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

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Abstract

Using a novel and comprehensive dataset, we provide the first systematic study of liquidity in the foreign exchange (FX) market. Contrary to common perceptions, we find significant variation in liquidity across exchange rates, substantial costs due to FX illiquidity, and strong commonality in the liquidities of different currencies. We analyze the impact of liquidity risk on the carry trade, which is a popular trading strategy that borrows in low interest rate currencies and invests in high interest rate currencies. We find that low (high) interest currencies tend to offer insurance against (exposure to) liquidity risk. A liquidity risk factor has a strong impact on daily carry trade returns from January 2007 to December 2009, suggesting that liquidity risk is priced in currency returns. Finally, we provide evidence that liquidity spirals may trigger these findings.

KEYWORDS: Foreign Exchange Market, Liquidity, Commonality in Liquidity, Liquidity Spiral, Liquidity Risk Premium, Carry Trade

JEL CODES: F31, G01, G12, G15

I. Introduction

Over the last three decades, liquidity in equity and bond markets has been studied extensively in the finance literature.[1] By contrast, we still know very little about liquidity in the foreign exchange (FX) market. This is 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 ten 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 limited transparency, heterogeneity of participants, and decentralized dealership structure of the market (Lyons, 2001), FX liquidity is not well understood. Moreover, the recent financial crisis and the study on currency crashes by Brunnermeier, Nagel, and Pedersen (2009) highlight the importance of liquidity in the FX market.[2] Short-term money market positions are extensively funded via FX markets. 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

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

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

multiple-listed equity shares and American depositary receipts. FX market liquidity is crucial for arbitrage trading, which keeps prices tied to fundamental values and enables market efficiency (Shleifer and Vishny, 1997).

The first contribution of this paper is to provide the first systematic study of liquidity in the FX market. Using a novel comprehensive dataset of intraday data, we analyze 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 as much as 25%.

Our analysis provides ample evidence of strong commonality in liquidity, i.e., large comovements of FX rate liquidities over time. This suggests that FX liquidity is largely driven 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 foreign exchange, 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.

[3]The separate appendix discusses the advantages of EBS data over other datasets 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, which has fueled the search for risk factors driving these returns. However, the impact of liquidity risk on carry trades has not yet been explored. Our main finding is that low interest rate currencies tend to exhibit negative liquidity betas, thus offering insurance against liquidity risk. Liquidity betas for high interest rate currencies, however, tend to be positive, thus 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 and 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 which is long in the most illiquid 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 latent market-wide FX liquidity extracted via Principal Component Analysis.

Another contribution of this paper is to show that liquidity spirals may trigger the findings above. The theory of liquidity spirals has been formalized by Brunnermeier and Pedersen (2009); Morris and Shin (2004) provide a related model for "liquidity black holes." Their 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 TED and LIBOR-OIS spread) 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 Lehman bankruptcy 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 calmer, in relative terms. These findings support the conjecture in Burnside (2009) that liquidity frictions may explain

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

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

II. Related Literature

Despite its importance, only very few studies exist on liquidity in the FX market. Most studies focus on the contemporaneous correlation between order flow and exchange rate returns documented by Evans and Lyons (2002). Using a unique dataset 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, Chaboud, Chernenko, Howorka, and Wright (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 is done in this paper.

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.[5] The second approach aims to provide non-risk based explanations.[6] Lustig, Roussanov, and Verdelhan (2011) provide a fairly complete survey of both approaches. Recently, Burnside, Eichenbaum, Kleshchelski, and Rebelo (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 which 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, Sarno, Schmeling, and Schrimpf (2011) 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 with liquidity risk provides a more fundamental explanation of carry trade returns.

[5]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 (2009), Verdelhan (2010), and Farhi and Gabaix (2011).
[6]This strand of literature includes, for example, Froot and Thaler (1990), Lyons (2001), Bacchetta and van Wincoop (2010), and Plantin and Shin (2011).

III. Measuring Foreign Exchange Liquidity

A. The Dataset

Apart from the fact that the FX market is more opaque and fragmented than stock markets, the main reason why liquidity in FX markets has not been studied previously in more detail is the paucity of available data. Through the Swiss National Bank, it was possible to gain access to a new dataset from EBS, including 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 dataset (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, in other words, they reliably represent the prevalent spot exchange rate. Moreover, all dealers on the EBS platform are prescreened for credit and bilateral credit lines and are monitored continuously by the system, so counterparty risk is virtually negligible when analyzing this dataset.[7] This feature implies that all our findings pertain to liquidity issues and are not affected by potential counterparty risk. The separate appendix discusses further advantages of EBS data compared to datasets

[7]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 a foreign exchange 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.

from Reuters, Datastream, Carry trade ETF as well as customer order flow data from custodian banks.

In this paper, nine currency pairs will be investigated 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, the irregularly spaced raw data are processed 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, these FX returns are multiplied by 10,000 to obtain basis points as the unit of measurement. Observations between Friday 10 p.m. and Sunday 10 p.m. GMT[8] are excluded, since only minimal trading activity is observed during these non-standard hours.[9]

This high-frequency dataset 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.

[8]GMT is used throughout the paper.

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

B. Liquidity Measures

This section presents the liquidity measures used in our study. Liquidity is a complex concept with different facets, thus, we break down our measures into three categories, namely price impact and return reversal, trading cost as well as price dispersion.[10]

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 greater 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 will be 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 dataset allows for an accurate estimation of price impact and return reversal, 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

[10]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 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.

reversal can be modeled as

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

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 can 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.[11] It is expected that the price impact of a trade $L^{(pi)} = \varphi_t$ will be 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 bouncing. Hence, one-second data needs to be aggregated. Furthermore, a lower frequency or a longer lag length K has the advantage of capturing delayed return reversal. On the other hand, the frequency should be high enough 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 are collected in the separate appendix and 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 which predicts that assets which are more liquid should exhibit narrower spreads and lower price impact. In line with Foucault, Kadan, and Kandel (2005), prices recover quickly from overshooting following a market

[11] The robust estimation is described in detail in the separate appendix.

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.

Trading Cost

The second group of liquidity measures covers the cost aspect of illiquidity, i.e., 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.[12] 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 dataset includes quotes and trades we do not have to rely on proxies for the effective spread (e.g., Roll, 1984; Holden, 2009; 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.

[12]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 which are not reflected in quoted spreads.

Price Dispersion

When large dealers hold undesired inventories, the higher the volatility the more reluctant these dealers are to provide liquidity; e.g., 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; e.g., 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) developed a nonparametric estimator which 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.

Latent Liquidity

All liquidity measures presented above capture different aspects of liquidity. A natural approach to extracting the common information across these measures is Principal Component Analysis (PCA). Principal components can be interpreted as latent 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 de-meaned, 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, and $\mathbf{D}_j$ the 5×5 diagonal matrix of eigenvalues. The time-series evolution of all five latent 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.

IV. Liquidity in the Foreign Exchange Market

A. Liquidity of Exchange Rates During the Financial Crisis

Using the large dataset described above, we estimate our six liquidity measures (price impact, return reversal, bid-ask spread, effective cost, price dispersion, and latent liquidity) for each trading day and each exchange rate. Table I shows the mean and standard deviation for all of the liquidity measures.[13]

[Table I about here.]

The average return reversal, i.e., the temporary price change accompanying order flow, is negative and therefore captures illiquidity. The median is larger than the mean indicating negative skewness in daily liquidity. Depending on the currency pair, one-minute returns are reduced by 0.013 to 0.172 basis points on average, if there was an order flow of 1–5 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, Chaboud, Chernenko, Howorka, and Wright (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 5.9% and 14%.

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

[13] Additional descriptive statistics are collected in the separate appendix along with statistics for exchange rate returns and order flow.

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.

Figure 1 shows 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 again in FX markets. 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 unprecedented turmoil and uncertainty in financial markets caused by the bankruptcy. During 2009, FX liquidity returned, slowly but steadily.

There were large cross-sectional differences in FX rate liquidities.[14] For instance, the fall in AUD/USD liquidity following the Lehman Brothers bankruptcy was quicker and

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

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.

[Figure 1 about here.]

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.[15]

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. Pinning down FX illiquidity cost is a challenging task.[16] However, we abstract from additional costs which might impact carry trade returns and focus on the direct effect of FX illiquidity on investors' profits. We keep

[15]The separate 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.

[16]One reason for this is that 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.

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 will be discussed below.

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 1 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, namely bid-ask spreads are small and given by 2.64bps for AUD/USD and 0.90bps for USD/JPY (minimum pre-crisis level; see separate appendix). If the U.S. speculator unwinds the 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.[17]

Suppose now 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 investor's marginal utility is high due to additional losses. Thus, the carry

[17]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 vice versa 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 bid price and 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.

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 54.03bps, 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 2.64bps to 54.03bps) 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.[18] 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 (2009). 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 fall 2008. In this scenario the carry trader has to bear a substantial loss.

[18]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.

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.

Illiquidity of the FX market does not only affect speculators. Every investor or company that owns assets denominated in foreign currencies is subject to FX illiquidity risk. Given the sizeable 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, Giambona, Graham, and Harvey (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 affects all exchange rates. This commonality in FX liquidity will be investigated in the next section.

V. Commonality in Foreign Exchange 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, a market-wide liquidity time-series is constructed to represent 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 Principal Component Analysis (PCA). For completeness we implement both methods, but most of the analysis will be 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 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 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 $L^{(\cdot)}_{M,t}$.[19]

Instead of averaging, both Hasbrouck and Seppi (2001) and Korajczyk and Sadka (2008) rely on PCA to extract market-wide liquidity. For each exchange rate, a given

[19]The separate 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. We report graphs of market-wide FX liquidity based on a process of averaging each liquidity measure. Time series patterns of all market-wide liquidity measures resemble the ones in Figure 1.

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 separate 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 which 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.

[Table II about here.]

B. Testing for Commonality in FX Liquidity

To formally test for commonality, for each exchange rate j, the time series of daily liquidity measure $L_{j,t}^{(\cdot)}, t = 1, \ldots, T$ is regressed 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 of commonality. The commonality, already strong at daily frequency, increases even more when aggregating liquidity measures at weekly and monthly horizons.

[Figure 2 about here.]

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).[20] 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 which include the USD results in R^2 of the same magnitude, lends further support to the presence of strong commonality.[21]

C. Latent Market-wide Liquidity Across Measures

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 latent liquidity factor. Unobserved market-wide liquidity is extracted by assuming a latent factor model, which is

[20]For example Korajczyk and Sadka (2008) report adjusted-R^2 ranging between 2% and 30%, depending on the liquidity measure.
[21]Detailed results are collected in the separate appendix.

estimated using PCA:

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

where $\widetilde{\mathbf{L}}_t = \left[\widetilde{\mathbf{L}}_t^{(pi)}, \widetilde{\mathbf{L}}_t^{(rr)}, \widetilde{\mathbf{L}}_t^{(ba)}, \widetilde{\mathbf{L}}_t^{(ec)}, \widetilde{\mathbf{L}}_t^{(pd)}\right]'$ denotes the vector which stacks all five liquidity measures for all N exchange rates and $\widetilde{\mathbf{L}}_t^{(\cdot)} = \left[\widetilde{L}_{1,t}^{(\cdot)}, \ldots, \widetilde{L}_{N,t}^{(\cdot)}\right]'$. $\boldsymbol{\beta}$ is the matrix 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 latent factor as proxy for market-wide liquidity, $L_{M,t}^{(pca)}$, combining the information across exchange rates as well as across liquidity measures.

VI. 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? This subsection tries 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 of uncertainty in the economy, which leads to a decrease in funding liquidity. Difficulty in securing funding for business activities in turn lowers market liquidity, especially if investors are forced to liquidate positions. This induces prices to move away from fundamentals, leading to increasing losses on existing positions and a further reduction in funding liquidity, which reinforces the downward spiral (Brunnermeier and Pedersen, 2009).

Figure 3 illustrates latent market-wide FX liquidity 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, 2009).[22] The severe financial crisis is reflected in a TED spread which is significantly larger than its long-run average of 30–50 basis points.

[Figure 3 about here.]

Interestingly, the VIX as well as the TED spread are strongly negatively correlated with FX liquidity (-0.87 and -0.35 for daily latent 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, i.e., after the bankruptcy of Lehman Brothers, the negative correlations prevail (-0.66 and -0.36 for daily latent liquidity). These comovements are consistent with 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 latent FX liquidity on lagged VIX and lagged TED spread. Both past VIX and past TED spread are strongly negatively related to current common FX liquidity. For instance, an increase in VIX by one standard deviation on day $t-1$ is followed on average by a drop of -8.37 in FX liquidity on day t. This drop is

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

highly relevant when compared to the standard deviation of FX liquidity of 10.02. Thus, an increase in investors' uncertainty and a reduction of 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, e.g., 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 to 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,[23] as proxy for perceived FX inventory risk. Then, we regress latent FX liquidity on 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 of the TED spread is largely unchanged and significantly negative, supporting the presence of liquidity spirals. This is true regardless of whether or not lagged FX market liquidity and VIX are included in the regression.

[Table III about here.]

[23] The separate appendix provides a description of the VXY index.

The separate appendix reports regression results for the same models as in Table III, but only using data from January 2007 to mid-September 2008, i.e., 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 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: If liquidity deteriorates in the FX market, which is the world's largest financial market, this is a signal warning of a liquidity crisis with effects in all financial markets. Moreover, a link between the two market liquidities 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 well enter pricing kernels for equity and FX markets.

To investigate the relation between liquidity in the two markets, the measures of market-wide FX liquidity presented in the previous section are compared to market-wide liquidity in the U.S. equity market. This is estimated on the basis of (i) return reversal[24] (Pástor and Stambaugh, 2003) and (ii) Amihud's (2002) measure utilizing return and volume data of all stocks listed at the New York Stock Exchange (NYSE) and the American Stock Exchange (AMEX). Figure 4 compares liquidity in FX and equity markets based on a sample of 36 non-overlapping monthly observations.

[Figure 4 about here.]

The monthly correlation between latent FX liquidity 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 equal 0.67 and 0.35, respectively, suggesting comovements between liquidity in equity and FX 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 dataset includes more accurate order flow data and that Model (1) is estimated robustly at a higher frequency.[25]

Table II reports monthly correlations between FX and equity liquidity as well as

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

[25] 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 the Amihud's measure and is somewhat less well correlated with market-wide FX liquidity than the Amihud's measure itself.

market-wide liquidity measures for the corporate bond market[26] and the U.S. 10-year Treasury bonds. The latter is computed using BrokerTec data[27] and then averaging bid-ask spreads of all intraday transactions during New York trading hours. Excluding the 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.[28]

Glen and Jorion (1993) and Campbell, Serfaty-de Medeiros, and Viceira (2010) show that holding certain currencies allows to reduce 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.

C. Currency Liquidity Sensitivity to Market-Wide FX Liquidity

Having documented the strong commonality of FX liquidity, a natural question arises as to 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 liquidity, $L^{(\cdot)}_{j,t}$, on common liquidity $L^{(\cdot)}_{M,t}$:

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

[26]The corporate bond market liquidity measure is from Dick-Nielsen, Feldhütter, and Lando (2011) and available at the authors' website.

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

[28]The separate appendix shows graphs of market-wide FX liquidity along with bond market liquidities.

where $L^{(\cdot)}_{I,j,t}$ 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 $L^{(ec)}_{M,t}$.[29] Table IV shows estimation results. 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 positively depends 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 greatest liquidity sensitivity. For instance, a one basis point decrease in market-wide FX liquidity leads to a 3.1bps 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), it is frequently used as an investment currency, and carry traders experienced severe funding constraints during the recent crisis.

[Table IV about here.]

We also run regression (6) in log variables, i.e., we regress $\log(L^{(ec)}_{j,t})$ on $\log(L^{(ec)}_{M,t})$ for each FX rate j. The estimation results are collected in the separate 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

[29]Otherwise $L^{(ec)}_{j,t}$ would enter both sides of Equation (6) in a linear way. As a robustness check we re-run regression (6), including $L^{(ec)}_{j,t}$ in the computation of $L^{(ec)}_{M,t}$ for each FX rate j. Regression results are collected in the separate appendix and largely confirm those in Table IV below. In particular, the slope coefficients b_j are relatively stable and tend to be somewhat larger, as expected. R^2s are larger as well.

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.

VII. Liquidity Risk Premiums

A. Shocks to Market-wide FX Liquidity

Given the evidence for liquidity spirals and strong declines in market-wide FX liquidity, the question arises as to whether investors demand a premium for being exposed to liquidity risk. To our knowledge, a theoretical model for currency returns which accommodates liquidity risk, in the same spirit as, e.g., Lustig, Roussanov, and Verdelhan (2011) has not yet been developed. However, if liquidity shocks vanish quickly it appears 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). This may be the case because investors will probably suffer higher costs during long and unexpected illiquid environments, and will consequently require a premium for that risk.[30] The separate appendix shows the autocorrelation 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

[30]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).

liquidity is unlikely to be reversed 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 base currency, which helps in interpreting the factors. To preserve a sufficiently large cross-section of currencies we extend our dataset by including the Danish krone (DKK), the New Zealand dollar (NZD), and the Swedish krona (SEK).[31]

The variable of interest is 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 at day t, respectively, and $\Delta p_{j,t+1}$ is the daily return of currency j at day $t+1$ from the perspective of a U.S. investor. The interest rate differential for each currency is computed using LIBOR interest rates obtained from Datastream. 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 (Gilmore and Hayashi, 2008). Descriptive

[31] These currencies were not included in the previous analysis because their relatively light trading resulted in somewhat unreliable measures of return reversal. Including these currencies, for example, in the calculation of market-wide FX liquidity based on bid-ask spread or effective cost has virtually no impact on the results.

statistics for exchange rate returns, interest rate differentials as well as daily carry trade returns are depicted in Table V.

[Table V about here.]

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 occur. 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) have 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 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.[32]

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

[32]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, the enormous injection of liquidity into USD (in particular via central bank swap lines) and the Fed's quantitative easing operations probably kept interest rates low in the U.S., 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.

further analysis, which is undertaken below.

C. Liquidity and Carry Trade Returns

Recently, a number of studies have documented comovements in carry trade returns; e.g., Lustig, Roussanov, and Verdelhan (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2011). The significant variation and commonality in currency liquidities documented above suggest that liquidity risk may contribute to this common variation. The separate 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 latent market-wide liquidity, as outlined in Section V. 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 latent market-wide liquidity, respectively. Typical high interest rate currencies during our sample period, such as AUD, Canadian dollar (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. Vice versa, 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 pound sterling (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 return 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 small number of risk factors (Ross, 1976). In particular, we introduce a liquidity risk factor given by a currency portfolio which 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.[33] As IML is a tradable risk factor, its computation is straightforward and currency investors can easily hedge associated liquidity risk exposures. The separate appendix compares IML to a non-tradable risk factor computed as shocks to latent market-wide liquidity. 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 which 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

[33]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.

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. 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 separate appendix this level risk factor does not exhibit significant variation compared to both IML and HML.

We now estimate a factor model to assess the relative importance and cross-sectional differences in exposure to the risk factors IML and AER. The following asset pricing model is estimated on a daily basis for each FX rate j:

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

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. The regression results are shown in Table VI.

[Table VI about here.]

Equation (9) provides a good fit to the data with adjusted-R^2s ranging from approximately 60% to 90%. Thus, the vast majority of variation in carry trade returns can be explained by exposure to two risk factors. Moreover, no currency pair exhibits a significant α_j, indicating that the pricing model appropriately captures the characteristics of carry trade returns. 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.[34] Unreported results show that adjusted-R^2s attain 60% 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 therefore helps to explain the average level of carry trade returns. In contrast, liquidity betas, $\beta_{IML,j}$, vary significantly across exchange rates.[35]

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. Vice versa, 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.

[Figure 5 about here.]

When FX liquidity improves, high interest rate currencies appreciate further, because

[34] These findings are not driven by the events after the bankruptcy of Lehman Brothers. 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 separate appendix collects these results for all currencies in our sample.

[35] Unreported regression results show that estimates of $\beta_{IML,j}$ remain largely the same when adding HML as a regressor in Equation (9), although standard errors are obviously unreliable due to collinearity between IML and HML.

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 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 U.S. dollar 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.

[Figure 6 about here.]

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 which is reflected in large positive liquidity betas (Table VI). Vice versa, 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. Such lower returns are the "insurance premiums" for holding currencies which will tend to deliver higher returns in bad times, i.e., when FX liquidity drops.

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

The separate 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 be one. Again, all liquidity betas are almost unchanged. Third, in Equation (9) we replace IML by latent unexpected shocks to market-wide FX liquidity. The new liquidity betas largely share the same pattern as liquidity betas in Table VI. Fourth, we use Equation (9) to explain carry trade index returns, namely the returns of the Deutsche Bank's "G10 Currency Harvest" (DBV) exchange traded fund.[36] 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. This finding confirms the key role of liquidity risk in explaining carry trade returns.

All in all, our findings suggest that liquidity risk is an important risk factor for FX returns. The presence of this factor is consistent with the theory of liquidity spirals and currency crashes. Investors are exposed to these spirals and will thus demand a risk premium as compensation for bearing liquidity risk. It remains to be investigated, with a longer sample, whether liquidity risk is also priced in the cross-section of carry trade returns and during other periods. There are at least two reasons to expect that this will be 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, recently Banti, Phylaktis, and Sarno (2011) followed our work and studied the risk premium of FX liquidity. Although they consider only the return reversal aspect of liquidity and use data from custodian banks,[37] they provide some evidence of liquidity risk being priced in currency portfolios.

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

[37]The separate appendix compares our EBS dataset to data from custodian banks. Besides dataset and liquidity measures there are other important differences between the two studies related to identification of liquidity risk, analysis of commonality, and inference procedure.

VIII. Conclusion

Using a novel and comprehensive dataset of intraday data, this paper provides the first systematic study of liquidity in the foreign exchange 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, i.e., strong comovements across the liquidity of different currencies. Such commonality implies that FX liquidity is largely driven by shocks that affect the FX market as whole rather than individual FX rates. It also implies that the FX market is likely to become illiquid precisely when the U.S. equity and bond markets are illiquid - given the large liquidity comovements across markets that we document - 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. 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 which 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 which 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. 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 "borrowing" ("investment") currencies. Our empirical evidence on liquidity spirals also appears insightful. To use the same example, 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.

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. In fact, our liquidity risk factor turns out to be highly correlated with another carry trade risk factor which is shown to have a large impact on carry trade returns over decades. Investigating the impact of liquidity risk on carry trade returns during other periods appears to be a promising direction for future research.

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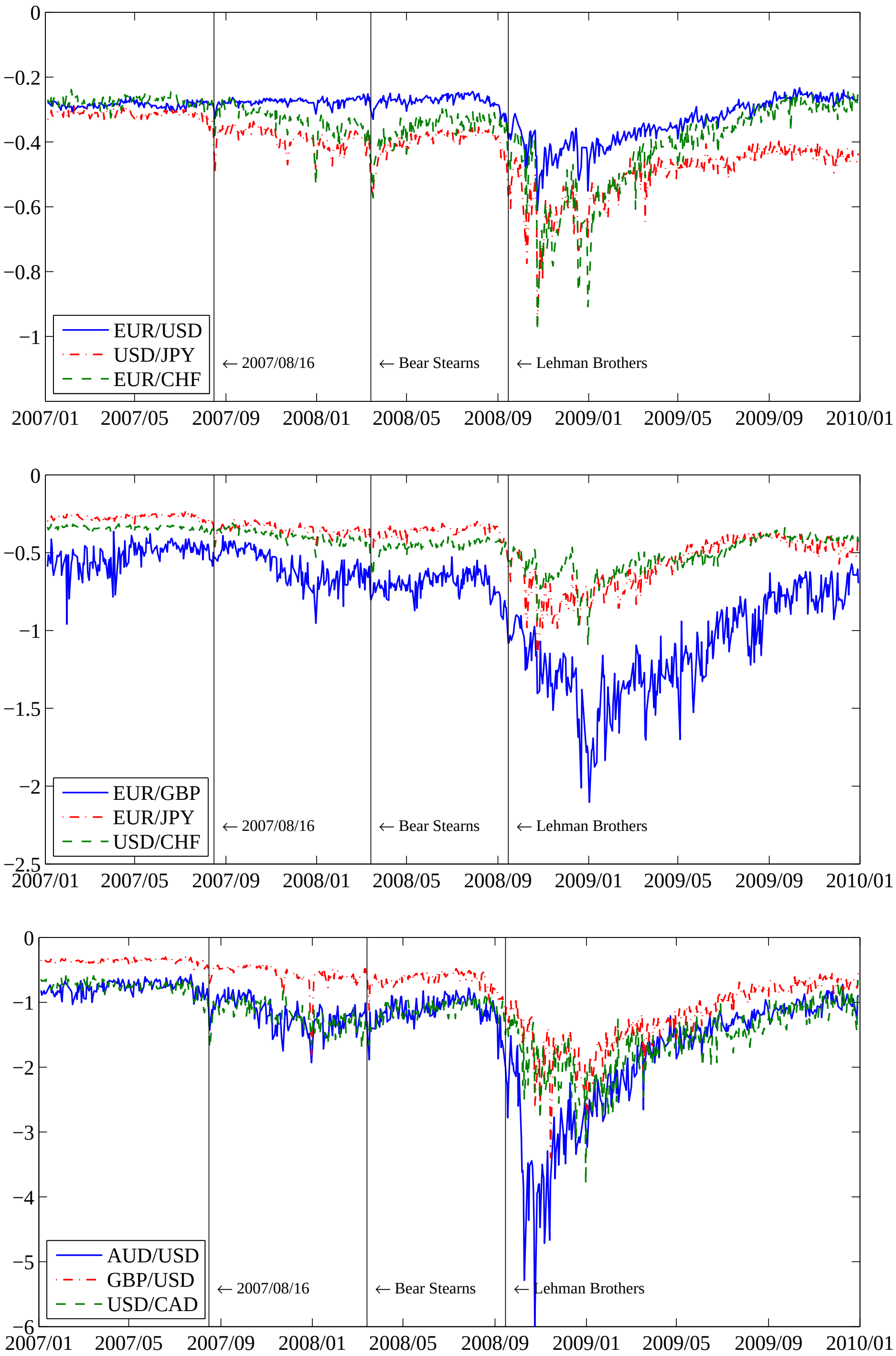


Figure 1: Daily liquidity estimates based on effective cost. Upper graph shows effective cost for most liquid exchange rates (EUR/USD, USD/JPY, EUR/CHF); middle graph for intermediate liquidity exchange rates (EUR/GBP, EUR/JPY, USD/CHF); lower graph for most illiquid exchange rates (AUD/USD, GBP/USD, 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 transaction price and P^M mid quote price. The sample is January 2, 2007 – December 30, 2009.

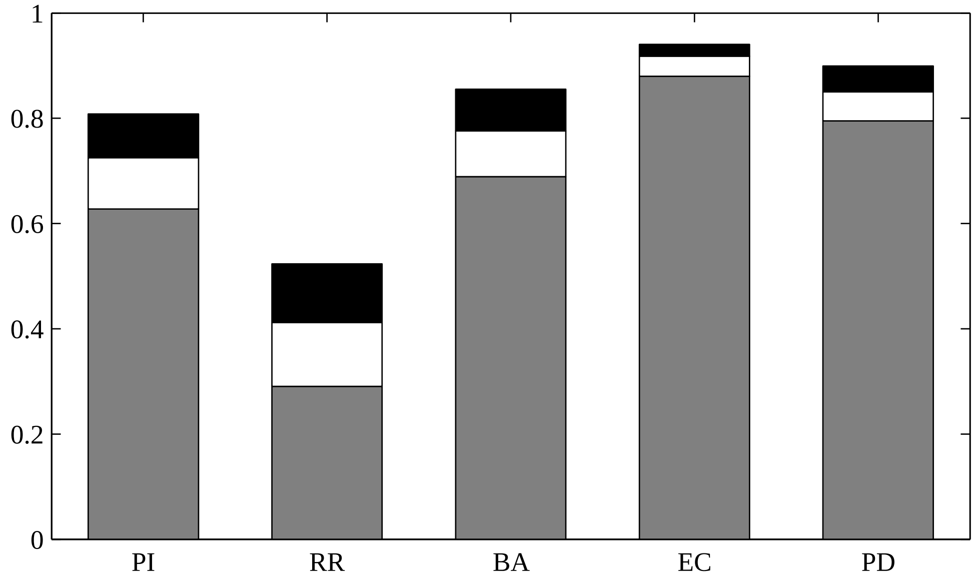


Figure 2: For each daily standardized measure of liquidity the first three common factors are extracted using principle component analysis. Then, for each exchange rate and each standardized liquidity measure, liquidity is regressed on its common factors. Each bar represents the average adjusted-R^2 of these regressions using one, two, and three common factors. 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 – December 30, 2009.

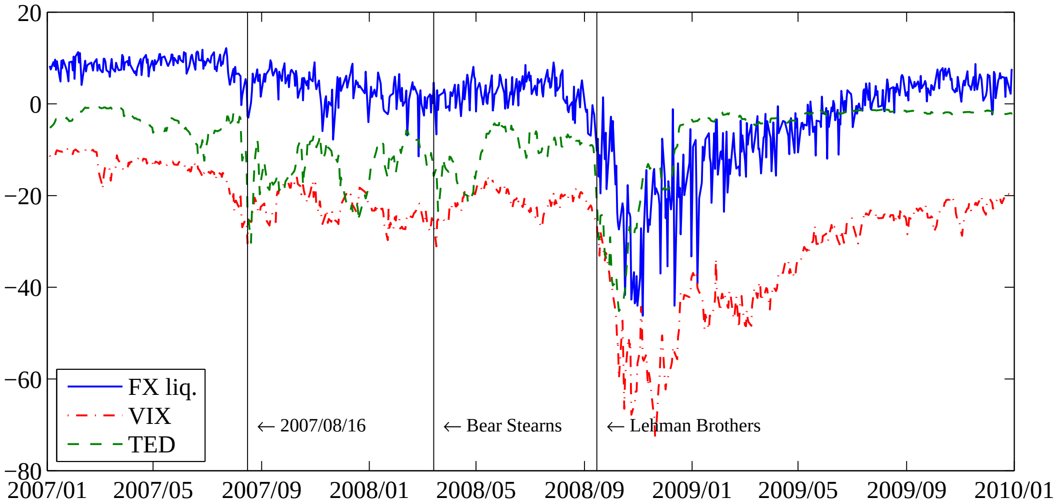
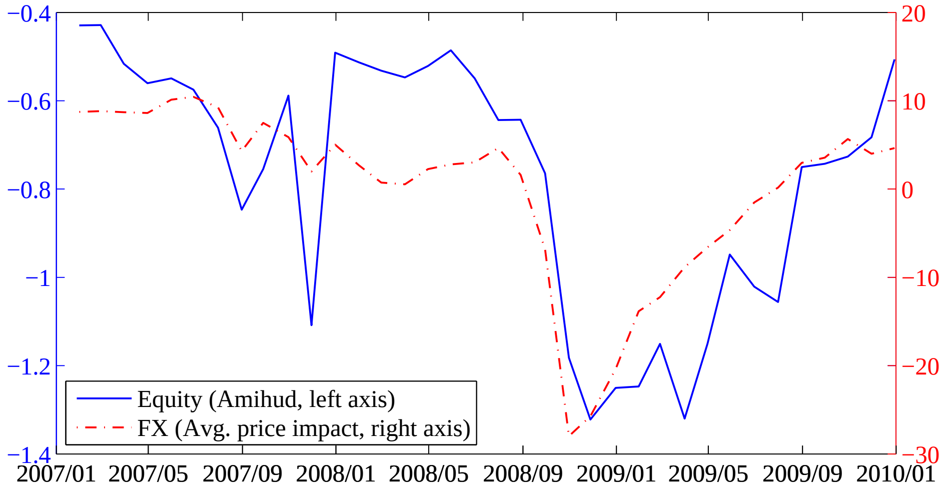
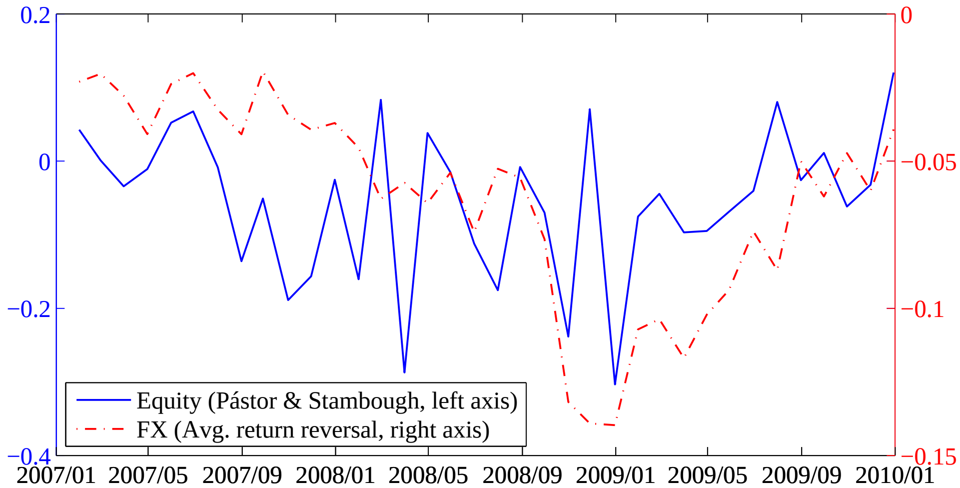


Figure 3: Latent market-wide FX liquidity (Equation (5)), the negative of the Chicago Board Options Exchange Volatility Index (VIX) as well as the negative of the TED spread. The sample is January 2, 2007 – December 30, 2009.



(a)



(b)

Figure 4: Non-overlapping monthly market-wide FX liquidity and US equity liquidity (estimated from stocks listed on the NYSE and AMEX). In Panel (a), latent FX liquidity 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 – December 2009.

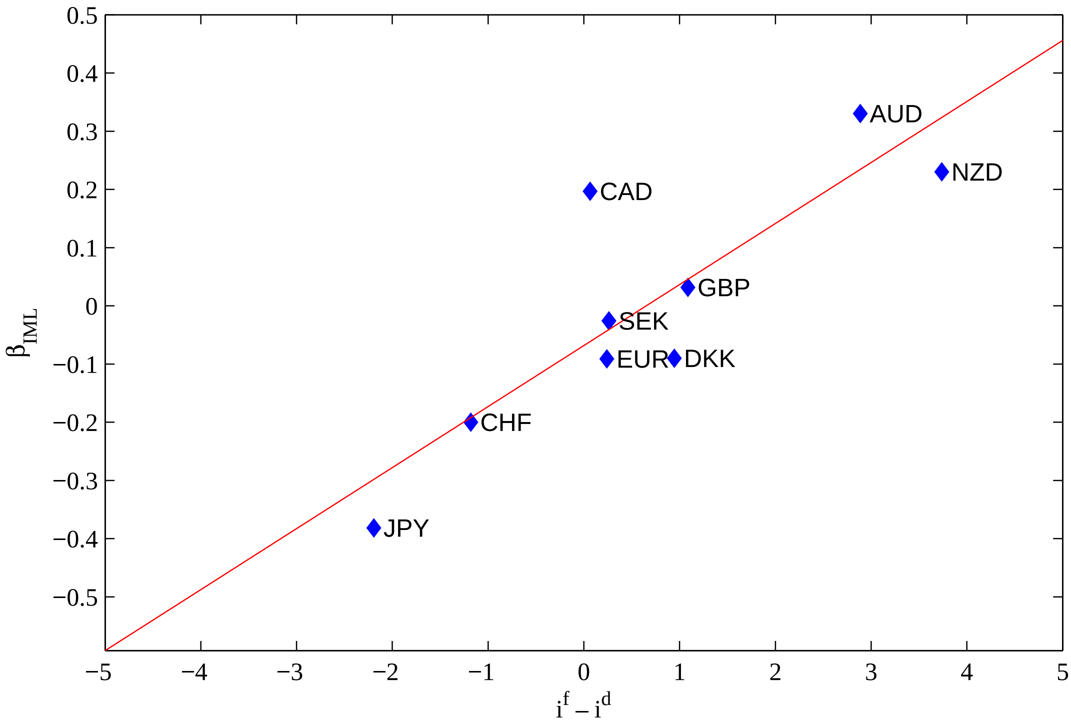
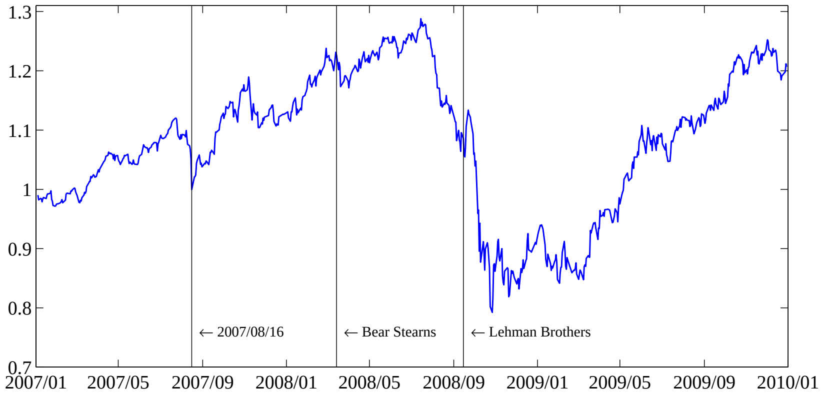
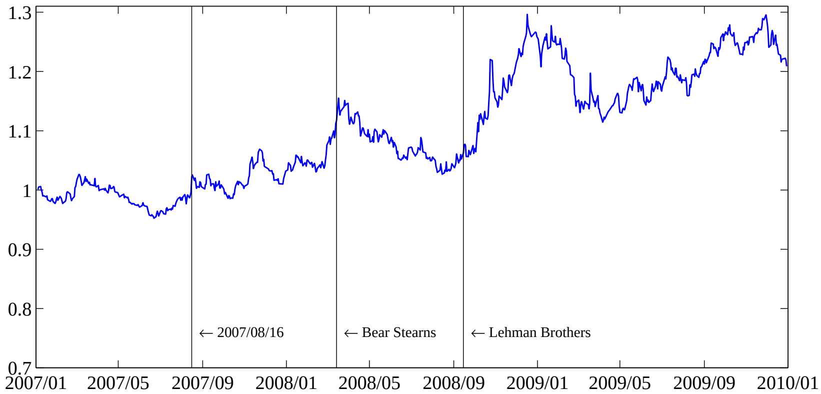


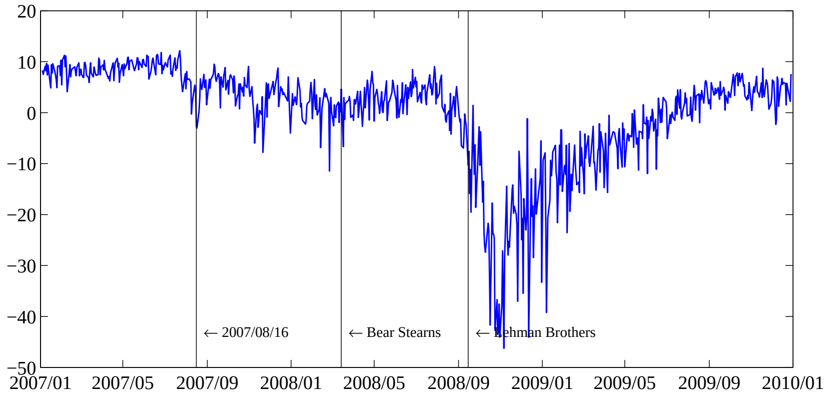
Figure 5: Liquidity beta and interest rate differential. Taking the perspective of a U.S. investor, for each currency, the graph shows on the x-axis the interest rate differential, i.e., foreign interest rate minus domestic interest rate, and on the y-axis the liquidity beta, β_{IML}, in the asset pricing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



(a) Cumulative AUD/USD carry trade returns



(b) Cumulative JPY/USD carry trade returns



(c) Market-wide FX liquidity

Figure 6: Carry trade returns and FX liquidity. Panel (a) depicts the cumulative return of investing one dollar in the AUD/USD carry trade. Panel (a) depicts the cumulative return of investing one dollar in the JPY/USD carry trade. Panel (c) market-wide FX liquidity. The sample is January 2, 2007 – December 30, 2009.

Table I: Daily liquidity measures

	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

Notes: 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 proportional bid-ask spread computed using intraday data for each trading day. Effective cost is the average difference between the transaction price and the bid/ask quote prevailing at the time of the trade. Price dispersion for each trading day is estimated using two-scale realized volatility (TSRV). It is expressed in percentage on an annual basis. The sample is January 2, 2007 – December 30, 2009.

Table II: Correlation between liquidity of different asset classes

		FX						Equity		Bond	
		Average					PCA				
		RR	PI	BA	EC	PD	LL	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	latent liquidity	0.927	0.955	0.953	0.923	0.938	1				
Equity	Pastor/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

Notes: Correlations between market-wide liquidity measures for the FX market (return reversal; price impact; bid-ask spread; effective cost; price dispersion; latent liquidity), for the equity market (Pastor/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 non-overlapping monthly observations. The sample is January 2007 – December 2009.

Table III: Evidence for liquidity spirals in the FX market

	$const$	$L^{pca}_{M,t-1}$	VIX_{t-1}	TED_{t-1}	VXY_{t-1}	Adj. 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)	

Notes: Regression of daily latent market-wide FX liquidity ($L^{(pca)}_{M,t}$) on lagged VIX and TED spread. Various specifications of the regression model are estimated. The last specification additionally control for the JP Morgan Implied Volatility Index for the G7 currencies, VXY. Heteroscedasticity and autocorrelation (HAC) robust standard errors are shown in parentheses. The number of observation is 733. The sample is January 2, 2007 – December 30, 2009.

Table IV: Sensitivity to changes in common liquidity

	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

Notes: 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. Heteroscedasticity and autocorrelation (HAC) robust standard errors are shown in parenthesis. 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 – December 30, 2009.

Table V: Descriptive statistics for carry trade returns

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

Notes: This table reports descriptive statistics for different exchange rates with USD being the base currency. Namely, the average log-return, the average interest rate differential as well as 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.

Table VI: Factor model time series regression results

	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 Lehman bankruptcy					
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 Lehman bankruptcy					
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

Notes: 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 which is long in the two most illiquid and short in the two most liquid exchange rates. Heteroscedasticity and autocorrelation (HAC) robust standard errors are shown in parenthesis. 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.