bid-ask spread (from 2.64 to 54.03 bps) is not an isolated event during the crisis. Indeed, there were comparable increases in the bid-ask spreads of various other currencies and common stocks during that period.[20] This suggests that FX illiquidity costs can be quite substantial and comparable, to some extent, to illiquidity costs for other assets.

Now consider the illiquidity cost in a slightly more realistic example. At times of low liquidity and unwinding of carry trades, low interest rate currencies (JPY in the example) usually appreciate whereas high interest rate currencies (AUD in the example) depreciate due to supply and demand pressure; see, for example, Brunnermeier, Nagel, and Pedersen (2008). Carry traders refer to these sudden movements in exchange rates as "going up the stairs and coming down with the elevator." Additionally, speculators often use leverage, which further magnifies potential losses. Suppose the U.S. speculator has levered her investment 4:1 and the AUD depreciates by 8% before the carry trader manages to unwind the position. Such a scenario is realistic given the sharp movements in exchange rates during the fall of 2008. In this scenario the carry

[19] These illiquidity costs are obtained by cumulating the costs due to bid-ask spread, converting JPY into USD and then USD into AUD to initiate the carry trade, and then conversely when unwinding the carry trade. More precisely, the cost at time t of the investment leg of the carry trade, AUD/USD, is determined as carry volume in USD multiplied by $(1/P^{B}_{\mathrm{AUD/USD,t}} - 1/P^{M}_{\mathrm{AUD/USD,t}})$. The rationale for computing the illiquidity cost as the difference between the bid price and the mid-quote price is that if the bid-ask spread is zero, then the illiquidity cost is zero as well. The cost of the funding leg is determined analogously but the USD/JPY ask price is used rather than the bid price. The costs of unwinding the carry trade are also computed analogously.

[20] For instance, the average daily bid-ask spread of the 30 stocks always in the Dow Jones Composite Average during our sample period ranged from USD 0.021 to USD 0.427, exhibiting a 20-fold increase, like the AUD/USD bid-ask spread.

trader has to bear a substantial loss. Without illiquidity cost in FX markets, the speculator loses 2.56% of the carry volume, which corresponds to a loss of 10.24% of her capital. This loss is increased by 25% under illiquid FX market conditions, resulting in a 12.81% decrease in capital.[21]

Illiquidity of the FX market affects not only speculators. Every investor or company that owns assets denominated in foreign currencies is subject to FX illiquidity risk. Given the sizable illiquidity costs, it would appear that currency investors should manage liquidity risk by managing cash holdings, credit lines, and investment decisions, as highlighted by Campello et al. (2011). Moreover, Figure 1 suggests that, rather than being limited to a particular currency pair, the phenomenon of diminishing liquidity and the economic importance of FX illiquidity cost affect all exchange rates. We investigate this commonality in FX liquidity in the next section.

IV. Commonality in FX Liquidity

Testing for commonality in FX liquidity is crucial as shocks to market-wide liquidity have important implications for investors as well as regulators. Documenting such commonality is also a necessary first step before examining whether liquidity is a risk factor for carry trade returns. Commonality in liquidity has been extensively documented in stock and bond markets. Given the segmented structure of the FX market and the heterogeneity of economic players acting in this market, it is unclear a priori whether commonality in liquidity is present in the FX market. From a theoretical point of view, the model of Brunnermeier and Pedersen (2009) implies that assets liquidities include common components across securities, because the theory predicts a decline in assets liquidities when investors' funding liquidity diminishes. To test for commonality in the FX market, we construct a market-wide liquidity time-series that represents the common component in liquidity across exchange rates.

A. Common Liquidity across Exchange Rates

Two approaches have been proposed to extract market-wide liquidity: averaging and PCA. For completeness we implement both methods, but most of the analysis is based on the latter. In the first approach, an estimate for market-wide FX liquidity is computed simply as the cross-sectional average of liquidity at the individual exchange rate level. Chordia, Roll, and Subrahmanyam (2000) and Pástor and Stambaugh (2003) use this method for determining aggregate liquidity in equity markets. In our setting, given a measure of liquidity, daily

[21] The illiquidity cost does not depend on the holding period of the carry trade. If this period is less than a year, the annualized illiquidity cost is obviously a multiple of the cost computed above.

market-wide liquidity $L^{(\cdot)}_{M,t}$ can be estimated as

$$L^{(\cdot)}_{M,t} = \frac{1}{N}\sum_{j=1}^{N} L^{(\cdot)}_{j,t}, \tag{4}$$

where N is the number of exchange rates and $L^{(\cdot)}_{j,t}$ the liquidity of exchange rate j on day t. In order for market-wide liquidity to be less influenced by extreme values, a common practice is to rely on a trimmed mean. Therefore, we exclude the currency pairs with the highest and lowest value for $L^{(\cdot)}_{j,t}$ in the computation of $L^{(\cdot)}_{M,t}$.[22]

Instead of averaging, Hasbrouck and Seppi (2001) and Korajczyk and Sadka (2008) rely on PCA to extract market-wide liquidity. For each exchange rate, a given liquidity measure is standardized by the time-series mean and standard deviation of the average of the liquidity measure obtained from the cross-section of exchange rates. The first three principle components across exchange rates are then extracted for each liquidity measure, with the first principal component representing market-wide liquidity. The Internet Appendix reports factor loadings and shows that the first principal component loads more or less equally on the liquidity of each exchange rate. Thus, for each liquidity measure, market-wide liquidity based on PCA can be interpreted as a level factor that behaves similarly to the trimmed mean in equation (4).

Table II shows correlations between the various market-wide FX liquidity measures. The lowest correlation is 0.85, suggesting strong comovements among liquidity measures. Such high correlations present a strong contrast to the low correlations between several liquidity measures for emerging markets reported in Bekaert, Harvey, and Lundblad (2007). Differences between FX and emerging markets as well as data frequencies can explain the gap in correlations.

B. Testing for Commonality in FX Liquidity

To formally test for commonality, for each exchange rate j we regress the time series of daily liquidity measure $L^{(\cdot)}_{j,t}, t = 1, \ldots, T$ on the first three principle components described above. Figure 2 shows the cross-sectional average of the adjusted-R^2 and provides ample evidence of strong commonality. The first principle component explains between 70% and 90% of the variation in daily FX liquidity, depending on which measure is used. As additional support, the R^2 increases further when two or three principle components are included as explanatory variables. The reversal measure exhibits the lowest level

[22] The Internet Appendix computes market-wide liquidities using simple mean, rather than trimmed mean. As expected, these market-wide liquidities are somewhat more volatile but share the same pattern as market-wide liquidities based on a trimmed mean. Graphs of market-wide liquidities based on each liquidity measure are collected in the Internet Appendix. Time-series patterns of all market-wide liquidities resemble those in Figure 1.

Table II

Correlation between Liquidity of Different Asset Classes

This table reports correlations between market-wide liquidity measures for the FX market (return reversal, price impact, bid-ask spread, effective cost, price dispersion, principal component), for the equity market (Pástor and Stambaugh, Amihud), for the corporate bond market (Corporate), and for the U.S. 10-year Treasury bond market (10y Treasury). Correlations are computed using 36 nonoverlapping monthly observations. The sample is January 2, 2007 to December 30, 2009.

		FX						Equity		Bond	
		Average									
		RR	PI	BA	EC	PD	PCA	PS	AM	CO	10y
FX avg.	ret. reversal	1									
	price impact	0.895	1								
	bid-ask spread	0.853	0.890	1							
	effective cost	0.895	0.897	0.954	1						
	price dispersion	0.860	0.900	0.949	0.946	1					
FX PCA		0.927	0.955	0.953	0.923	0.938	1				
Equity	Pástor/Stambaugh	0.274	0.399	0.300	0.282	0.377	0.337	1			
	Amihud	0.672	0.639	0.645	0.640	0.721	0.677	0.356	1		
Bond	Corporate	0.909	0.883	0.916	0.909	0.922	0.929	0.401	0.725	1	
	10y Treasury	0.869	0.798	0.863	0.880	0.879	0.841	0.219	0.673	0.931	1

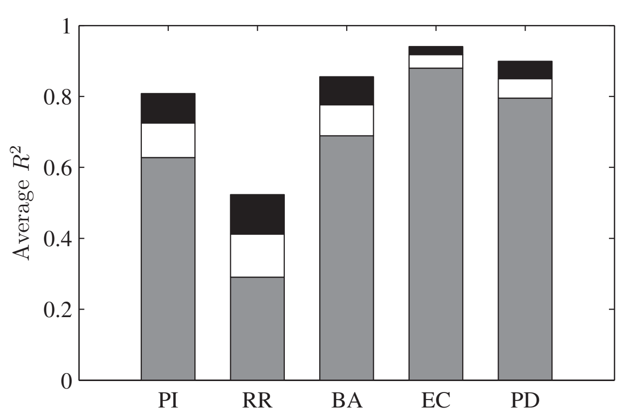

Figure 2. Commonality in liquidity. For each daily standardized measure of liquidity, the first three common factors are extracted using PCA. Then, for each exchange rate and each standardized liquidity measure, liquidity is regressed on its common factors. Each bar represents the average adjusted-R^2 of these regressions using one, two, and three common factors. The gray part of the bar is the adjusted-R^2 when using only the first common factor in the regression. The white part is the increase in the adjusted-R^2 when adding the second common factor. The black part is the increase in the adjusted-R^2 when adding the third common factor. PI denotes price impact, RR return reversal, BA proportional bid-ask spread, EC effective cost, and PD price dispersion. The number of observations is 733. The sample is January 2, 2007 to December 30, 2009.

of commonality. The commonality, already strong at the daily frequency, increases even more when aggregating liquidity measures at weekly and monthly horizons.

The R^2 statistics are significantly larger than those typically found for equity data and reported, for instance, in Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001), and Korajczyk and Sadka (2008).[23] This would imply that commonality in the FX market is stronger than in equity markets. However, it remains to be seen whether this phenomenon is specific to our sample period, namely, the financial crisis of 2007 to 2009, as comovements among financial assets and liquidities are reinforced during crisis periods. The nature of the FX market, with triangular connections between exchange rates, does not explain the strong commonality. Repeating the regression analysis based on only the six exchange rates that include the USD results in an R^2 of the same magnitude, lending further support to the presence of strong commonality.[24]

C. Market-Wide Liquidity Index

Korajczyk and Sadka (2008) take the idea of using PCA to extract common liquidity one step further by combining the information contained in various liquidity measures. The strong empirical evidence on commonality in the previous subsection suggests that alternative liquidity measures proxy for the same underlying liquidity factor. We construct a market-wide liquidity index by assuming a latent factor model of liquidity, which is estimated using PCA:

$$\widetilde{\mathbf{L}}_t = \boldsymbol{\beta} L^{(pca)}_{M,t} + \boldsymbol{\xi}_t, \tag{5}$$

where $\widetilde{\mathbf{L}}_t = [\widetilde{\mathbf{L}}^{(pi)}_t, \widetilde{\mathbf{L}}^{(rr)}_t, \widetilde{\mathbf{L}}^{(ba)}_t, \widetilde{\mathbf{L}}^{(ec)}_t, \widetilde{\mathbf{L}}^{(pd)}_t]'$ denotes the vector that stacks all five liquidity measures for all N exchange rates, $\widetilde{\mathbf{L}}^{(\cdot)}_t = [\widetilde{L}^{(\cdot)}_{1,t}, \ldots, \widetilde{L}^{(\cdot)}_{N,t}]'$, $\boldsymbol{\beta}$ is the vector of factor loadings, and $\boldsymbol{\xi}_t$ represents FX rate- and liquidity measure-specific shocks on day t. The first principle component explains the majority of variation in the liquidity of individual exchange rates, further substantiating the evidence for commonality. We use the first factor as a proxy for market-wide liquidity, $L^{(pca)}_{M,t}$, combining the information across exchange rates as well as across liquidity measures.

V. Properties of FX Liquidity

A. Relation to Proxies of Investors' Fear and Funding Liquidity

What are the reasons for the strong decline in FX liquidity during the crisis? We try to answer this question by investigating the link between funding liquidity and market-wide FX liquidity. The typical starting point of liquidity spirals is an increase in uncertainty in the economy, which leads to a decrease

[23] For example, Korajczyk and Sadka (2008) report adjusted-R^2 ranging between 2% and 30%, depending on the liquidity measure.

[24] Detailed results are collected in the Internet Appendix.

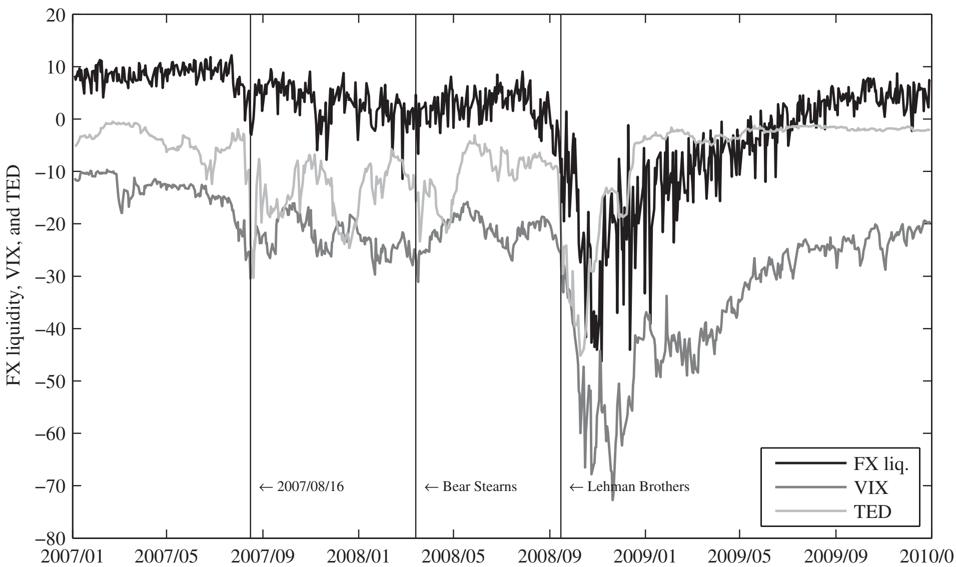

Figure 3. Relation to VIX and TED spread. Market-wide FX liquidity index (equation (5)), minus the Chicago Board Options Exchange Volatility Index (VIX) and minus the TED spread (multiplied by 10). The sample is January 2, 2007 to December 30, 2009.

in funding liquidity. Difficulty in securing funding for business activities leads in turn to lower market liquidity, especially if investors are forced to liquidate positions. This induces prices to move away from fundamentals, leading to increased losses on existing positions and a further reduction in funding liquidity, which reinforces the downward spiral (Brunnermeier and Pedersen (2009)).

Figure 3 illustrates the market-wide FX liquidity index extracted by PCA over time together with the Chicago Board Options Exchange Volatility Index (VIX) and the TED spread. Primarily an index for the implied volatility of S&P 500 options, the VIX is frequently used as a proxy for investors' fear and uncertainty in financial markets. The TED spread is a proxy for the level of credit risk and funding liquidity in the interbank market (e.g., Brunnermeier, Nagel, and Pedersen (2008)).[25] The severe financial crisis is reflected in a TED spread that is significantly larger than its long-run average of 30 to 50 bps.

Interestingly, the VIX as well as the TED spread are strongly negatively correlated with FX liquidity (−0.87 and −0.35 for daily liquidity), indicating that investors' fear measured by equity-implied volatility and funding liquidity in the interbank market may have spillover effects to other asset classes. Even when excluding observations from mid-September 2008 to December 2009, that is, after the bankruptcy of Lehman Brothers, the negative correlations prevail (−0.66 and −0.36 for daily liquidity). These comovements are consistent with

[25] An alternative proxy for funding liquidity is the LIBOR-OIS spread. The results based on this proxy are collected in the Internet Appendix and largely confirm the results reported here.

Table III

Evidence for Liquidity Spirals in the FX Market

This table reports results from regressions of the daily market-wide FX liquidity index ($L^{(pca)}_{M,t}$) on the lagged VIX and the lagged TED spread. Various specifications of the regression model are estimated. The last specification additionally controls for the JP Morgan Implied Volatility Index for the G7 currencies, VXY. Heteroskedasticity and autocorrelation (HAC) robust standard errors are shown in parentheses. R^2 is the adjusted-R^2. The number of observations is 733. The sample is January 2, 2007 to December 30, 2009.

	const	$L^{(pca)}_{M,t-1}$	VIX_{t-1}	TED_{t-1}	VXY_{t-1}	R^2
Coefficient	18.941		−0.691	−1.263		0.765
Std. error	(0.988)		(0.040)	(0.446)		
Coefficient	18.620		−0.719			0.756
Std. error	(1.038)		(0.047)			
Coefficient	3.851			−4.711		0.141
Std. error	(1.077)			(1.346)		
Coefficient	10.968	0.418	−0.398	−0.808		0.804
Std. error	(1.380)	(0.075)	(0.052)	(0.278)		
Coefficient	14.857	0.357	−0.207	−1.544	−0.700	0.815
Std. error	(1.598)	(0.076)	(0.057)	(0.337)	(0.138)	

a theory of liquidity spirals. After the bankruptcy of Lehman Brothers, in particular, the VIX and the TED spread surged while FX market liquidity dropped.

In Table III we regress daily FX liquidity on lagged VIX and lagged TED spread. Both past VIX and past TED spread are strongly negatively related to current FX liquidity. For instance, a one-standard-deviation increase in the VIX on day $t - 1$ is followed on average by a -8.37 decline in FX liquidity on day t. This drop is highly relevant when compared to the standard deviation of FX liquidity of 10.02. Thus, an increase in investors' uncertainty and a reduction in funding liquidity are followed by significantly lower FX market liquidity. These effects are statistically significant at any conventional level and explain most of the variation in market-wide FX liquidity, with an adjusted-R^2 of 76%. Changing the specification of the regression model, for example, by controlling for lagged FX market liquidity, does not alter the conclusion.

Standard inventory models (e.g., Stoll (1978)) predict that an increase in volatility leads to a widening of bid-ask spreads and lower liquidity in general as soon as market makers hold undesired inventories. In these models, commonality in FX liquidity arises if volatilities of various exchange rates are driven by a common factor, providing a complementary or alternative explanation for our findings above. However, inventory models do not accommodate the potential impact of a decline in funding liquidity on market liquidity. To test the implications of these models, we rely on the JP Morgan Implied Volatility Index for the G7 currencies, VXY,[26] as a proxy for perceived FX inventory risk. We then regress FX liquidity on the lagged TED spread and lagged VIX, controlling for lagged FX implied volatility. An inventory model would imply a negative slope for VXY, but only a liquidity spiral theory would predict a negative slope for the TED spread. Table III presents regression results and confirms both predictions. In particular, the estimated slope coefficient on the TED spread is largely unchanged and significantly negative, supporting the presence of liquidity spirals. This is true regardless of whether lagged FX market liquidity and VIX are included in the regression.

The Internet Appendix reports regression results for the same models as in Table III, but only using data from January 2007 to mid-September 2008, that is, discarding all observations after the Lehman bankruptcy. Lagged VIX still has a negative and statistically strong impact on FX liquidity, although to a lesser extent. Depending on the model specification, the slope of the lagged TED spread is or is not statistically different from zero. These findings are consistent with liquidity spiral effects being stronger during crisis periods. However, funding liquidity still impacts market-wide FX liquidity even during the relatively calmer period from January 2007 to mid-September 2008. This is consistent with funding liquidity constraints being important even before they actually become binding, as predicted by Brunnermeier and Pedersen (2009). Simply the risk of hitting these constraints seems to induce lower market-wide FX liquidity.

B. Relation to Liquidity of the U.S. Equity and Bond Markets

There are a number of reasons why we might expect a connection between equity and FX illiquidities. First, if liquidity deteriorates in the FX market, which is the world's largest financial market, this could be a signal warning of a liquidity crisis with effects in all financial markets. Moreover, a link between the liquidities of the two markets is consistent with liquidity spirals, as described in the previous subsection. Also, while central bank interventions have a direct impact on the FX market, they also have strong effects on other markets and the worldwide economy, due, for instance, to portfolio rebalancing or revaluation effects. Finally, common factors may enter pricing kernels for equity and FX markets.

To investigate the relation between liquidity in the two markets, we compare the measures of market-wide FX liquidity presented in the previous section to market-wide liquidity in the U.S. equity market, which is estimated on the basis of (i) return reversal[27] (Pástor and Stambaugh (2003)) and (ii) Amihud's (2002) measure using return and volume data of all stocks listed at the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX).

[26] The Internet Appendix provides a description of the VXY index.

[27] Equity return reversal estimates are available at Ľuboš Pástor's website: http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2010.txt .

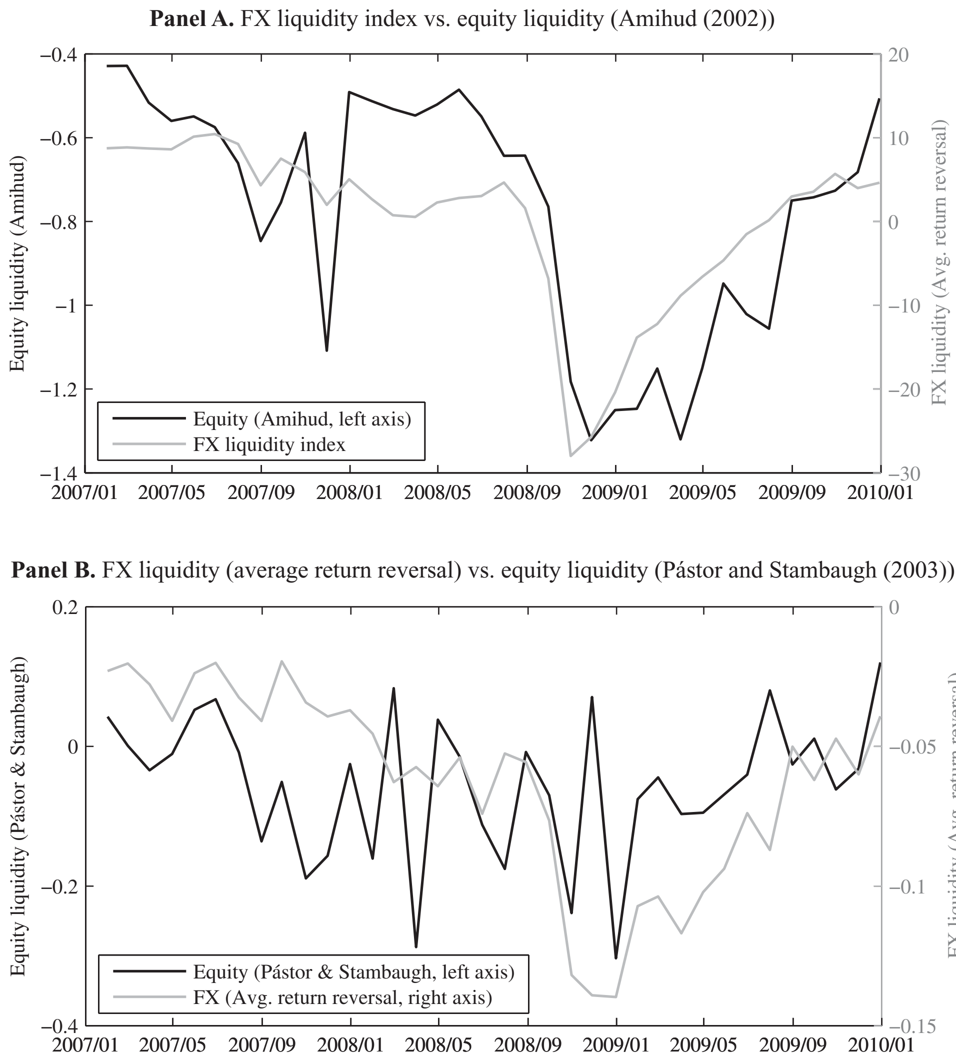

Figure 4. Commonality with equity liquidity. The figure plots non-overlapping monthly market-wide FX liquidity and U.S. equity liquidity (estimated from stocks listed on the NYSE and AMEX). In Panel A, the FX liquidity index obtained from PCA across different liquidity measures is plotted together with Amihud's (2002) measure of equity liquidity. Panel B shows the average FX return reversal obtained from model (1) and equity return reversal (Pástor and Stambaugh (2003)). Each observation represents estimated liquidity for a given month. Daily FX liquidity is averaged to obtain monthly estimates. The sample is January 2007 to December 2009.

Figure 4 compares liquidity in FX and equity markets based on a sample of 36 nonoverlapping monthly observations.

The monthly correlation between the FX liquidity index extracted by PCA and Amihud's measure of equity liquidity is 0.81 (Panel A of Figure 4), while the correlation between average FX and equity return reversal is only 0.34 (Panel B of Figure 4). Similarly, Spearman's rho is equal to 0.67 and 0.35, respectively, suggesting comovements between liquidity in FX and equity markets. Such comovements confirm that financial markets are integrated and support the notion that liquidity shocks are systematic across asset classes. The significantly lower correlation between average FX and equity return reversal could be explained by the noise inherent in the latter. Compared to Pástor and Stambaugh's (2003) reversal measure for equity markets, aggregate FX return reversal for monthly data is negative over the whole sample. This desirable result might be due to the fact that the EBS data set includes more accurate order flow data and model (1) is estimated robustly at a higher frequency.[28]

Table II reports monthly correlations between FX and equity liquidity as well as market-wide liquidity measures for the corporate bond market[29] and the U.S. 10-year Treasury bonds. We compute the latter using BrokerTec data[30] and then averaging bid-ask spreads of all intraday transactions during New York trading hours. Excluding Pástor–Stambaugh's equity measure, all correlations between liquidities in FX, equity, and bond markets are above 0.64. Such high correlations further confirm that liquidity shocks appear to be a global phenomenon across asset classes.[31]

Glen and Jorion (1993) and Campbell, Serfaty-de Medeiros, and Viceira (2010) show that holding certain currencies reduces portfolio risk of international equity and bond investors. Our findings suggest that the FX market is likely to become illiquid precisely when the U.S. equity or bond markets are illiquid. Thus, the diversification benefits provided by some currencies should be taken with caution and investors should consider liquidity risks across asset classes when making investment decisions.[32]

C. Currency Liquidity Sensitivity to Market-Wide FX Liquidity

Having documented the strong commonality of FX liquidity, a question that arises is how the liquidity of individual exchange rates relates to market-wide FX liquidity. To analyze the sensitivity of the liquidity of exchange rate j to a change in market-wide liquidity, we run a time-series regression of individual

[28] We have also extracted the first principal component via PCA from Amihud's price impact and Pástor–Stambaugh's return reversal. Because of the noisier nature of the latter, the first principal component is essentially Amihud's measure and is somewhat less well correlated with market-wide FX liquidity than Amihud's measure itself.

[29] The corporate bond market liquidity measure is from Dick-Nielsen, Feldhütter, and Lando (2012) and available at the authors' website.

[30] BrokerTec is the leading electronic interdealer platform for trading U.S. Treasuries in North America.

[31] The Internet Appendix shows graphs of market-wide FX liquidity along with bond market liquidities.

[32] As daily data for market-wide liquidity and volatility of FX and U.S. Treasury bond markets are available, the Internet Appendix reports Granger causality tests among these variables. Test results show that there exist liquidity spillover effects between FX and U.S. Treasury bond markets above and beyond comovements in market-wide volatilities.

liquidity, $L_{j,t}^{(\cdot)}$, on common liquidity $L_{M,t}^{(\cdot)}$,

$$L_{j,t}^{(\cdot)} = a_j + b_j L_{M,t}^{(\cdot)} + L_{I,j,t}^{(\cdot)}, \tag{6}$$

where $L_{I,j,t}^{(\cdot)}$ represents an idiosyncratic liquidity shock. The sensitivity is captured by the slope coefficient b_j. For the sake of interpretability, we rely on effective cost as a measure of liquidity. To avoid potentially upward-biased sensitivities, we exclude exchange rate j in the computation of $L_{M,t}^{(ec)}$.[33] Estimation results in Table IV show that equation (6) provides a good fit to the data with most of the R^2s above 70%. All estimated slope coefficients are positive and statistically significant at any conventional level. Thus, the liquidity of every FX rate depends positively on market-wide liquidity. Given the evidence on liquidity spirals, this finding implies that all FX rates are affected by funding liquidity constraints. The most liquid FX rates like EUR/USD and USD/JPY have the lowest liquidity sensitivity to market-wide FX liquidity. The least liquid FX rates like AUD/USD and USD/CAD have the highest liquidity sensitivity. For instance, a decrease of one bp in market-wide FX liquidity leads to a 3.1 bps drop in the liquidity of AUD/USD. This finding is consistent with the fact that in our sample AUD is the most illiquid FX rate (see Table I), AUD is frequently used as an investment currency, and carry traders experienced severe funding constraints during the recent crisis.

We also run the regression in equation (6) in log variables, that is, we regress $\log(L_{j,t}^{(ec)})$ on $\log(L_{M,t}^{(ec)})$ for each FX rate j. The estimation results are collected in the Internet Appendix and confirm that relative changes in AUD/USD liquidity are the most sensitive to relative changes in market-wide FX liquidity, excluding GBP/USD, which is mostly traded on Reuters. The liquidity of EUR/USD is again the least sensitive.

These findings suggest that managing the liquidity risk of illiquid currencies is particularly challenging. Not only is the level of liquidity lower, but it is also more sensitive to changes in market-wide liquidity. In contrast, the most liquid currencies may offer a "liquidity hedge" as they tend to remain relatively liquid, even when market-wide liquidity drops.

VI. Liquidity Risk Premiums

A. Shocks to Market-Wide FX Liquidity

Given the evidence for liquidity spirals and strong declines in market-wide FX liquidity, a question that arises is whether investors demand a premium for being exposed to liquidity risk. To our knowledge, a theoretical model for

[33] Otherwise $L_{j,t}^{(ec)}$ would enter both sides of equation (6) in a linear way. As a robustness check we re-run the regression, including $L_{j,t}^{(ec)}$ in the computation of $L_{M,t}^{(ec)}$ for each FX rate j. Results are collected in the Internet Appendix and largely confirm those in Table IV. In particular, the slope coefficients b_j are relatively stable and tend to be somewhat larger, as expected. The R-squares are larger as well.

Table IV

Liquidity Sensitivity to Changes in Market-Wide FX Liquidity

For each exchange rate j, daily individual liquidity (effective cost) $L_{j,t}^{(ec)}$ is regressed on average market-wide FX liquidity $L_{M,t}^{(ec)}$ (equation (6)). Liquidity of FX rate j is excluded before computing $L_{M,t}^{(ec)}$. Panel A shows the regression results. Heteroskedasticity and autocorrelation (HAC) robust standard errors are shown in parentheses. R^2 is the adjusted-R^2. Panel B shows the standard deviation of idiosyncratic liquidity, which is defined as the residuals of the regression in equation (6). The number of observations is 733. The sample is January 2, 2007 to December 30, 2009.

	AUD/ USD	EUR/ CHF	EUR/ GBP	EUR/ JPY	EUR/ USD	GBP/ USD	USD/ CAD	USD/ CHF	USD/ JPY
Panel A: Sensitivity to Changes in Common Liquidity									
Whole sample									
a_j	0.525	−0.102	−0.077	−0.022	−0.178	0.448	−0.245	−0.195	−0.199
	(0.042)	(0.004)	(0.016)	(0.005)	(0.002)	(0.016)	(0.022)	(0.004)	(0.003)
b_j	3.145	0.354	1.089	0.563	0.173	1.861	1.624	0.348	0.307
	(0.066)	(0.005)	(0.023)	(0.007)	(0.003)	(0.022)	(0.032)	(0.005)	(0.004)
R^2	0.759	0.853	0.762	0.908	0.816	0.905	0.777	0.857	0.885
Pre-Lehman									
a_j	0.301	−0.086	−0.172	−0.073	−0.285	0.297	0.072	−0.137	−0.126
	(0.042)	(0.006)	(0.023)	(0.005)	(0.004)	(0.027)	(0.044)	(0.008)	(0.005)
b_j	2.771	0.411	0.807	0.448	−0.013	1.511	2.276	0.460	0.426
	(0.087)	(0.011)	(0.043)	(0.010)	(0.006)	(0.049)	(0.091)	(0.014)	(0.009)
R^2	0.708	0.771	0.455	0.841	0.010	0.694	0.602	0.718	0.859
Post-Lehman									
a_j	0.976	0.003	−0.373	−0.090	−0.127	0.222	−0.364	−0.184	−0.259
	(0.116)	(0.009)	(0.035)	(0.013)	(0.003)	(0.035)	(0.050)	(0.010)	(0.007)
b_j	3.642	0.441	0.830	0.508	0.220	1.664	1.491	0.354	0.253
	(0.143)	(0.009)	(0.038)	(0.013)	(0.003)	(0.038)	(0.059)	(0.010)	(0.007)
R^2	0.672	0.896	0.607	0.833	0.932	0.858	0.674	0.815	0.810
Panel B: Standard Deviation of Idiosyncratic liquidity									
Whole sample	0.374	0.048	0.125	0.058	0.028	0.100	0.176	0.041	0.038
Pre-Lehman	0.132	0.024	0.072	0.020	0.022	0.070	0.143	0.031	0.024
Post-Lehman	0.527	0.067	0.137	0.074	0.035	0.119	0.212	0.051	0.045

currency returns that accommodates liquidity risk, in the same spirit as, for example, Lustig, Roussanov, and Verdelhan (2011), has not yet been developed. However, if liquidity shocks vanish quickly it seems unlikely that investors would be concerned about liquidity risk. Only long-lasting shocks to market-wide liquidity are likely to affect investors and require liquidity risk premia (Korajczyk and Sadka (2008)). Investors probably suffer higher costs during long and unexpected illiquid environments, and consequently require a premium for that risk.[34] The Internet Appendix shows the autocorrelation

[34] This interpretation may also help to explain why liquidity in equity markets is persistent (Chordia, Roll, and Subrahmanyam (2000, 2001)) and priced (Pástor and Stambaugh (2003)).

functions for the various market-wide FX liquidities. Invariably, all aggregate liquidity proxies exhibit strong positive autocorrelation, even after several months. Hence, a drop in aggregate liquidity is unlikely to reverse quickly, suggesting that liquidity risk may indeed be priced.

B. Carry Trade Returns

To investigate the role of liquidity risk in asset pricing, daily log-returns are computed from spot FX rates. In contrast to the previous analysis, all returns use the USD as the base currency, which helps in interpreting the factors. To preserve a sufficiently large cross-section of currencies, we extend our data set by including the Danish krone (DKK), the New Zealand dollar (NZD), and the Swedish krona (SEK).[35]

The variable of interest is the excess return over UIP,

$$r^e_{j,t+1} = i^f_t - i^d_t - \Delta p_{j,t+1}, \tag{7}$$

where i^f_t and i^d_t are the foreign and domestic interest rates on day t, respectively, and $\Delta p_{j,t+1}$ is the daily return of currency j on day $t+1$ from the perspective of a U.S. investor. We compute the interest rate differential for each currency using LIBOR interest rates obtained from Datastream. The excess return $r^e_{j,t+1}$ can also be interpreted as the daily return from a carry trade in which a U.S. investor who borrows at the domestic interest rate and invests at the foreign interest rate is exposed to exchange rate risk. For the purpose of the asset pricing study, gross excess returns are used, because excess returns net of bid-ask spreads overestimate the true cost of trading. Descriptive statistics for exchange rate returns, interest rate differentials, and daily carry trade returns are reported in Table V.

Panel A shows that the annualized returns of individual exchange rates between January 2007 and December 2009 are larger in absolute value than those in the longer sample of Lustig, Roussanov, and Verdelhan (2011). Prior to the bankruptcy of Lehman Brothers (Panel B), the difference in magnitude is rather small. After the collapse (Panel C), larger average and extremely volatile returns occurred. Interest rate differentials tend to be lower in absolute value in the last subsample, mirroring the joint efforts of central banks to alleviate the economic downturn by lowering interest rates.

Typical low interest rate currencies (JPY, CHF) had a positive excess return over the whole sample with the appreciation being strongest after September 2008. Immediately after the Lehman bankruptcy, high interest rate currencies (AUD, NZD) depreciated strongly, mirroring liquidity spirals and the unwinding of carry trades. However, in the course of 2009, these currencies appreciated against the USD, resulting in a negative excess return on the USD.[36]

[35] These currencies were not included in the previous analysis because their relatively light trading resulted in unreliable measures of return reversal.

[36] A common explanation for this appreciation of high interest rate currencies versus USD is the fact that, at that time, the outlook for the U.S. economy had worsened in relative terms. Also,

Table V

Descriptive Statistics for Carry Trade Returns

This table reports descriptive statistics for exchange rates with USD being the base currency. Average log-return, average interest rate differential, and daily excess log-returns over UIP are shown. Panel A gives results for the whole sample, which ranges from January 2, 2007 to December 30, 2009. Summary statistics for two subsamples prior to and after the bankruptcy of Lehman Brothers are reported in Panels B and C, respectively.

Currency	AUD	CAD	DKK	EUR	JPY	NZD	SEK	CHF	GBP
Panel A: Whole Sample									
FX return: $\Delta p_{j,t+1}$									
Mean	−3.58	−3.30	−2.43	−3.43	−8.61	−0.77	−0.21	−5.32	6.34
Std. dev.	20.48	13.93	11.51	11.40	12.93	19.74	16.56	12.15	12.73
Interest rate differential: $i_t^f - i_t^d$									
Mean	2.89	0.06	0.95	0.24	−2.19	3.74	0.26	−1.18	1.09
Std. dev.	1.41	0.73	1.60	1.24	1.93	1.42	1.51	1.28	0.99
Carry trade return: $r_{j,t+1}^e$									
Mean	6.41	3.37	3.36	3.66	6.47	4.44	0.47	4.16	−5.27
Std. dev.	20.47	13.93	11.51	11.39	12.93	19.73	16.56	12.15	12.72
Panel B: Prior to Bankruptcy of Lehman Brothers									
FX return: $\Delta p_{j,t+1}$									
Mean	−3.01	−6.64	−5.05	−5.11	−6.56	3.09	−1.82	−5.18	2.84
Std. dev.	12.83	9.63	7.87	7.87	10.60	14.39	9.57	9.38	7.95
Interest rate differential: $i_t^f - i_t^d$									
Mean	2.52	−0.14	0.16	−0.10	−3.57	4.01	−0.17	−1.92	1.31
Std. dev.	1.68	0.75	1.44	1.42	1.26	1.46	1.73	1.24	1.06
Carry trade return: $r_{j,t+1}^e$									
Mean	5.48	6.50	5.20	5.01	3.05	0.84	1.65	3.29	−1.55
Std. dev.	12.82	9.63	7.86	7.87	10.60	14.38	9.57	9.37	7.94
Panel C: After Bankruptcy of Lehman Brothers									
FX return: $\Delta p_{j,t+1}$									
Mean	−4.34	1.10	1.01	−1.21	−11.33	−5.88	1.91	−5.51	10.95
Std. dev.	27.51	18.12	15.04	14.83	15.50	25.14	22.73	15.07	17.11
Interest rate differential: $i_t^f - i_t^d$									
Mean	3.37	0.34	1.98	0.69	−0.37	3.37	0.83	−0.20	0.79
Std. dev.	0.67	0.59	1.16	0.74	0.83	1.27	0.89	0.29	0.81
Carry trade return: $r_{j,t+1}^e$									
Mean	7.65	−0.77	0.93	1.89	10.97	9.18	−1.10	5.31	−10.17
Std. dev.	27.51	18.12	15.04	14.83	15.50	25.13	22.72	15.07	17.10

The crisis led to significant volatility in exchange rates. Standard deviations of carry trade returns doubled for many currencies when comparing the samples before and after the Lehman bankruptcy. This large variation and significant carry trade returns require further analysis, which we undertake below.

C. Liquidity and Carry Trade Returns

Recently, a number of studies document comovements in carry trade returns; see, for example, Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012). The significant variation and commonality in currency liquidities documented above suggest that liquidity risk may contribute to this common variation. The Internet Appendix reports correlations between carry trade returns and FX liquidity, and provides evidence for contemporaneous comovements between the two. FX liquidity is given by liquidity levels, liquidity shocks, and unexpected liquidity shocks. The liquidity level is the market-wide liquidity index, as outlined in Section IV. As in Pástor and Stambaugh (2003) and Acharya and Pedersen (2005), liquidity shocks and unexpected liquidity shocks are defined as the residuals from an AR(1) model and an AR(2) model fitted to market-wide liquidity, respectively. Typical high interest rate currencies during our sample period, such as AUD, CAD, or NZD, exhibit the largest positive correlations (with AUD reaching 70% at monthly frequency), meaning that they depreciate contemporaneously with a decrease in liquidity. In contrast, JPY, a typical low interest rate currency, exhibits a negative correlation, meaning that it appreciates when liquidity drops. Moreover, with the exception of CAD and GBP, a nearly monotone relation exists between sorting currencies based on decreasing interest rate differentials (Table V) and increasing liquidity-carry trade return correlations. This finding is also consistent with liquidity spirals (Table III). The correlation between FX liquidity and carry trade returns is largest in absolute value for shocks at the monthly frequency. Correlations between liquidity shocks and carry trade returns are often twice the correlations between liquidity levels and returns. Such strong comovements between carry trade returns and unexpected changes in liquidity are consistent with liquidity risk being a risk factor for carry trade returns.

D. Liquidity Risk Factor

To formally test whether liquidity risk affects carry trade returns, variation in the cross-section of returns is assumed to be caused by different exposure to a

the enormous injection of liquidity into USD (in particular, via central banks' swap lines) and the Fed's quantitative easing operations probably kept interest rates low in the United States, thereby weakening the USD. Moreover, investors may have started to set up carry trades again, because the historically low U.S. interest rates had fueled the search for yields and allowed the USD to be used as a funding currency. Commodity prices increased again in 2009, thus supporting commodity-related currencies such as the AUD.

small number of risk factors (Ross (1976)). In particular, we introduce a liquidity risk factor given by a currency portfolio that is long in the two most illiquid and short in the two most liquid FX rates on each day t. We label this liquidity risk factor *IML* (illiquid minus liquid). *IML* has a natural interpretation as the return in dollars on a zero-cost strategy that goes long in illiquid currencies and short in liquid currencies.[37] As *IML* is a tradable risk factor, its computation is straightforward and currency investors can easily hedge associated liquidity risk exposures. The Internet Appendix compares *IML* to a nontradable risk factor computed as shocks to our market-wide liquidity index. Both liquidity factors exhibit similar patterns with a correlation of 0.20 (0.71 for monthly data) and much larger variation after the bankruptcy of Lehman Brothers.

Lustig, Roussanov, and Verdelhan (2011) introduce a carry trade risk factor, *HML*, given by a currency portfolio that is long in high interest rate currencies and short in low interest rate currencies. They find that *HML* explains the common variation in carry trade returns and suggest that this risk factor captures "global risk" for which carry traders earn a risk premium. Our liquidity risk factor *IML* is strongly correlated (0.92) with *HML* during our sample period. Thus, the risk of liquidity spirals, which is captured by *IML*, appears to contribute significantly to "global risk."

The second risk factor we consider is the "market" risk factor or average excess return, *AER*, from Lustig, Roussanov, and Verdelhan (2011),

$$AER_t = \frac{1}{N}\sum_{j=1}^{N} r^e_{j,t}, \tag{8}$$

which is the average return for a U.S. investor who goes long in all N exchange rates available in the sample. The factor *AER* has also a natural interpretation as the currency "market" return in USD available to a U.S. investor and is driven by the fluctuations of the USD against a broad basket of currencies. As shown in the Internet Appendix, this level risk factor does not exhibit significant variation compared to both *IML* and *HML*.

For each FX rate j, we estimate the following factor model to assess the relative importance of the risk factors *IML* and *AER*:

$$r^e_{j,t} = \alpha_j + \beta_{AER,j} AER_t + \beta_{IML,j} IML_t + \varepsilon_{j,t}, \tag{9}$$

where $\beta_{AER,j}$ and $\beta_{IML,j}$ denote the exposure of the carry trade return j to the market risk factor and liquidity risk factor, respectively. Any unusual or abnormal return that is not explained by the FX risk factors is captured by the constant α_j. Table VI shows the regression results.

Equation (9) provides a good fit to the data with adjusted-R^2s ranging from 60% to 90%. Thus, the vast majority of daily variation in carry trade returns during the crisis can be explained by exposure to two risk factors. Moreover, no

[37] As all FX rates use USD as their base currency, to construct the portfolio *IML* an investor pays USD 2 to buy the two most illiquid currencies and receives USD 2 for selling the two most liquid currencies.

Table VI

Factor Model Time-Series Regression Results

This table reports time-series regression results for the daily factor model in equation (9). $\beta_{AER,j}$ is the factor loading of the market risk factor defined as the average excess FX rate return from the perspective of a U.S. investor. $\beta_{IML,j}$ is the factor loading of the liquidity risk factor defined as the excess return of a portfolio that is long in the two most illiquid and short in the two most liquid exchange rates. Heteroskedasticity and autocorrelation (HAC) robust standard errors are shown in parentheses. R^2 is the adjusted-R^2. Panel A shows regression results for the whole sample, which ranges from January 2, 2007 to December 30, 2009. Regression results for two subsamples prior to and after the bankruptcy of Lehman Brothers are reported in Panels B and C, respectively.

Currency	AUD	CAD	DKK	EUR	JPY	NZD	SEK	CHF	GBP
				Panel A: Whole Sample					
α	0.014	0.006	0.000	0.001	0.018	0.004	−0.015	0.003	−0.031
	(0.016)	(0.017)	(0.008)	(0.008)	(0.016)	(0.021)	(0.018)	(0.013)	(0.019)
β_{AER}	1.049	0.651	1.108	1.093	0.608	1.157	1.366	1.137	0.831
	(0.026)	(0.029)	(0.013)	(0.014)	(0.026)	(0.034)	(0.031)	(0.021)	(0.032)
β_{IML}	0.330	0.197	−0.090	−0.091	−0.382	0.230	−0.026	−0.200	0.032
	(0.009)	(0.010)	(0.004)	(0.005)	(0.009)	(0.011)	(0.010)	(0.007)	(0.011)
R^2	0.892	0.714	0.913	0.903	0.730	0.802	0.774	0.803	0.576
				Panel B: Prior to Bankruptcy of Lehman Brothers					
α	0.002	0.015	0.008	0.007	0.010	−0.017	−0.009	0.001	−0.017
	(0.015)	(0.019)	(0.008)	(0.008)	(0.016)	(0.024)	(0.015)	(0.010)	(0.018)
β_{AER}	1.170	0.605	1.092	1.092	0.683	1.202	1.198	1.208	0.751
	(0.035)	(0.043)	(0.018)	(0.018)	(0.038)	(0.055)	(0.034)	(0.023)	(0.041)
β_{IML}	0.288	0.226	−0.082	−0.082	−0.405	0.298	−0.036	−0.233	0.026
	(0.011)	(0.014)	(0.006)	(0.006)	(0.012)	(0.017)	(0.011)	(0.007)	(0.013)
R^2	0.852	0.606	0.904	0.904	0.750	0.720	0.756	0.882	0.481
				Panel C: After Bankruptcy of Lehman Brothers					
α	0.029	−0.006	−0.010	−0.006	0.029	0.029	−0.020	0.005	−0.049
	(0.030)	(0.032)	(0.016)	(0.016)	(0.029)	(0.035)	(0.038)	(0.026)	(0.038)
β_{AER}	0.982	0.684	1.119	1.098	0.567	1.173	1.426	1.093	0.859
	(0.039)	(0.042)	(0.021)	(0.022)	(0.039)	(0.046)	(0.050)	(0.034)	(0.051)
β_{IML}	0.355	0.181	−0.095	−0.096	−0.368	0.201	−0.028	−0.182	0.031
	(0.013)	(0.014)	(0.007)	(0.007)	(0.013)	(0.016)	(0.017)	(0.012)	(0.017)
R^2	0.907	0.757	0.916	0.903	0.721	0.846	0.784	0.768	0.606

currency pair exhibits a significant α_j. Liquidity betas, $\beta_{IML,j}$, are economically and statistically significant at any conventional level. For example, when our liquidity factor decreases by one standard deviation, AUD depreciates by 0.53 standard deviations, whereas JPY appreciates by 0.98 standard deviations. These findings are not driven by the events after the bankruptcy of Lehman Brothers.[38] The Internet Appendix shows that adjusted-R^2s attain up to 60%

[38] When only considering the period before the bankruptcy, the number of standard deviations for AUD and JPY are 0.51 and 0.86, respectively. The Internet Appendix collects these results for all currencies in our sample.

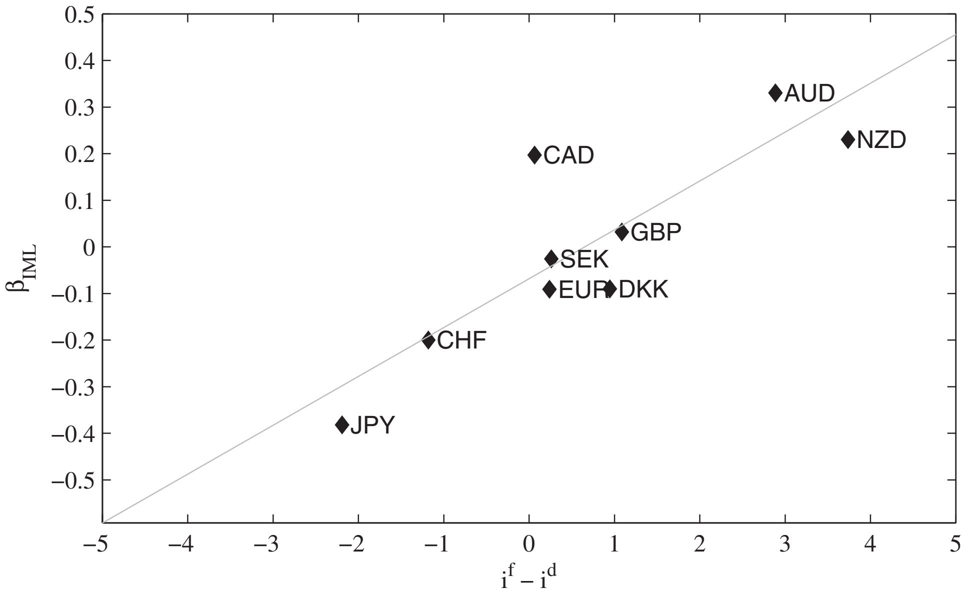

Figure 5. Liquidity beta and interest rate differential. Taking the perspective of a U.S. investor for each currency, the graph shows on the x-axis the interest rate differential, that is, the foreign interest rate minus the domestic interest rate, and on the y-axis the liquidity beta, β_{IML}, in the asset pricing model (9). The sample is January 2, 2007 to December 30, 2009.

when only *IML* is included as regressor, highlighting the crucial role of liquidity risk. In line with Lustig, Roussanov, and Verdelhan (2011), all exchange rates load fairly equally on the market risk factor, which helps explain the average level of carry trade returns. In contrast, liquidity betas, $\beta_{IML,j}$, vary significantly across exchange rates.[39]

An interesting pattern emerges from Table VI. Typical high interest rate currencies, such as AUD or NZD, exhibit the largest positive liquidity betas, thus providing exposure to liquidity risk, while low interest rate currencies, such as JPY or CHF, exhibit the largest negative liquidity betas, thus offering insurance against liquidity risk. To help visualize the relation between liquidity betas and interest rate differentials, Figure 5 shows the corresponding scatter plot.

When FX liquidity improves, high interest rate currencies appreciate further, because of positive liquidity betas, while low interest rate currencies depreciate further, because of negative liquidity betas, increasing the deviation of FX rates from UIP. During an unwinding of carry trades (i.e., when high interest currencies are sold and low interest rate currencies are bought), because of liquidity spirals, market-wide FX liquidity drops, inducing a higher price impact of trades. Because FX liquidity falls and liquidity betas have opposite signs, high interest rate currencies depreciate further and low interest rate currencies

[39] Estimates of $\beta_{IML,j}$ remain largely the same when adding *HML* as a regressor in equation (9). However, standard errors are obviously unreliable due to collinearity between *IML* and *HML*.

appreciate further, exacerbating currency crashes and inflicting large losses on carry traders.

Figure 6 illustrates this phenomenon for the AUD-JPY carry trade. Cumulative returns of one USD invested in AUD/USD and JPY/USD carry trades are depicted along with market-wide FX liquidity. The Australian dollar has a positive liquidity beta (0.33) and the cumulative AUD/USD carry trade return tends to comove with market-wide FX liquidity. In contrast, JPY has a negative liquidity beta (−0.38) and the cumulative JPY/USD carry trade return tends to mirror FX liquidity fluctuations. The unwinding of carry trades on August 16, 2007 results in a drop in the FX liquidity and sharp movements in AUD and JPY in opposite directions. Similar opposite movements are evident around the Lehman bankruptcy.

Liquidity betas reflect the liquidity features of the various currencies. High interest rate currencies tend to have low liquidity (Table I) and high liquidity sensitivity to fluctuations in market-wide FX liquidity (Table IV). Such low liquidity features appear to command a liquidity risk premium that is reflected in large positive liquidity betas (Table VI). Conversely, low interest rate currencies tend to have higher liquidity and less liquidity sensitivity to market-wide FX liquidity. Such high liquidity features are reflected in negative liquidity betas and thus lower returns when market-wide FX liquidity improves. These lower returns are the "insurance premiums" for holding currencies that tend to deliver higher returns in bad times, that is, when FX liquidity drops.

Finally, the trigger of this mechanism appears to be a liquidity spiral. As shown in Section V, when traders' funding liquidity deteriorates, market-wide FX liquidity drops (Table III) with an impact on currency returns that is diametrically opposite, depending on the sign of their liquidity betas. Consistent with this interpretation, highly liquid currencies, which are usually not involved in carry trades and the liquidity of which is least sensitive to market-wide liquidity, such as the euro (EUR), have a liquidity beta close to zero.

The Internet Appendix presents four robustness checks that confirm our results. First, in the same spirit as Lustig, Roussanov, and Verdelhan (2011), we regress FX rate returns, $-\Delta p_{j,t+1}$, rather than carry trade returns, $r^e_{j,t+1}$, on liquidity and market risk factors. All liquidity betas are virtually the same as in Table VI. This implies that low interest rate currencies offer insurance against liquidity risk because they appreciate when market-wide FX liquidity drops, not because the interest rates on these currencies increase. On the other hand, high interest rate currencies expose carry traders to liquidity risk because they depreciate when FX liquidity drops, not because the interest rates on those currencies decline. Second, we add the interest rate differential, $i^d_t - i^f_t$, as an explanatory variable when regressing FX rate returns on liquidity and market risk factors. Model (9) is a special case of the latter when the slope of $i^d_t - i^f_t$ is restricted to one. Again, all liquidity betas are almost unchanged. Third, we replace *IML* by unexpected shocks to the market-wide FX liquidity index in equation (9). The new liquidity betas largely share the same pattern as liquidity betas in Table VI. Fourth, we use equation (9) to

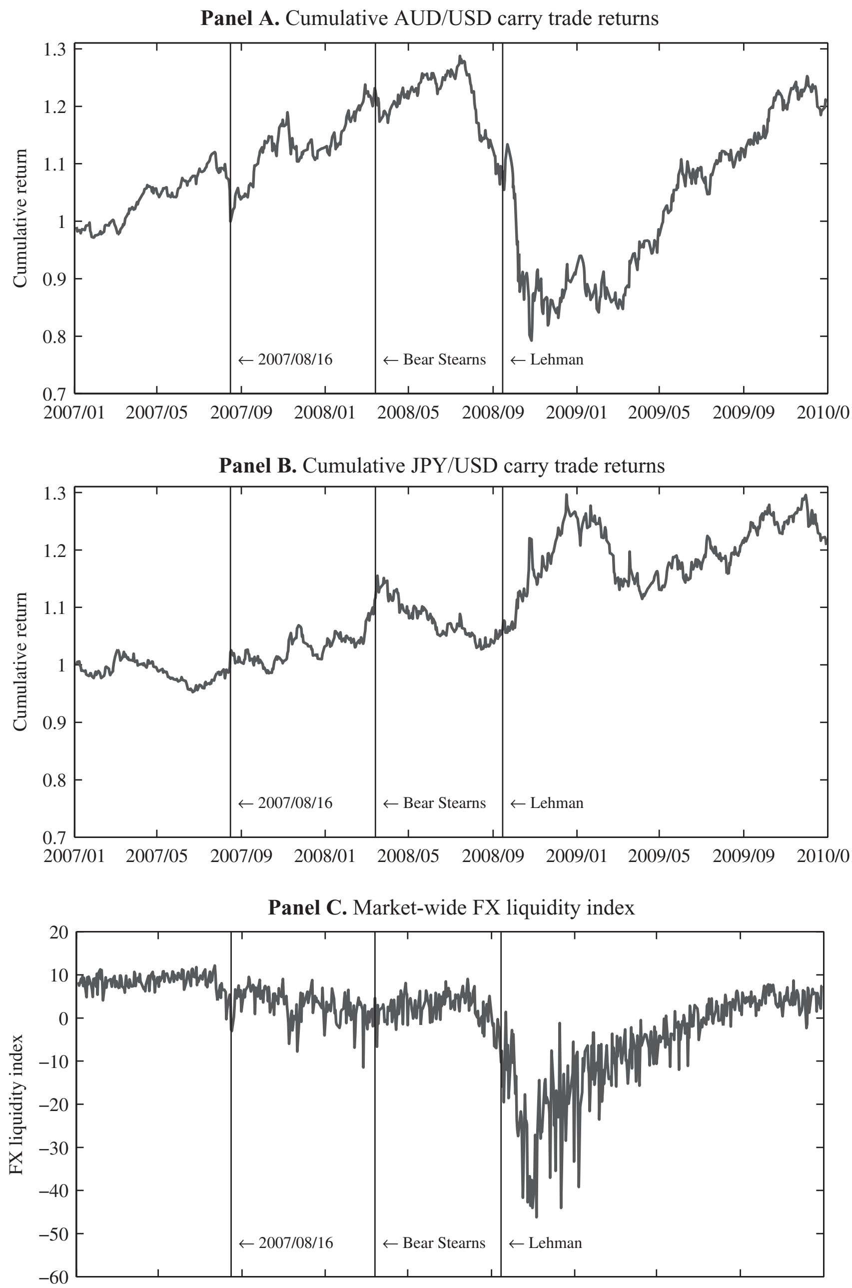

Figure 6. Carry trade return and FX liquidity. Panel A shows the cumulative return of investing one USD in the AUD/USD carry trade. Panel B shows the cumulative return of investing one USD in the JPY/USD carry trade. Panel C shows our market-wide FX liquidity index obtained from PCA. The sample is January 2, 2007 to December 30, 2009.

explain carry trade index returns, namely, the returns of the Deutsche Bank's "G10 Currency Harvest" (DBV) exchange traded fund.[40] The liquidity beta for DBV is significant at any conventional level and very close to the liquidity beta for AUD. The corresponding intercept is not statistically different from zero.

All in all, our findings suggest that liquidity risk is an important risk factor for FX returns during our sample period. The presence of this factor is consistent with the theory of liquidity spirals and currency crashes. Investors are exposed to these spirals and thus demand a risk premium as compensation for bearing liquidity risk.

Previous studies suggest other potential explanations of carry trade returns. For example, Lustig, Roussanov, and Verdelhan (2011) and Menkhoff et al. (2012) show that innovations to volatility in global equity and FX markets account for a large fraction of carry trade returns. Lustig and Verdelhan (2007) find that high interest rate currencies are on average more exposed to aggregate consumption growth risk than low interest rate currencies. Furthermore, based on our empirical evidence, we cannot definitely rule out a non–risk based explanation of carry trade returns. Thus, it remains to be investigated how the magnitude of liquidity effects compares to these complementary or alternative explanations for the profitability of carry trades with a longer sample. Such a longer sample would also allow us to analyze whether liquidity risk explains carry trade returns during other periods and whether it is priced in the cross-section of carry trade returns. There are at least two reasons to expect that this is the case. First, as mentioned above, our liquidity risk factor is strongly correlated (0.92) with the carry trade factor of Lustig, Roussanov, and Verdelhan (2011), which is shown to have a large impact on monthly carry trade returns from 1983 to 2008. Second, following our work, Banti, Phylaktis, and Sarno (2012) study the risk premium of FX liquidity. Although they consider only the return reversal aspect of liquidity and use data from custodian banks,[41] they provide some evidence of liquidity risk being priced in currency portfolios.

VII. Conclusion

Using a novel and comprehensive data set of intraday data, this paper provides the first systematic study of liquidity in the FX market. Contrary to common perceptions of the FX market being highly liquid at all times, we find significant cross-sectional and temporal variation in liquidities, substantial costs due to FX illiquidity for carry traders, and ample evidence of commonality in liquidities, that is, strong comovements across the liquidity of different currencies. Such commonality implies that FX liquidity is largely

[40] We thank an anonymous referee for suggesting this robustness check.

[41] The Internet Appendix compares our EBS data set to data from custodian banks. Besides data sets and liquidity measures there are other important differences between the two studies related to identification of liquidity risk, analysis of commonality, and inference procedure.

driven by shocks that affect the FX market as a whole rather than individual FX rates. The large liquidity comovements across markets that we document imply that the FX market is likely to become illiquid precisely when the U.S. equity and bond markets are illiquid, impairing the efficacy of international and cross-asset class diversification as a means of reducing liquidity risk.

Second, we analyze the impact of liquidity risk on carry trades. During our sample period, low interest rate currencies tend to have high liquidity, low liquidity sensitivities to market-wide FX liquidity, and negative liquidity betas, thus offering insurance against liquidity risk. The opposite is true for high interest rate currencies that provide exposure to liquidity risk. Negative liquidity betas reflect an "insurance premium" for relatively high liquidity features of low interest rate currencies. Positive liquidity betas reflect compensation for relatively low liquidity features of high interest rate currencies. These liquidity features and liquidity betas rationalize the impact of market-wide FX liquidity on carry trade returns. When FX liquidity improves, high interest rate currencies tend to appreciate, because of positive liquidity betas, while low interest rate currencies tend to depreciate, due to their negative liquidity betas, increasing the deviation of FX rates from UIP. During the unwinding of carry trades, because of liquidity spirals, market-wide FX liquidity drops and the price impact of trades increases. As FX liquidity falls and liquidity betas have opposite signs, high interest rate currencies tend to depreciate and low interest rate currencies tend to appreciate, exacerbating currency crashes.

To compute liquidity betas we introduce a novel tradable liquidity risk factor that is shown to have a strong impact on carry trade returns during our sample period from January 2007 to December 2009. This suggests that liquidity risk is priced in currency returns. As the use of EBS intraday data limits the extension of our sample, it remains to be investigated whether liquidity risk plays an important role in explaining carry trade returns in other periods as well. Finally, we provide evidence that liquidity spirals may trigger the mechanisms above. When traders' funding liquidity decreases, market-wide FX liquidity drops (a cross-market effect), impacting currency returns via their liquidity betas.

Several policy implications can be drawn from this study. From a central bank perspective, an implication of FX liquidity commonality is that providing liquidity for a specific FX rate may have positive spillover effects to other currencies as well. Take the example of high interest rate currencies during an unwinding of carry trade. A central bank's liquidity injection in its own currency could alleviate liquidity strains in other investment currencies and moderate the sudden appreciation (depreciation) of other funding (investment) currencies. Moreover, our empirical evidence on liquidity spirals implies that monetary policies aimed at relieving funding market constraints could also improve FX market liquidity in all exchange rates. But abundant liquidity may have adverse consequences. Overwhelming liquidity in one currency tends to spread to other currencies and even more so to investment currencies. In risk-taking environments with attractive carry trade opportunities, ample liquidity could bolster speculative trading.

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