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

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Abstract

A daily return reversal measure of liquidity is developed and estimated using a new comprehensive ultra-high frequency data set of foreign exchange rates during the financial crisis period of 2007–2008. The measure captures market participants' perception of periods with high and low liquidity in the expected manner. Tests for commonality in foreign exchange (FX) liquidity show that liquidity co-moves strongly across currencies. Systematic FX liquidity decreases dramatically during the subprime crisis, especially after the default of Lehman Brothers in September 2008. To investigate whether there exists a return premium for illiquidity, a factor model similar to Lustig, Roussanov, and Verdelhan (2009) is augmented by a liquidity risk factor constructed from shocks to systematic liquidity. Empirical results indicate that liquidity risk is a heavily priced state variable important for the determination of FX returns. Previously identified risk factors such as the carry trade and market risk factors are no longer significant once common liquidity risk is incorporated in the asset pricing model. This finding helps to explain deviations from uncovered interest rate parity as classical tests do not include liquidity risk.

1. Introduction

Recent events during the financial crisis of 2007–? have highlighted the fact that liquidity is a crucial yet elusive concept in all financial markets. With unprecedented coordinated efforts, central banks around the world had to stabilize the financial system by injecting billions of US dollars to restore liquidity. According to the Federal Reserves's chairman Ben Bernanke, "weak liquidity risk controls were a common source of the problems many firms have faced [throughout the crisis]" (Bernanke, 2008). Therefore, measuring liquidity and evaluating exposure to liquidity risk is of relevance not only for investors, but also for central bankers, regulators, as well as academics.

As a consequence of its crucial role in general and the potential of leading to devastating losses in particular, the concept of liquidity has been studied extensively in equity markets. However, liquidity in the foreign exchange (FX) market has mostly been neglected, although it is by far the world's largest financial market. The estimated average daily turnover of more than 3.2 trillion US dollar in 2007 (Bank for International Settlements, 2007) corresponds to almost eight times that of global equity markets (World Federation of Exchanges, 2008). A large variety of FX traders ranging from hedge funds to central banks is dispersed around the globe, keeping the market open 24 hours a day.

Despite the fact that the FX market is commonly regarded as the most liquid financial market, events during the financial crisis of 2007–? and recent studies on currency crashes (Brunnermeier, Nagel, and Pedersen, 2009) highlight the importance of liquidity in FX markets. Similarly, Burnside (2009) argues that liquidity frictions have the potential to play a crucial role in explaining the profitability of carry trades. In line with Brunnermeier and Pedersen (2009), "liquidity spirals" aggravate currency crashes and pose a great risk to carry traders. Therefore, investors require to be able to carefully monitor FX liquidity as they are averse to liquidity shocks.

Given the lack of previous studies and the importance of currency markets, the main contribution of this paper is to develop a liquidity measure particularly tailored to the FX market, to quantify the amount of commonality in liquidity across different exchange rates, and to determine the extent of liquidity risk premiums embedded in foreign exchange returns. To that end, a daily return reversal liquidity measure (Pástor and Stambaugh, 2003) accounting for the important role of contemporaneous order flow in the determination of exchange rates (Evans and Lyons, 2002) is developed and estimated using a new comprehensive data set including ultra high frequency return and order flow data for nine major exchange rates. Ranging from January 2007 to December 2008, the sample covers the financial crisis during which illiquidity played a major role. Thus, this period of distressed market conditions is highly relevant to analyze liquidity, compensating for the fact that the sample

extends over two years only. The proposed liquidity measure is based on structural microstructure models featuring a dichotomy between the fundamental price and the observed price. Empirically, the measure captures market participants' perception of periods with high and low liquidity in the expected manner. For instance, EUR/USD is found to be the most liquid exchange rate and liquidity of all currency pairs decreases during the financial crisis.

Testing for commonality in FX liquidity is crucial as sudden shocks to market-wide liquidity have important implications for regulators as well as investors. Regulators are concerned about the stability of financial markets, whereas investors worry about the risk–return profile of their asset allocation. Therefore, a time-series of systematic FX liquidity is constructed representing the common component in liquidity across different exchange rates. In line with expectations, results show that liquidity co-moves strongly across currencies. Systematic FX liquidity decreases dramatically during the financial crisis, especially after the default of Lehman Brothers in September 2008.

The last part of the paper investigates whether there exists a return premium for illiquidity. A factor model similar to Lustig, Roussanov, and Verdelhan (2009) is augmented by a liquidity risk factor constructed from unexpected shocks to systematic liquidity. Estimation results indicate that liquidity risk is a heavily priced state variable important for the determination of FX returns. This finding helps to explain deviations from Uncovered Interest Rate Parity (UIP) as classical tests do not include liquidity risk.

The remainder of this paper is structured as follows: In the following section literature related to the paper at hand will be summarized. In Section 2, a return reversal measure of liquidity will be derived and alternative intraday measures of liquidity will be presented. Liquidity in the FX market will be investigated empirically in Section 3. Section 4 introduces measures for systematic liquidity and documents commonality in liquidity between different currencies. Evidence indicating the presence of a return premium for systematic liquidity risk in the cross-section of exchange rates as well as robustness checks are presented in Sections 5 and 6, respectively. Section 7 concludes.

1.1. Related Literature

First and foremost this paper is related to the substantial strain of literature dealing with liquidity in equity markets. Motivated by the theoretical model of Amihud and Mendelson (1986), various authors have developed measures of liquidity for different time horizons. Among others, Chordia, Roll, and Subrahmanyam (2001) use trading activity and transaction cost measures to derive daily estimates of liquidity from intraday data. In case only daily data is available, the effective cost of

trades can be estimated by relying on the spread model presented by Roll (1984). Alternatively, Amihud (2002) advocates a measure of illiquidity computed as the average ratio of absolute stock return to its trading volume, which can be interpreted as a proxy of price impact. Pástor and Stambaugh (2003) suggest a measure of stock market liquidity based on return reversal, summarizing the link between returns and lagged order flow.

Additionally, commonality in liquidity of different stocks has been documented. Chordia, Roll, and Subrahmanyam (2000) as well as Hasbrouck and Seppi (2001) find that liquidity of individual stocks co-moves with industry- and market-wide liquidity. Korajczyk and Sadka (2008) rely on principle component analysis to extract a latent systematic liquidity factor both across stocks as well as across liquidity measures. Theoretically, the source of market illiquidity and the link to funding liquidity have been highlighted by Brunnermeier and Pedersen (2009).

Recently, these measures of (systematic) liquidity have been related to equity returns (Pástor and Stambaugh (2003), Hasbrouck (2006)) and market microstructure noise (Aït-Sahalia and Yu, 2009) of NYSE stocks. Taking liquidity into account also has important implications in an asset pricing context as investors require compensation for being exposed to liquidity risk. By augmenting the Fama and French (1993) three-factor model by a liquidity factor, Pástor and Stambaugh (2003) find that aggregate liquidity is a priced risk factor in the cross-section of stock returns. The studies by Acharya and Pedersen (2005), Sadka (2006) and Korajczyk and Sadka (2008) lend further support to this hypothesis.

Despite its importance, only very few studies exist on liquidity in FX markets, mainly focusing on the explanation of the contemporaneous correlation between order flow and exchange rate returns documented by Evans and Lyons (2002). Using a unique database from a commercial bank, Marsh and O'Rourke (2005) investigate the effect of customer order flows on exchange rate returns. Based on price impact regressions, the authors argue that the correlation between order flow and exchange rate movements varies among different groups of customers, suggesting that transitory liquidity effects do not cause the contemporaneous correlation described by Evans and Lyons (2002). On the contrary, Breedon and Vitale (2005) support the argument that portfolio balancing temporarily leads to liquidity risk premiums and, therefore, affects exchange rates as long as dealers hold undesired inventory. In line with this result, Berger, Chaboud, Chernenko, Howorka, and Wright (2008) find evidence indicating a prominent role of liquidity effects in the relation between order flow and exchange rate movements in their study of Electronic Brokerage System (EBS) data. However, none of these papers introduces a measure of liquidity or investigates commonality in liquidity as is done in this paper.

Burnside, Eichenbaum, Kleshchelski, and Rebelo (2008) document the profitability of carry trades, finding an average annual excess return of close to 5% over the period 1976–2007 for a simple carry trade strategy. Recently, Lustig, Roussanov, and Verdelhan (2009) developed a factor model in the spirit of Fama and French (1993) for foreign exchange returns. They argue that a single carry trade risk factor, which is related to the difference in excess returns for exchange rates with large and small interest rate differentials, is able to explain most of the variation in currency excess returns over uncovered interest rate parity. Menkhoff, Sarno, Schmeling, and Schrimpf (2009) adapt this model by stressing the role of volatility risk. The rationale for investigating excess returns is the plethora of papers which document the failure of UIP, rooted in the seminal works of Hansen and Hodrick (1980) as well as Fama (1984). Hodrick and Srivastava (1986) argue that a time-varying risk-premium which is negatively correlated with the expected rate of depreciation is economically plausible and might help to explain the forward bias. A survey of modeling and estimating the risk premium is presented by Engel (1996). These risk-based explanations for the failure of UIP motivate the study of excess currency returns in an asset pricing context. The paper at hand contributes to this strain of literature by showing that liquidity risk is a priced risk factor.

Finally, this paper has implications for crash risk in currency markets (Jurek (2008), Brunnermeier, Nagel, and Pedersen (2009), Farhi, Fraiberger, Gabaix, Ranciere, and Verdelhan (2009)). Typically funding as well as market liquidity dries up during currency crashes leading to further selling pressure on the currency. The liquidity measure introduced in this paper helps investors and central banks to monitor liquidity in FX markets supporting investment and policy decisions.

The next section establishes the basis for the analysis of liquidity in foreign exchange markets by introducing various liquidity measures.

2. Liquidity Measures

2.1. Return Reversal

In this section, a daily reversal measure of liquidity, inspired by Pástor and Stambaugh (2003), is developed for high-frequency data. When a currency is illiquid, net buying (selling) pressure leads to an excessive appreciation (depreciation) of the currency followed by a reversal to the fundamental value (Campbell, Grossman, and Wang, 1993). The magnitude of this resilience effect determines liquidity, i.e. the more liquid a currency, the smaller is the temporary price change accompanying

order flow. This can be modeled as

$$p_{t_i} - p_{t_{i-1}} = \theta_t + \varphi_t(v_{b,t_i} - v_{s,t_i}) + \gamma_t(v_{b,t_{i-1}} - v_{s,t_{i-1}}) + \varepsilon_{t_i}, \tag{1}$$

or in shorthand notation

$$r_{t_i} = \boldsymbol{\theta}_t \mathbf{x}_{t_i} + \varepsilon_{t_i}, \tag{2}$$

where $r_{t_i} = p_{t_i} - p_{t_{i-1}}$ is the intraday log-return of a currency, v_{b,t_i} and v_{s,t_i} denote the buying and selling volume at time t_i, respectively, and ε_{t_i} is an error term. The parameter vector to be estimated each day is $\boldsymbol{\theta}_t = [\theta_t \quad \varphi_t \quad \gamma_t]$. It is expected that the trade impact φ_t is positive due to the supply and demand effect of net buying pressure as presented by Evans and Lyons (2002). Liquidity at day t is measured by the parameter γ_t, which is expected to be negative as it captures return reversal. The intraday frequency should be low enough to distinguish return reversal from simple bid-ask bouncing. On the other hand, the frequency should be sufficiently high to obtain an adequate number of observations for each day, so a good choice is to rely on one minute data.

While having a similar form, there exist a number of important differences compared to the liquidity measure of Pástor and Stambaugh (2003). First of all, order flow is computed as the difference between buying and selling volume, whereas Pástor and Stambaugh (2003) approximate order flow by volume signed by the excess stock return of the same period. The former method is more accurate if the direction of the trades is known. Furthermore, contemporaneous order flow is included in Model (1) to account for the fact that order flow is one of the main determinants of FX returns (Evans and Lyons, 2002). Most importantly, Pástor and Stambaugh (2003) developed a measure for monthly data, whereas the measure at hand is designed to obtain a daily measure from high-frequency data. Therefore, the intraday reversal measure introduced above is more closely related to the classical market microstructure literature. It can be derived from structural models featuring a dichotomy between the fundamental price and the observed price, as for instance in Glosten and Harris (1988) as well as Madhavan, Richardson, and Roomans (1997). In an efficient market model, security prices move in response to the arrival of new information. However, in practice various imperfections inherent in the trading process lead to additional intraday price movements. These two effects can be combined in a joint model:

$$p_{t_i}^* = p_{t_{i-1}}^* + \alpha_t(v_{b,t_i} - v_{s,t_i}) + \zeta_{t_i} \tag{3}$$

$$p_{t_i} = p_{t_i}^* + \beta_t(v_{b,t_i} - v_{s,t_i}) + \xi_{t_i}. \tag{4}$$

In efficient markets, changes in the unobservable fundamental log-price $p^*_{t_i}$ stem from public news announcements ζ_{t_i}. Moreover, contemporaneous order flow $(v_{b,t_i} - v_{s,t_i})$ is assumed to contain information of the fundamental asset value as some traders might possess private information. The strength of the impact of order flow is measured by the coefficient α_t, which refers to the degree of asymmetric information. Observable log-prices p_{t_i} are set by market makers[1] conditional on the order flow. If a trade is buyer (seller) initiated, the market maker augments (reduces) the fundamental price to obtain compensation for transaction cost and inventory risk. Thus β_t reflects liquidity cost, capturing the transitory effect of order flow on asset prices. The term ξ_{t_i} represents further microstructure noise, for instance due to price discreteness.

This structural model of price formation can easily be related to Model (1). Taking first differences of Equation (4) and relying on (3) yields:

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\begin{aligned}
p_{t_i} - p_{t_{i-1}} &= p^*_{t_i} - p^*_{t_{i-1}} + \beta_t(v_{b,t_i} - v_{s,t_i}) - \beta_t(v_{b,t_{i-1}} - v_{s,t_{i-1}}) + \xi_{t_i} - \xi_{t_{i-1}} \\
&= (\alpha_t + \beta_t)(v_{b,t_i} - v_{s,t_i}) - \beta_t(v_{b,t_{i-1}} - v_{s,t_{i-1}}) + \zeta_{t_i} + \xi_{t_i} - \xi_{t_{i-1}} \qquad (5)\\
&\equiv (\alpha_t + \beta_t)(v_{b,t_i} - v_{s,t_i}) - \beta_t(v_{b,t_{i-1}} - v_{s,t_{i-1}}) + u_{t_i} + \eta_t u_{t_{i-1}},
\end{aligned}
$$

which can be estimated using Equation (1) setting $(\alpha_t + \beta_t) = \varphi_t$, $-\beta_t = \gamma_t$, and $u_{t_i} + \eta_t u_{t_{i-1}} = \varepsilon_{t_i}$. To summarize, the link between asset returns and lagged order flow is predominantly determined by liquidity cost, while asymmetric information is the main cause of returns and order flow being contemporaneously correlated.

2.2. Estimation

The classic choice to estimate Model (1) is ordinary least squares (OLS) regression. However, high frequency data is likely to contain outliers especially if a prior filtering was conducted conservatively. Unfortunately, classic OLS estimates are adversely affected by these atypical observations which are separated from the majority of the data. In line with this reasoning, Pástor and Stambaugh (2003) warn that their reversal measure can be very noisy for individual securities.

Removing outliers from the sample is not a meaningful solution since subjective outlier deletion or algorithms as described by Brownlees and Gallo (2006) have the drawback that there is a risk of deleting legitimate observations which diminishes the value of the statistical analysis. The approach adopted in this paper is to rely on robust regression techniques.[2] The aim of robust statistics is to

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[1] Market makers may also be traders using limit orders.
[2] Alternatively, Model (1) can be estimated by the Generalized Method of Moments, which could also be robustified (Ronchetti and Trojani, 2001).

obtain parameter estimates, which are not adversely affected by the presence of potential outliers (Hampel, Ronchetti, Rousseeuw, and Stahel, 2005). As Model (1) is a simplistic representation of the unknown true process generating FX returns, it is desirable to obtain accurate parameter estimates even if the data stems from a perturbed model in the neighborhood of the Model (1). Robust parameter estimates are the solutions to:

$$\min_{\boldsymbol{\theta}} \sum_{i=1}^{I} \rho \left(\frac{\varepsilon_{t_i}(\boldsymbol{\theta})}{\sigma} \right), \tag{6}$$

where σ is the scale of the error term and $\rho(\cdot)$ is a bisquare function:

$$\rho(y) = \begin{cases} 1 - \left[1 - (y/k)^2 \right]^3 & \text{if} \quad |y| \leq k \\ 1 & \text{if} \quad |y| > k \end{cases}. \tag{7}$$

The first order condition for this optimization problem is:

$$\sum_{i=1}^{I} \rho' \left(\frac{\varepsilon_{t_i}(\widehat{\boldsymbol{\theta}})}{\widehat{\sigma}} \right) \mathbf{x_{t_i}} = \mathbf{0}. \tag{8}$$

Moreover, the constant $k = 4.685$ ensures 95% efficiency of $\widehat{\boldsymbol{\theta}}$ when ε_{t_i} is normally distributed. Computationally, the parameters are found using iteratively reweighed least squares with a weighting function corresponding to the bisquare function (7) and an initial estimate for the residual scale of $\widehat{\sigma} = \frac{1}{0.675} \text{median}_{i=1}^{I} \left(|\varepsilon_{t_i}| | \varepsilon_{t_i} \neq 0 \right)$.

Compared to standard OLS, by construction robust regression estimates are less influenced by potential contamination in the data. Furthermore, standard errors of the robust estimates are typically smaller as outliers inflate confidence intervals of classic OLS estimates (Maronna, Martin, and Yohai, 2006).

In the next section, alternative measures of liquidity will be presented.

2.3.   Alternative Measures of Liquidity

Various measures of liquidity have been introduced in the finance literature. Due to the fact that liquidity is a complex concept, each measure captures a different facet of liquidity. Consequently, it is important to consider alternative measures that can be used for comparison with the return reversal measure. Table 1 summarizes the definition and units of measurement of all daily liquidity measures that are utilized in this paper.

[Table 1 about here.]

The first two alternative measures cover the cost aspect of liquidity. In line with the implementation shortfall approach of Perold (1988), the cost of executing a trade can be assessed by investigating bid-ask spreads. A market is regarded as liquid if the proportional bid-ask spread is low. However, in practice trades are not always executed exactly at the posted bid or ask quotes.[3] Instead, deals frequently transact at better prices, deeming quoted spread measures inappropriate for an accurate assessment of execution costs. Therefore, effective cost are computed by comparing transaction prices with the quotes prevailing at the time of execution. The main advantage of spreads and effective cost is that these measures can be calculated quickly and easily on a real-time basis. A drawback, however, is that bid and ask quotes are only valid for limited quantities and amounts of time, implying that the spread only measures the cost of executing a single trade of restricted size (Fleming, 2003).

If markets are volatile, market makers require a higher compensation for providing liquidity due to the additional risk incurred. Therefore, if volatility is high, liquidity tends to be lower and, thus, volatility can be used as a proxy for liquidity. To that end, volatility is estimated based on ultra-high frequency data, which allows for a more accurate estimation compared to relying solely on daily or monthly data. Given the presence of market frictions, utilizing classic 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 is subject to microstructure noise.

The last measure used in this paper is the trade impact coefficient φ_t in Equation (1), which can be interpreted as an indirect measure of illiquidity (Kyle, 1985). Following the argument of Grossman and Stieglitz (1980) agents in the market are not equally well informed, thus, asymmetric information might lead to illiquidity in the market as, for instance, a potential seller might be afraid that the buyer has private information. As discussed above, the contemporaneous relation between order flow and prices can be used to proxy asymmetric information. In foreign exchange markets asymmetric information might arise for instance in the context of central bank interventions.

As more active markets tend to be more liquid, trading activity measured by the number of intraday trades is frequently used as an indirect measure of liquidity. Unfortunately, the relation between liquidity and trading volume is not unambiguous. Jones, Kaul, and Lipson (1994) show that

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[3]For instance new traders might come in, executing orders at a better price or the spread might widen if the size of an order is particularly large.

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. Therefore, trading activity is not used as a proxy for liquidity in this paper. All alternative measures will be applied in the next section to empirically analyze liquidity in foreign exchange markets.

3. Liquidity in Foreign Exchange Markets

3.1. The Data Set

Next to the fact that the FX market is less transparent than stock and bond markets, the main reason why liquidity in FX markets has not been studied previously in more detail is the paucity of available data. However, in recent years two electronic platforms have emerged as the leading trading systems providing an excellent source of currency trade and quote data. These electronic limit order books match buyers and sellers automatically, leading to the spot interdealer reference price. Via the Swiss National Bank it was possible to gain access to a new data set from EBS including historical data on a one second basis of the most important currency pairs between January 2007 and December 2008. With a market share of more than 60%, EBS has become the leading global marketplace for interdealer trading in foreign exchange. For the two most important currency pairs, EUR/USD and USD/JPY, the vast majority of spot trading is represented by the EBS data set (Chaboud, Chernenko, and Wright, 2007). EBS best bid and ask prices as well as volume indicators are available to determine the liquidity measures presented above. Furthermore, in this data set the direction of trades is known, which is crucial for an accurate computation of effective cost and order flow. See Chaboud, Chernenko, and Wright (2007) for a descriptive study of the EBS database.

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. Further, less frequently traded exchange rates are available, however, increasing the cross-section would lead to a diminishing accuracy of liquidity estimates. Choosing nine currency pairs optimally balances the tradeoff between sample size and accuracy. In the EBS system no record is created if neither prices or volume changed nor a trade occurred, therefore the raw data is brought to a regular format with 86,400 entries per day to construct second-by-second price and volume series. Almost 7GB of irregularly spaced raw data were processed to obtain a total of more than 40 million observations for a single currency pair. At 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 improved

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interpretability, these returns are multiplied by 10^4 to obtain basis points as the unit of exchange rate returns. Observations between Friday 10pm to Sunday 10pm GMT[4] are excluded since only minimal trading activity is observed during these non-standard hours. Moreover, US holidays and other days with unusual light trading activity[5] have been dropped from the data set. For four less frequently traded currency pairs, namely AUD/USD, EUR/GBP, GBP/USD and USD/CAD, the trading activity during nighttime in both countries is very low leading to irregular moves in quotes. Hence, these hours are removed prior to computing the daily liquidity measures.

As there are a number of faulty records and obvious outliers in the data[6] which need to be discarded, the data is cleaned using the detection rule proposed by Brownlees and Gallo (2006). More precisely, the observation at time t is removed from the sample if both the bid as well as the ask price are zero or if

$$|p_t(\alpha, k) - \bar{p}_i(\alpha, k)| > 3s_i(\alpha, k) + \nu, \tag{9}$$

where $\bar{p}_i(\alpha, k)$ and $s_i(\alpha, k)$ denote the α-trimmed sample mean and standard deviation based on k observations in the neighborhood of t, respectively. To avoid zero variance for a sequence of equal prices, ν is added on the right hand side of Equation (9). As the purpose of this filtering is to only remove the most obvious outliers, ν is chosen to be equal to five pips[7]. Relying on α-trimmed mean and standard deviation ensures that a given price is compared with valid observations in the neighborhood. Choosing $\alpha = 5\%$ and $k = 100$ implies that the 100 prices closest to price p_t are chosen as the neighborhood, however, the largest and smallest 2.5% of these prices are discarded for the computation of the mean and variance.

As it is impossible to disentangle bid-ask bouncing and reversal effects at the one second frequency, the data is aggregated to one-minute price series. To that end, one minute order flow and return series are constructed by summing one second order flow and log-returns.

3.2. Foreign Exchange Liquidity

Using the large data set described in the previous section, liquidity is estimated for each trading day. Descriptive statistics for exchange rate returns, order flow and various liquidity measures are shown in Panel I of Table 2.

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[4]GMT is used throughout this paper.

[5]There are unusually few trades recorded on July 27 and there are no trade records at all between December 3rd and December 5th, 2007.

[6]For instance on March 30 one bid quote is 0.803 instead of 0.8073 for AUD/USD; On June 15 two bid quotes are 100.11 instead of 165.1 for EUR/JPY.

[7]A pip is the smallest price change of a currency and corresponds to 0.01 for JPY and 0.0001 for all other currencies.

Average daily returns reveal that AUD and GBP depreciated, while EUR, CHF and particularly JPY appreciated during the sample period. For USD/CHF and USD/JPY, the average order flow is large and positive, nevertheless, USD depreciated against CHF as well as JPY. In line with expectations, EUR/USD and USD/JPY are traded most frequently while trading activity is the smallest for AUD/USD and USD/CAD.

Panel II of Table 2 depicts summary statistics of daily estimates for various liquidity measures. Interestingly, the average return reversal, γ_t, 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 on average reduced by 0.014 to 0.083 basis points if there was an order flow of 1–5 million in the previous minute. This reduction is economically significant given the fact that average one-minute returns are virtually zero. In line with the results of Evans and Lyons (2002) as well as Berger, Chaboud, Chernenko, Howorka, and Wright (2008), the trade impact coefficient, φ_t, is positive. Effective cost are smaller than half the bid-ask spread hinting at within quote trading. Annualized foreign exchange return volatility ranges from 6.9% to almost 17%.

Comparing the liquidity estimates across different currencies, EUR/USD seems to be the most liquid exchange rate, which corresponds to the perception of market participants and the fact that it has by far the largest market share in terms of turnover (Bank for International Settlements, 2007). On the other hand, the least liquid currency pairs 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 rather illiquid, which is explained by the fact that GBP/USD is mostly traded on Reuters rather than the EBS trading platform (Chaboud, Chernenko, and Wright, 2007). The high liquidity of EUR/CHF and USD/CHF during the sample period might be related to "flight-to-quality" effects due to save heaven properties of the Swiss franc (Ranaldo and Söderlind, 2009). Nevertheless, the overall ranking of the exchange rates according to their liquidity is in line with market participants' expectations and roughly coincides across different measures.

All daily liquidity measures of individual exchange rates fluctuate significantly over time. For the return reversal this observation is shared by Pástor and Stambaugh (2003) who conclude that their reversal measure is a rather noisy proxy for liquidity at the individual asset level. To alleviate this problem, overlapping weekly and monthly liquidity series are constructed by computing time-series averages of the daily estimates. This "within exchange rate" averaging has similar effects

as Pástor and Stambough's (2003) approach of computing the cross-sectional mean across stocks. From Figures 1 and 2, which depict weekly and monthly liquidity respectively, this smoothing effect becomes apparent.

[Figure 1 about here.]

[Figure 2 about here.]

While the weekly estimates are still rather noisy, the overlapping monthly estimates exhibit less variation. Most currencies are relatively stable and liquid at the beginning of the sample. However, after the subprime crisis started to significantly effect financial markets in the course of 2007, a downward trend in liquidity becomes visible for all exchange rates. In line with Melvin and Taylor (2009), who identify August 16, 2007 to be the start of the crisis in FX markets, liquidity decreased during the major unwinding of carry trades in August 2007. In the following months liquidity tended to rebound for most currency pairs before starting a downward trend in the end of 2007. This decline was mainly due to changes in risk appetite and commodity related selling of investment currencies which led investors to deleverage by unwinding carry trades. The decrease in liquidity continued after the collapse of Bear Stearns in March 2008. In the second quarter of 2008 investors started to believe that the crisis might be over soon, thus, liquidity increased as investors began to invest again in FX markets. However, in September 2008, liquidity dramatically dropped following the default of Lehman Brothers. This decline reflects the unprecedented turmoil in financial markets caused by the bankruptcy.

Figure 1 and especially Figure 2 suggest that liquidity co-moves across currencies. Consequently, commonality in FX liquidity will be investigated in the next section.

4. Commonality in Foreign Exchange Liquidity

Testing for commonality in FX liquidity is crucial as the presence of shocks to market-wide liquidity has important implications for investors as well as regulators. Therefore, a time-series of systematic FX liquidity is constructed representing the common component in liquidity across different exchange rates.

4.1. Averaging Liquidity Across Currencies

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. This method of determining aggregate

liquidity has been applied to equity markets by Pástor and Stambaugh (2003). Formally, systematic liquidity based on liquidity measure L is estimated as follows:

$$L_t^M = \frac{1}{N} \sum_{j=1}^{N} L_{j,t}, \tag{10}$$

where N is the number of exchange rates. In order for common liquidity to be less influenced by extreme currency pairs, it is estimated by relying on a trimmed mean. More precisely, the currency pairs with the highest and lowest value for $L_{j,t}$ are excluded in the computation of L_t^M. Systematic FX liquidity based on different measures is depicted in Figure 3. The sign of each measure is adjusted such that the measure represents liquidity rather than illiquidity. Consequently, an increase in the measure is associated with higher liquidity.

[Figure 3 about here.]

Bid-ask spreads, volatility and the trade impact coefficient increase towards the end of the sample, which is in line with the decrease in the reversal measure. All measures uniformly indicate a steep decline in liquidity after September 2008 when the default of Lehman Brothers as well as the rescue of American International Group (AIG) took place. The stabilization of liquidity at the very end of the sample might be related to governments' efforts to support the financial sector, for instance by initiating the Troubled Asset Relief Program (TARP) in the United States.

Compared to Pástor and Stambough'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 caused by the fact that the EBS data set includes more accurate order flow data and that Model (1) is estimated robustly at a higher frequency.

Given the estimate of market-wide FX liquidity, basic empirical evidence for commonality in FX liquidity can be obtained by regressing percentage changes in liquidity of individual exchange rates on changes in systematic liquidity:

$$DL_{j,t} = \alpha_j + \beta_j DL_t^M + \varepsilon_{j,t}, \tag{11}$$

where $DL_{j,t} \equiv (L_{j,t} - L_{j,t-1})/L_{j,t-1}$ is the relative change of liquidity measure L for exchange rate j. Analogously, DL_t^M is defined for relative changes in market liquidity. Similar to Chordia, Roll, and Subrahmanyam (2000), relative changes in liquidity, rather than levels, are investigated as the objective is to highlight co-movement in liquidity. Table 3 shows the regression results.

[Table 3 about here.]

The cross-sectional average of the slope coefficients β_j is positive and significant for all measures. Of the individual β_j's approximately 89% are positive and 78% are positive as well as significant based on the reversal measure while all slopes are positive and significant for the alternative measures. Average adjusted-R^2s are higher than those for daily equity liquidity of Chordia, Roll, and Subrahmanyam (2000). This finding might be explained by the fact that daily noise is averaged out at the monthly horizon. These preliminary results are indicative of strong commonality in FX liquidity. Investigating commonality more rigorously by relying on principle component analysis will be the objective of the next section.

4.2. Latent Liquidity

Instead of averaging, Korajczyk and Sadka (2008) rely on principle component analysis (PCA) to document commonality. To that end, liquidity measure L for each exchange rate is standardized by the time-series mean and standard deviation of the average of measure L obtained from the cross-section of exchange rates. Then, the first three principle components across exchange rates are extracted for each liquidity measure. Finally, for each currency pair, the time-series of liquidity measure L is regressed on the principle components. To assess the level of commonality, the cross-sectional average of the coefficient of determination as well as the adjusted-R^2 are shown in Table 4.

[Table 4 about here.]

Similar to the regressions in the previous section, Table 4 reveals ample evidence of strong commonality. The first principle component explains between 70% and 90% of the variation in monthly FX liquidity depending on which measure is used. As additional support, the (adjusted-) R^2 increases further when two or three principle components are included as explanetory variables. As in the previous section, the reversal measure exhibits the lowest level of commonality. Moreover, the R^2 statistics are still significantly larger than those for equity data computed by Korajczyk and Sadka (2008). To summarize, all empirical results suggest a high level of commonality in FX liquidity. This commonality is stronger than in equity markets when comparing the results of this paper to the studies by Chordia, Roll, and Subrahmanyam (2000), Hasbrouck and Seppi (2001) as well as Korajczyk and Sadka (2008).

Korajczyk and Sadka (2008) take the idea of using PCA to extract common liquidity one step further. Empirical evidence on commonality and visual inspection of Figure 3 show that alternative

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liquidity measures yield qualitatively similar results. Indeed, the correlation between different aggregate liquidity measures is around 0.8 for weekly and 0.9 for monthly data. This high correlation indicates that all measures proxy for the same underlying liquidity factor. Therefore, Korajczyk and Sadka (2008) introduce the idea of latent liquidity, combining the information contained in the various liquidity measures. If each liquidity measure proxies for the same latent liquidity factor, systematic liquidity can be extracted by assuming a latent factor model for the vector of standardized liquidity measures, which can again be estimated using PCA. Given that the first principle component explains the majority of variation in liquidity of individual exchange rates, the first latent factor is used as measure for systematic liquidity. Similar to the simple measures, the sign of the factor is chosen such that it represents liquidity. Figure 4 illustrates latent market-wide FX liquidity over time together with the Chicago Board Options Exchange Volatility Index (VIX) as well as the TED-spread.

[Figure 4 about here.]

The graph of systematic FX liquidity estimated by PCA resembles the one obtained by averaging liquidity of individual exchange rates. Again market-wide FX liquidity decreases after the beginning of the subprime crisis and there is a steep decline in the aftermath of the collapse of Lehman Brothers. This similarity in estimated common liquidity is confirmed by correlations between 0.8 and 0.9 depending on which measure is used when averaging. More remarkable is the relation to the 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 inherent in financial markets, whereas the TED-spread proxies the level of credit risk and funding liquidity in the interbank market. During most of 2007 and 2008, the severe financial crisis is reflected in a TED-spread which is significantly larger than its long-run average of 30–50 basis points.

Interestingly, the VIX as well as the TED-spread are strongly negatively correlated with FX liquidity (approximately −0.8 and −0.7 for latent liquidity) indicating that investors' fear measured by implied volatility of equity options and credit risk has spillover effects to other financial markets as well. The increasing integration of international financial markets might be a reason for this linkage as, for instance, the default of Lehman Brothers led to severe repercussions in all financial markets. To investigate this issue further, the relation between systematic FX liquidity and liquidity of equity markets is investigated in the next section.

4.3. Relation to Liquidity of Equity Markets

Given the high correlation to the VIX, it is promising to investigate commonality in liquidity across different financial markets. To that end, the measures of market-wide FX liquidity presented in the previous subsections are compared to systematic equity liquidity estimated by return reversal as put forward in Pástor and Stambaugh (2003)[8]. Figure 5 shows a comparison of liquidity in FX and equity markets based on a sample of 24 non-overlapping observations.

[Figure 5 about here.]

The results support the notion that liquidity shocks are systematic across markets. Moreover, the correlation between equity and FX liquidity is 0.46 and 0.34 depending on whether the latter is obtained from averaging return reversal or from principle component analysis across different liquidity measures. Similarly, a Spearman's rho of 0.40 and 0.41 indicates co-movement, further substantiating the finding of integrated financial markets.

Having analyzed liquidity of individual exchange rates and illustrated the strong degree of commonality across exchange rates as well as with equity liquidity, the question arises whether systematic liquidity risk is priced in the cross-section. The presence of such a liquidity risk premium in FX markets would further underline the importance of the previous analysis.

5. Liquidity Risk Premiums

5.1. Monthly data

To investigate the role of liquidity in cross-sectional asset pricing, monthly dollar log-returns are constructed from daily spot rates in units of foreign currency per USD. Hence, in contrast to the previous analysis, all returns are based on USD as base currency, which allows for better interpretation of the factors. Additional to FX data, interest rates are necessary to construct risk factors and to analyze liquidity risk premiums as well as excess returns over UIP. Thus, similar to Liu and Maynard (2005) the interest rate differential for the various currencies is computed from LIBOR interest rates, which are obtained from Datastream. LIBOR rates are converted to continuously compounded rates to allow for comparison with monthly FX log-returns, which are computed at the same point in time.

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[8]Current estimates for the equity liquidity factor are obtained from Ľuboš Pástor's website: `http://faculty.chicagobooth.edu/lubos.pastor/research/liq_data_1962_2008.txt`.

Combining these data sets, the variable of interest is the excess return over UIP:

$$r_{j,t+1}^e = i_t^f - i_t^d - \Delta p_{j,t+1}, \tag{12}$$

where i_t^f and i_t^d represent the one-month foreign and domestic LIBOR interest rates at day t, respectively. $r_{j,t+1}^e$ denotes the one month excess return of currency pair j at day t from the perspective of US investors. Alternatively, it can be interpreted as the return from a carry trade in which a US investor who borrows at the domestic and invests in 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. In practice, foreign exchange swaps are often preferred over spot trading to maintain currency portfolio positions due to their minimal trading cost (Gilmore and Hayashi, 2008). Descriptive statistics for exchange rate returns, interest rate differentials as well as excess returns are depicted in Table 5.

[Table 5 about here.]

Panel I shows that the annualized returns of individual exchange rates between January 2007 and December 2008 are very large in absolute value compared to the longer sample of Lustig, Roussanov, and Verdelhan (2009). While prior to the default of Lehman Brothers (Panel II) the difference in magnitude is rather small, extreme average returns of up to 85% per annum occur after the collapse (Panel III). In general, the interest rate differentials are 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 carry trade funding currencies of low interest rate countries (JPY and CHF) have a positive excess return while the excess return is negative for investment currencies which are associated with high interest rates (AUD, NZD). This holds true for the whole sample, but the differences are more substaintial after September 2008. These negative excess returns indicate an increased risk and deteriorated profitability of carry trades.

These significant excess returns over UIP in combination with the large literature on risk-based explanations of this failure warrants further analysis. Therefore, a factor model for excess FX returns including liquidity risk will be presented next.

5.2. Risk Factors for Foreign Exchange Returns

Following the arbitrage pricing theory of Ross (1976), variation in the cross-section of returns is assumed to be caused by different exposure to a small number of risk factors. To estimate a factor

model and to quantify the market prices of risk, potential factors to explain excess exchange rate returns are introduced in this section.

The first two risk factors are similar to the ones introduced by Lustig, Roussanov, and Verdelhan (2009). The "market risk factor" AER_t is constructed as

$$AER_t = \frac{1}{N} \sum_{j=1}^{N} r_{j,t}^e, \qquad (13)$$

and describes the average excess return, i.e. the return for a US investor who goes long in all N exchange rates available in the sample. The second risk factor, HML_t, is the excess return of a portfolio which is long the two exchange rates with the largest interest rate differential and short the two exchange rates with the smallest interest rate differential. Therefore, it can be interpreted as a "slope" or "carry trade risk factor"; see Lustig, Roussanov, and Verdelhan (2009) for further details on the interpretation and construction of these two factors.

Investors might require only a small premium for the absolute level of liquidity of individual exchange rates as cross-sectional differences can be accounted for in portfolio strategies. In contrast, the risk of market-wide shocks to liquidity might command significant risk premiums. Therefore, to obtain a liquidity risk factor, the estimates for systematic liquidity presented above are decomposed into expected changes and unanticipated shocks. Similar to the approaches of Pástor and Stambaugh (2003) as well as Acharya and Pedersen (2005), a "common liquidity shock risk factor" CLS_t^{PCA} is defined to be the residuals from an AR(2) model fitted to latent systematic liquidity. CLS_t^{AVG} is analogously defined when using the average liquidity of individual exchange rates as proxy for aggregate liquidity. Estimating an AR(2) model for the level of systematic liquidity is equivalent to an AR(1) model for ΔL_t^M. Thus, CLS_t captures the unpredicted change of liquidity in month t. Figure 6 depicts the time series of risk factors.

[Figure 6 about here.]

In particular after the collapse of Lehman Brothers, there are negative shocks to aggregate liquidity independent of which measure has been used to proxy for aggregate liquidity. While the two CLS measures differ to some extent in the beginning and middle of the sample, they co-move closely after September 2008. Moreover, the average excess return as well as HML are negative during the latter subperiod. The carry trade risk factor seems to be influenced by liquidity as the two exhibit a rather strong correlation of 0.43 for CLS^{AVG} and 0.51 for CLS^{PCA}. Hence, to separate the influences of general macro risk and liquidity effects, HML is orthogonalized to CLS. To that end, HML_t^O is

defined to be the residuals of the following regression:

$$HML_t = \alpha_0 + \alpha_1 CLS_t + u_t. \tag{14}$$

In particular after the default of Lehman Brothers, the orthogonalized slope factor, HML^O, is not as negative as HML, which can be explained by the fact that liquidity plays an important role in the increased risk after the default of Lehman Brothers. Furthermore, the period of large unexpected shocks to aggregate liquidity coincides with a depreciation of USD against the basket of foreign currencies.

Having described candidate risk factors for explaining excess returns in FX markets, the next section will introduce asset pricing models to assess the relative importance of the factors and to compute their associated market prices of risk.

5.3. Cross-sectional Asset Pricing and Market Prices of Risk

This section investigates whether there exists a return premium for illiquidity. To that end, asset pricing models based on the previously introduced factors will be estimated. As a first step, the model of Lustig, Roussanov, and Verdelhan (2009) is augmented by a liquidity risk factor. Thus, the asset pricing model of interest is:

$$\mathbb{E}\left[r_j^e\right] = \delta_{AER}\beta_{AER,j} + \delta_{HML}\beta_{HML,j} + \delta_{CLS}\beta_{CLS,j}, \tag{15}$$

where $\delta_{AER,t}$, $\delta_{HML,t}$, and $\delta_{CLS,t}$ denote the market prices of risk. Excess returns of individual exchange rates are used as dependent variables. Compared to the more common approach of using portfolios, relying on individual excess returns increases the dispersion around beta estimates, however, the asymptotic standard errors of factor risk premiums will be lower (Ang, Liu, and Schwarz, 2008). The betas can be obtained from a time-series regression of excess returns on the factors:

$$r_{j,t}^e = \beta_{0,j} + \beta_{AER,j}AER_t + \beta_{HML,j}HML_t + \beta_{CLS,j}CLS_t + \varepsilon_{j,t}. \tag{16}$$

It is more convenient to express this expected return-beta factor model in an equivalent stochastic discount factor (SDF) representation (Cochrane, 2005):

$$m_t = 1 - b_{AER}AER_t - b_{HML}HML_t - b_{CLS}CLS_t. \tag{17}$$

The factor loadings in the SDF, $\mathbf{b} = [b_{AER} \quad b_{HML} \quad b_{CLS}]$, and the market prices of risk, $\boldsymbol{\delta} = [\delta_{AER} \quad \delta_{HML} \quad \delta_{CLS}]$, are related by

$$\boldsymbol{\delta} = \mathbb{E}[\mathbf{ff}']\mathbf{b},$$

where $\mathbb{E}[\mathbf{ff}']$ denotes the variance-covariance matrix of the factors. While b_k can be used to test whether factor k helps to price assets given the other factors, a significant δ_k indicates whether factor k is priced in the cross-section.

Under the assumption of absence of arbitrage opportunities, the excess return of currency j satisfies the following pricing equation:

$$\mathbb{E}_t\left[m_{t+1}r^e_{j,t+1}\right] = 0. \tag{18}$$

Consequently, the Generalized Method of Moments (GMM) of Hansen (1982) naturally lends itself as an ideal estimation technique for the parameters in the discount factor framework. Relying on Equation (18) as moment conditions, GMM estimates are found by minimizing the weighted sum of squared pricing errors. Usually, the solution is found in a two-step procedure. In the first step, the weighting matrix, W, is chosen to be the identity matrix, yielding consistent and asymptotically normal first-step GMM estimates as solution to the minimization problem. Asymptotic efficiency with regard to the specified set of moment conditions can be achieved by using the inverse of the long-run variance-covariance matrix of the excess returns in the moment conditions as weighting matrix. Given the estimated parameters from step one, this long-run variance-covarinace matrix is estimated using the Newey–West estimator together with the Bartlett kernel (Newey and West, 1987). It is possible to iterate these two steps until convergence, which has been shown to be more efficient in small samples compared to the two-step GMM estimator (Ferson and Foerster, 1994). However, the increase in efficiency comes at the cost of a potential loss in robustness. Therefore, parameters will also be estimated by one-step GMM ($W = I$) to reveal possible misspecifications. To increase the sample size, overlapping monthly returns are computed for every trading day t. Moving average effects are accounted for by reporting Newey and West (1987) standard errors with 21 lags.

Recalling the differences in descriptive statistics and due to the severe implications of the Lehman Brothers collapse for every financial market, a structural break in September 2008 is expected. Contrary to Bear Stearns, the Federal Reserve and US Treasury did not treat Lehman Brothers as "too big to fail" creating turmoil in financial markets that was unlike anything witnessed before (Melvin and Taylor, 2009). Unfortunately, it is not possible to formally test for such a breakpoint as

there are not enough observations to reliably estimate the model for the subsample after the default of Lehman Brothers for comparison. Nevertheless, the focus of the interpretation lies on the estimation results for the subsample prior to September 13, 2008. Table 6 shows two-stage GMM regression results for alternative specifications of the asset pricing model for this subsample. First-stage GMM results are similar and are therefore omitted for brevity, but are available from the authors upon request.

[Table 6 about here.]

The first column of Table 6 reports estimation results for the benchmark model of Lustig, Roussanov, and Verdelhan (2009). In line with their results, the carry trade risk factor receives a positive premium of 18% per year. However, similar to the market risk factor, the market price of carry trade risk is not significantly different from zero. On the contrary, the positive estimate for the market price is significant for the models including liquidity risk only, which are shown in columns two and three. Both using latent liquidity risk as well as aggregate liquidity risk obtained by averaging lead to significant market prices of liquidity risk. A currency pair with a β_{CLS} of one earns a risk premium of 7% and 13% per year, depending on whether latent or average liquidity is used for constructing common liquidity shocks. Furthermore, the factor loadings in the SDF are positive and significant. Consequently, these basic models suggest an important role of liquidity risk while the general slope factor representing macro risk has difficulties in explaining the variation in excess returns of individual exchange rates.

To support the previous results, columns four to seven of Table 6 show estimation results for asset pricing models including a combination of three factors. The models in columns four and six augment the asset pricing model of Lustig, Roussanov, and Verdelhan (2009) by a liquidity risk factor. Now, the market prices of slope and market risk are of the same magnitude as the ones found by Lustig, Roussanov, and Verdelhan (2009), however, both are not significant. On the other hand, CLS^{AVG} and CLS^{PCA} receive a significant premium of 10% and 27% in models four and six, respectively. Moreover, the SDF factor loadings for liquidity risk are positive and significant as well, whereas they are negative and/or not significant for HML. Furthermore, the fourth model including unexpected shocks to average liquidity yields the smallest pricing errors of all models. Lastly, models five and seven include the orthogonalized versions of the carry trade factor. As HML_t^O is not an excess return, one moment condition is lost for the GMM estimation. Again liquidity risk is priced while the results for HML_t^O contradict each other. Overall, the estimation results are clearly indicative of liquidity risk receiving a significant risk premium of as high as 20% per year. This premium is

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large compared to equity liquidity risk premiums (see for instance Pástor and Stambaugh (2003) and Acharya and Pedersen (2005)), which might be explained by the extraordinary sample period investigated in this paper. Additionally, liquidity risk helps to price assets in the cross-section of excess exchange rate returns.

The presence of strong liquidity risk effects is even more remarkable, because every measure of liquidity will always be an approximation. Thus, the effect of liquidity is in general hard to detect, since errors in variables typically lead to a downward bias in the estimated regression coefficients (Amihud, Mendelson, and Pedersen, 2005). Consequently, finding significant liquidity risk premiums in a crisis period, which is a challenge for every model, underlines the quality of the liquidity measure based on return reversal introduced above. Compared to the results of using latent systematic liquidity extracted from various different measures, the results of utilizing unexpected shocks to average return reversal are qualitatively similar and even lead to smaller pricing errors. Therefore, for the sample at hand it is not necessary to compute various liquidity measures and conduct a PCA, as very similar results are obtained when using solely the reversal measure. Moreover, the latter has the advantage of a clearer interpretation compared to latent liquidity.

Given the the extreme nature of excess returns after the default of Lehman Brothers, none of the models provides a good fit for the whole sample, supporting the hypothesis of a structural break. *J*-statistics reject the null hypothesis of zero pricing errors for all models. GMM estimates are available form the authors upon request. These results are not surprising as risk aversion and volatility rose to incredible levels in the aftermath of the default of Lehman Brothers. Dramatic fear in the market lead to extreme market conditions and an unprecedented deleveraging imposing large losses on firms across the industry.

The next section presents evidence regarding the robustness of the results.

6.   Robustness Analysis

6.1.   Robustness of the Return Reversal Liquidity Measure

To analyze the robustness of the liquidity estimates obtained from the return reversal measure, Model (1) is estimated only using the ten most busy trading hours of the day. Table 7 shows that the return reversal measure as well as the alternative measures indicate marginally higher liquidity, but the differences are of small magnitude.

[Table 7 about here.]

Moreover, the liquidity estimates obtained from the return reversal measure are robust to the choice of sampling frequency. Specifically, Panel I of Table 8 shows that the results are qualitatively similar and all conclusions remain valid when estimating Model (1) based on five minute return and order flow data. For most currencies the return reversal is even more pronounced compared to one minute data.

[Table 8 about here.]

Lastly, Model (1) is estimated using OLS regression. As anticipated, the estimates for return reversal and trading impact are more volatile over time compared to the robust estimates. Panels II and III of Table 8 show that the standard deviations of return reversals obtained using OLS are significantly larger, highlighting the fact that robust estimation leads to fewer extreme values as robust regression is less affected by extreme observations. Consequently, relying on robust regression techniques is preferable.

Having established the robustness of the return reversal liquidity measure, the next section investigates the robustness of commonality in FX liquidity.

6.2. Robustness of Commonality in FX Liquidity

Being derived from liquidity of individual exchange rates, the proxies for market-wide liquidity are robust to the estimation technique and sampling frequency of the individual liquidity measures as well. Figure 7 contrasts the evolution of estimates for systematic liquidity based on different sampling frequencies and estimation techniques.

[Figure 7 about here.]

When using five minute data or OLS estimation, the characteristics of the common liquidity series do not change significantly, thus, estimated market-wide FX liquidity continues to mirror important crisis events. Next, the stability of liquidity risk premiums will be investigated.

6.3. Robustness of Liquidity Risk Premiums

To test the robustness of liquidity risk premiums, the factor models for FX excess returns are re-estimated using different base currencies. As before, Tables 9 and 10 indicate the presence of liquidity risk premiums when using CHF or AUD as base currency. These currencies are of particular interest as they represent funding and investment currencies of carry trades. Thus, the conclusion that liquidity risk receives a significant risk premium is robust to the choice of base currency.

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[Table 9 about here.]

[Table 10 about here.]

As alternative to using overlapping monthly data, the asset pricing analysis is repeated with non-overlapping weekly data. GMM estimation results are shown in Table 11. Due to the fact that there are only 83 observations, first-stage GMM is preferable over two-stage GMM for robustness considerations (Cochrane, 2005). Again, the estimation results are indicative of large FX liquidity risk premiums. However, as had to be expected, the standard errors are large due to the short sample and the noise inherent in weekly return data.

[Table 11 about here.]

As further robustness check secured overnight index swaps (OIS) could be used instead of LIBOR rates for the computation of excess exchange rate returns. During the financial crisis, LIBOR rates tended to be larger than OIS rates due to embedded risk premiums. However, the magnitude of interest rates compared to FX returns is very small, in particular after the default of Lehman Brothers where differences between OIS and LIBOR are most pronounced. Consequently, the choice of interest rate does not qualitatively affect the finding of a significant liquidity risk premium.

7. Conclusion

In this paper, a return reversal liquidity measure for foreign exchange markets based on ultra-high frequency data has been developed. Using a large and comprehensive data set representing the interdealer FX spot market from January 2007 to December 2008, an empirical analysis of nine exchange rates illustrates that the reversal measure is in line with market participants perception of liquidity and mirrors important events during the financial crisis 2007–?. After developing measures for market-wide FX liquidity, it has been shown that liquidity of exchange rates exhibit a high degree of commonality. An extended factor model indicates that liquidity plays an important role in explaining the cross-sectional variation of excess currency returns. These results have several important implications. First of all, the results allow central banks to better assess the effectiveness of their policy by enabling them to monitor liquidity on a daily basis. Second, stressing the important role of liquidity helps carry traders to more adequately understand the risk of their investment, which is crucial in light of the potential losses from currency crashes coinciding with liquidity spirals.

For future research, it is interesting to investigate FX liquidity over an extended sample which also includes non-crisis periods. Moreover, the large and high-frequency data set allows for a detailed analysis of intraday patterns in FX returns and liquidity, in particular in conjunction with investigating the impact of news announcements.

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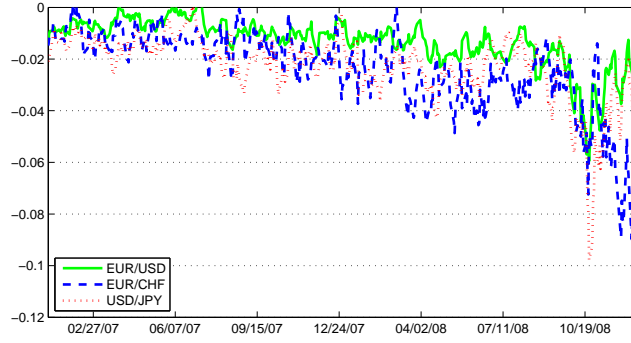
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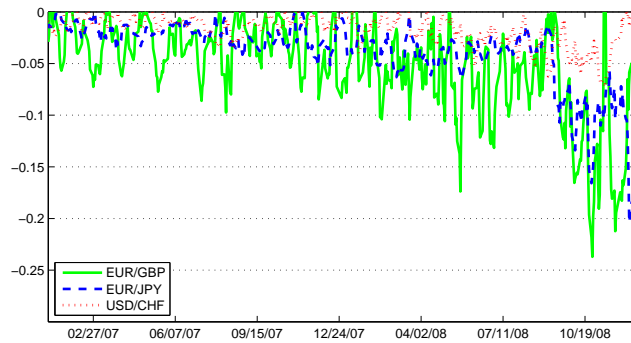
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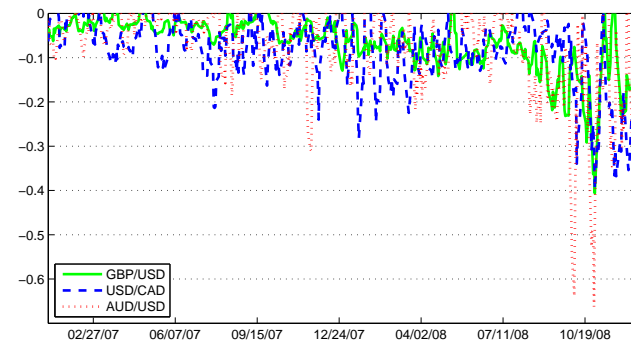
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Figure 1: Weekly liquidity estimates measured by return reversal using robust regression. A stronger (more negative) reversal indicates low liquidity as the temporary price change accompanying order flow is large: Panel (a) depicts liquidity over time for the most liquid exchange rates (EUR/USD, EUR/CHF, USD/JPY); Panel (b) shows return reversal for intermediate currency pairs (EUR/GBP, EUR/JPY, USD/CHF), whereas the time series of liquidity estimates for the most illiquid currencies (GBP/USD, USD/CAD, AUD/USD) are plotted in Panel (c). Each observation t represents estimated liquidity for the week following trading day t. The sample is January 3, 2007 – December 22, 2008 (487 observations).
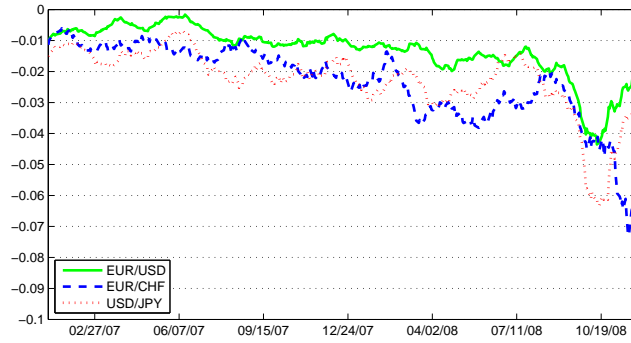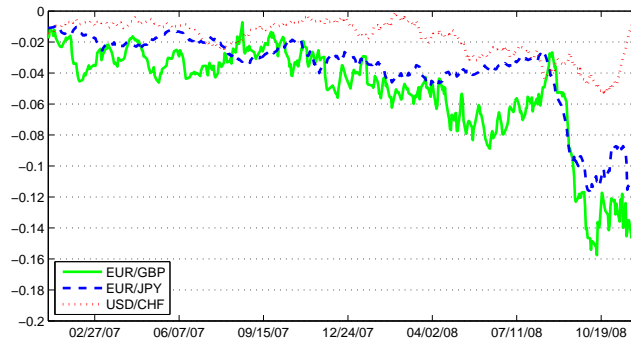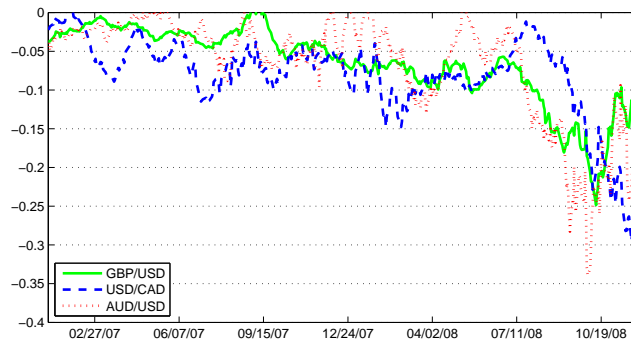
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Figure 2: Monthly liquidity estimates measured by return reversal using robust regression. A stronger (more negative) reversal indicates low liquidity as the temporary price change accompanying order flow is large: Panel (a) depicts liquidity over time for the most liquid exchange rates (EUR/USD, EUR/CHF, USD/JPY); Panel (b) shows return reversal for intermediate currency pairs (EUR/GBP, EUR/JPY, USD/CHF), whereas the time series of liquidity estimates for the most illiquid currencies (GBP/USD, USD/CAD, AUD/USD) are plotted in Panel (c). Each observation t represents estimated liquidity for the month following trading day t. The sample is January 3, 2007 – December 1, 2008 (472 observations).

(a)

(b)

Figure 3: Systematic liquidity based on averaging different measures (within measures). The sign of each measure is adjusted such that the measure represents liquidity rather than illiquidity. Every trading day t, overlapping weekly as well as monthly estimates of aggregate liquidity are constructed by computing the trimmed mean of liquidity measure l in the cross-section of exchange rates. In Panel (a) each observation t represents estimated liquidity for the week following trading day t. The sample is J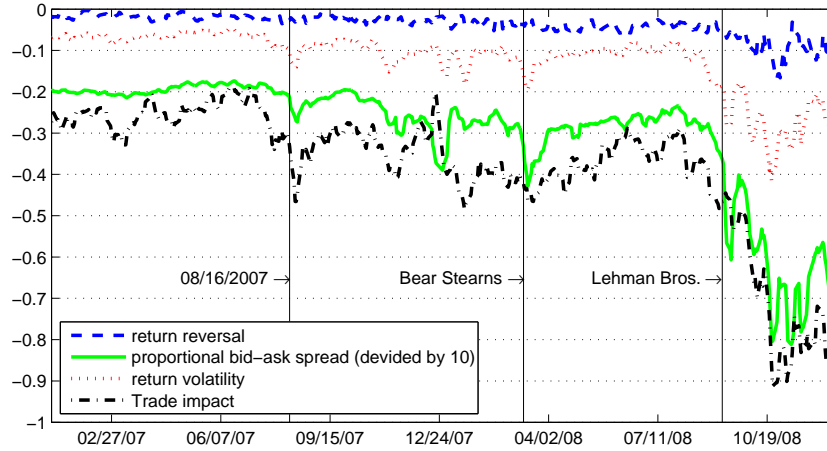anuary 3, 2007 – December 22, 2008 (487 observations). Panel 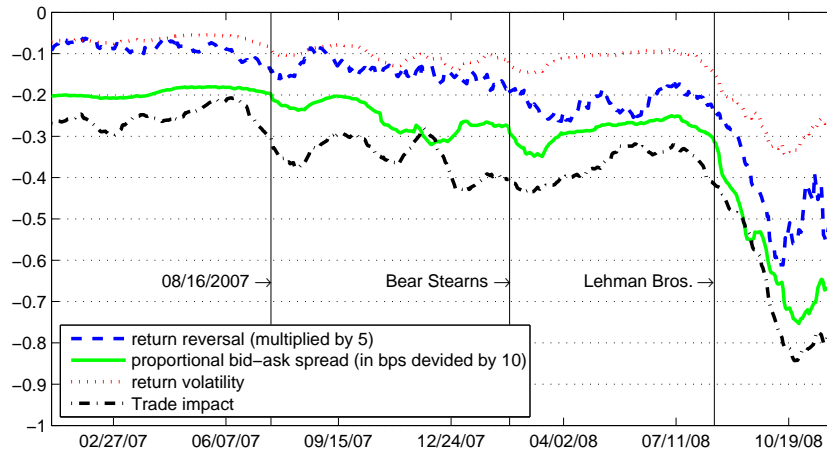(b) shows monthly systematic liquidity estimates. Each observation t represents estimated systematic liquidity for the month following trading day t. The sample is January 3, 2007 – December 1, 2008 (472 observations).

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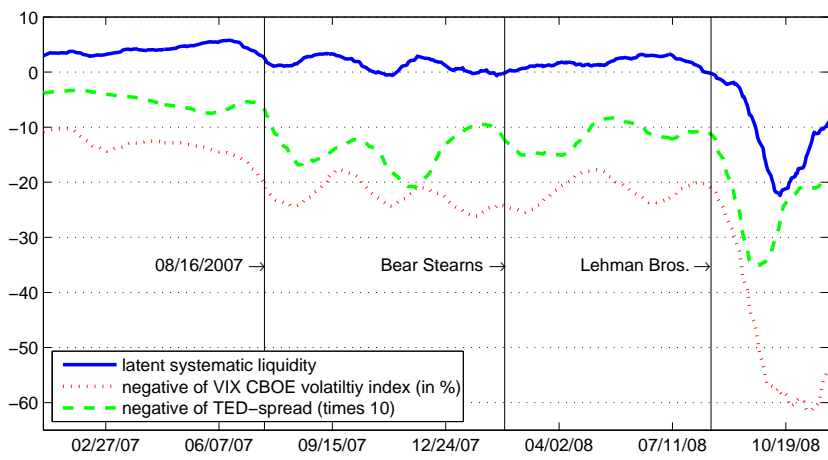
Figure 4: Latent systematic liquidity based on principle component analysis (across measures). The liquidity measure L for each exchange rate is standardized by the time-series mean and standard deviation of the average of liquidity measure L obtained from the cross-section of exchange rates. Assuming a latent factor model for the vector of standardized liquidity measures, systematic liquidity is extracted as the first principle component. The sign of the latent liquidity factor is adjusted such that the measure represents liquidity rather than illiquidity. Each observation t represents estimated systematic liquidity for the month following trading day t. Furthermore, overlapping monthly averages of the negative of the Chicago Board Options Exchange Volatility Index (VIX) as well as the TED-spread are plotted for comparison. The sample is January 3, 2007 – December 1, 2008 (472 observations).
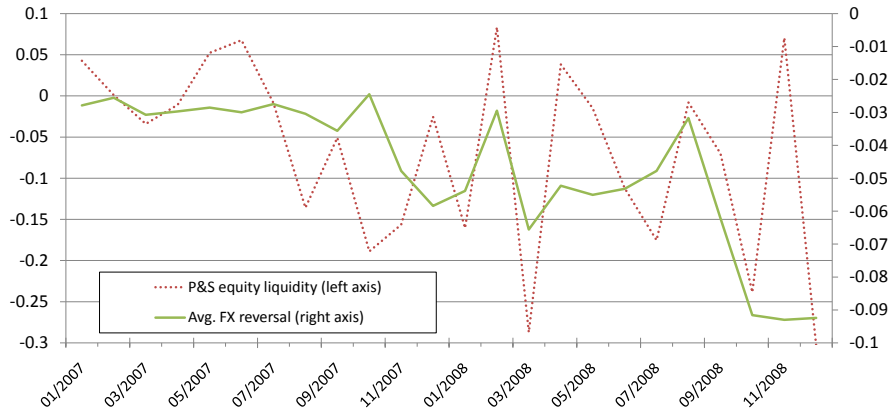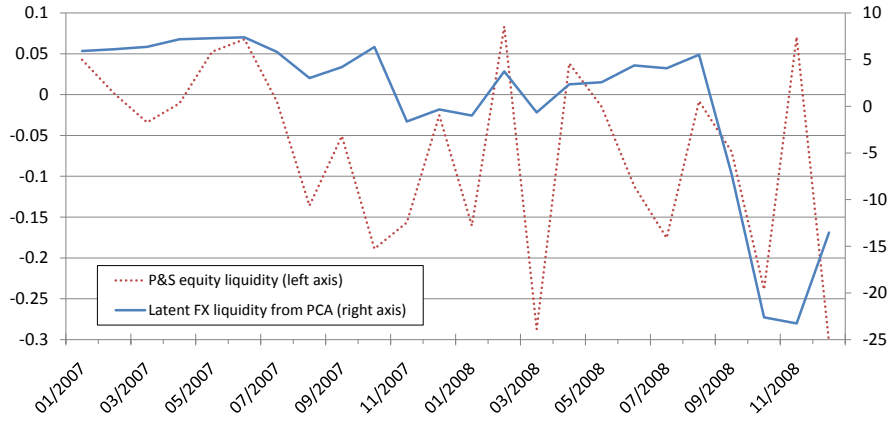
Figure 5: Comparison of non-overlapping monthly liquidity estimates for equity markets (measured by the return reversal measure of Pástor and Stambaugh (2003)) and systematic FX liquidity. Panel (a) shows the average FX return reversal obtained from Model (1), whereas latent FX liquidity obtained from PCA across different liquidity measures is plotted in Panel (b). Each observation t represents estimated liquidity for a given month. The sample is January 2007 – December 2008 (24 observations).
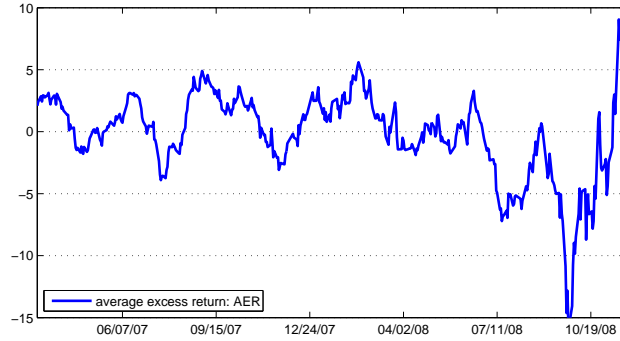
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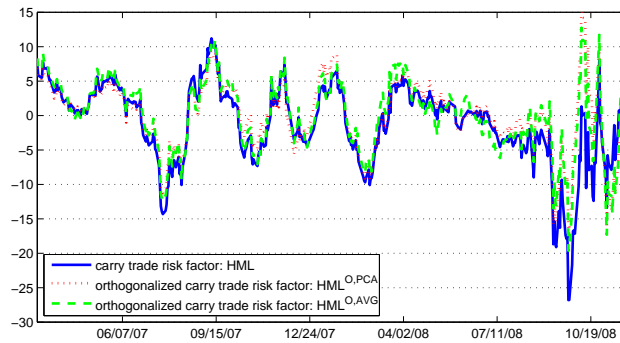
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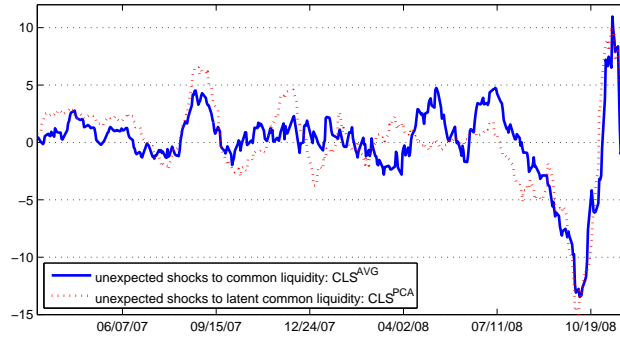
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Figure 6: Time series of risk factors: Panel (a) depicts the market risk factor *AER* which is constructed as the average excess return from investing in an equally weighted portfolio of foreign currencies from the perspective of a US investor. In Panel (b) slope or carry trade factors are shown. The solid line is the excess return of a portfolio which is long the two exchange rates with largest interest rate differential and short the two exchange rates with the smallest interest rate differential. The dotted and dashed lines represent the same factor which has been orthogonalized to unexpected liquidity risk constructed from PCA and averaging, respectively. These liquidity risk factors are shown in Panel (c). Unexpected shocks are obtained by fitting an AR(2) model to the measures of systematic FX liquidity and using the residuals as risk factor. The sample contains 427 observations and ranges from March 8, 2007 to November 26, 2008.
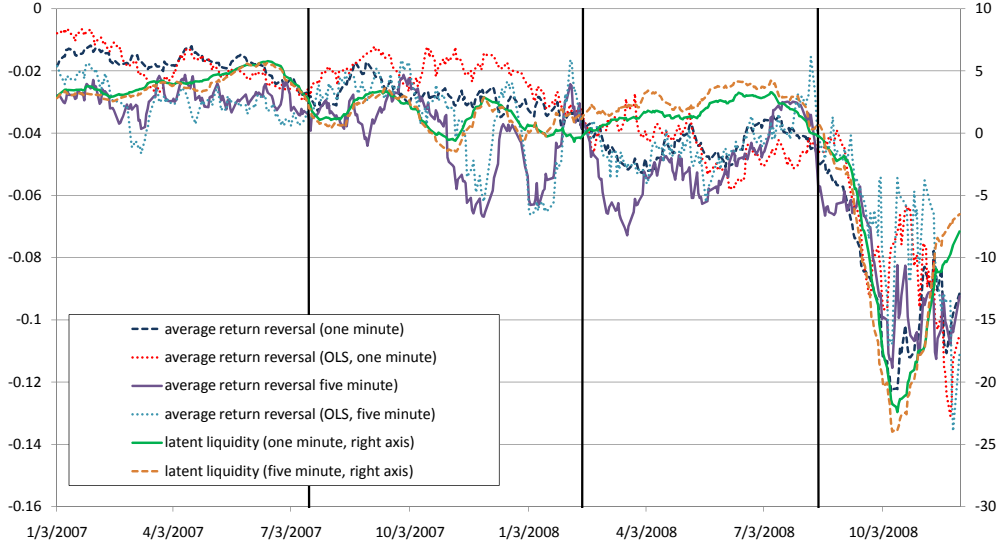
Figure 7: Systematic liquidity based on averaging different measures (within measures) as well as latent liquidity obtained from PCA for different sampling frequencies and estimation techniques. The sign of each measure is adjusted such that the measure represents liquidity rather than illiquidity. Every trading day t, overlapping monthly estimates of aggregate liquidity are constructed by computing the trimmed mean of return reversal in the cross-section of exchange rates.

In order to estimate latent systematic liquidity, liquidity measure L for each exchange rate is standardized by the time-series mean and standard deviation of the average of liquidity measure L obtained from the cross-section of exchange rates. Assuming a latent factor model for the vector of standardized liquidity measures, systematic liquidity is extracted as the first principle component.

The different series correspond to different intra-day sampling frequencies (one-minute and five-minute data) to compute the liquidity measures, as well as different estimation techniques (OLS and robust regression) used to estimate Model (1). Each observation t represents estimated systematic liquidity for the month following trading day t. The sample is January 3, 2007 – December 1, 2008 (472 observations).

Table 1: Definition of daily liquidity measures

Liquidity measures	Definition	Units
Return reversal	γ_t	basis points, per minute
Quoted bid-ask spreads	$S = (P^A - P^B)/P^M$	basis points
Effective cost	$E = \begin{cases} (P - P^M)/P^M & \text{for buy orders} \\ (P^M - P)/P^M & \text{for sell orders} \end{cases}$	basis points
Return volatility	Two-scale realized volatility	percentage, annualized
Trade impact coefficient	ρ_t	basis points, per minute

Notes: This table shows the definition and unit of measurement of the various liquidity measures. P denotes the transaction price, whereas the superscripts A, B and M indicate the ask, bid and mid quote, respectively. Trade impact and the reversal measure are the coefficients of contemporaneous and lagged order flow in a regression of one minute returns on these explanatory variables, which is conducted for for every trading day t in the sample.

Table 2: Daily FX data and liquidity measures

		AUD/USD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	USD/CAD	USD/CHF	USD/JPY
		Panel I: Descriptive statistics of daily exchange rate data (488 observations)								
return (in bps)	*mean*	−2.62	0.07	5.33	−3.19	0.52	−5.05	−0.69	−1.36	−3.94
order flow	*mean*	−10.56	−5.69	−4.13	−29.53	31.19	−4.60	−12.12	35.78	52.45
trades	*mean*	290	4182	491	7573	18911	852	310	6158	15415
		Panel II: Daily liquidity estimates (488 observations)								
return reversal	*mean*	−0.068	−0.024	−0.051	−0.038	−0.014	−0.067	−0.083	−0.017	−0.023
(in bps)	*median*	−0.045	−0.020	−0.043	−0.030	−0.012	−0.051	−0.070	−0.014	−0.021
	std	0.234	0.023	0.078	0.040	0.012	0.094	0.139	0.026	0.017
bid-ask spread	*mean*	5.14	2.20	3.50	2.23	1.09	4.38	5.65	2.60	1.56
(in bps)	*median*	3.86	1.80	3.13	1.87	0.96	2.82	4.71	2.21	1.43
	std	3.60	1.35	1.31	1.08	0.33	4.67	3.27	1.29	0.53
effective cost	*mean*	1.02	0.40	0.67	0.52	0.46	0.79	0.97	0.57	0.59
(in bps)	*median*	0.65	0.37	0.58	0.44	0.43	0.53	0.77	0.54	0.55
	std	1.25	0.16	0.41	0.29	0.11	0.82	0.76	0.15	0.19
volatility (in %,	*mean*	16.38	6.80	9.65	14.25	9.62	16.92	15.23	11.31	12.58
annualized)	*median*	10.65	5.38	7.28	10.38	7.58	8.79	11.58	9.64	10.88
	std	16.25	4.77	8.52	10.93	5.78	26.82	18.53	5.96	7.19
trade impact	*mean*	1.120	0.178	0.470	0.360	0.149	0.489	0.674	0.286	0.226
	median	0.854	0.155	0.391	0.297	0.123	0.391	0.600	0.260	0.202
	std	0.961	0.083	0.252	0.223	0.079	0.311	0.331	0.098	0.101

Notes: Panel I shows mean return (measured in basis points), order flow and number of trades per day for various exchange rates. Order flow is determined from volume indicators in the EBS data set.

Summary statistics for various daily measures of liquidity are depicted in Panel II. Return reversal is the robustly estimated coefficient of lagged order flow in a regression of one minute returns on contemporaneous and lagged order flow. 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. Volatility for each trading day is estimated using TSRV. It is expressed in percentages on an annual basis. Trade impact is the coefficient of contemporaneous order flow in the same regression as the one used to obtain return reversal. The sample, which starts on January 3, 2007 and ends on December 30, 2008, contains 488 observations.

Table 3: Basic evidence for commonality

liquidity measure	β	% positive	% + significant	Adjusted-R^2
return reversal	0.96	88.9%	77.8%	0.44
	(0.31)			
bid-ask spread	0.85	100.0%	100.0%	0.67
	(0.03)			
effective cost	1.03	100.0%	100.0%	0.68
	(0.03)			
return volatility	0.91	100.0%	100.0%	0.67
	(0.03)			
trade impact	1.15	100.0%	100.0%	0.68
	(0.03)			

Notes: This table shows the results of regressing the time-series of relative changes in individual exchange rate liquidity on relative changes in systematic liquidity. The first column reports the cross-sectional average of slope coefficients with standard errors in parenthesis. The second and third column give the percentages of estimates which are positive (column two) as well as positive and significantly different from zero (column three). The last column shows the adjusted-R^2.

Table 4: Commonality using within measure common factors

Measure	Statistic	Factor 1	Factors 1,2	Factors 1,2,3
return reversal	R^2	0.7011	0.7745	0.8275
	Adjusted-R^2	0.7004	0.7734	0.8263
bid-ask spread	R^2	0.9025	0.9431	0.9599
	Adjusted-R^2	0.9023	0.9428	0.9597
effective cost	R^2	0.8468	0.8885	0.9019
	Adjusted-R^2	0.8465	0.8879	0.9012
return volatility	R^2	0.8482	0.8819	0.9096
	Adjusted-R^2	0.8478	0.8813	0.9089
trade impact	R^2	0.7896	0.8494	0.9656
	Adjusted-R^2	0.7891	0.8487	0.9654

Notes: For each 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. The table shows the average R^2 and the mean adjusted-R^2 of these regressions using one, two and three factors.

Table 5: Descriptive statistics for monthly data

Currency	JPY	CHD	CAD	EUR	SEK	DKK	GBP	AUD	NZD
	Panel I: Whole sample (427 observations)								
	FX return: $\Delta p_{j,t+1}$								
Mean	−13.63	−2.80	2.76	−1.04	7.32	−0.87	12.89	11.71	14.87
Std	11.99	12.63	14.93	13.52	15.19	13.42	13.21	20.99	18.35
	Interest rate differential: $i_t^f - i_t^d$								
Mean	−3.23	−1.56	0.03	0.33	0.36	0.66	1.72	2.92	4.42
Std	0.38	0.35	0.22	0.41	0.51	0.46	0.31	0.48	0.40
	Excess return: $r_{j,t+1}^e$								
Mean	10.39	1.24	−2.73	1.37	−6.97	1.53	−11.17	−8.79	−10.45
Std	12.02	12.57	14.87	13.44	15.02	13.37	13.11	20.83	18.19
	Panel II: Prior to default of Lehman Brothers (350 observations)								
	FX return: $\Delta p_{j,t+1}$								
Mean	−4.53	−7.07	−7.33	−7.36	−6.64	−7.08	0.83	−4.51	1.83
Std	10.73	11.37	10.50	9.30	10.52	9.29	8.47	14.48	15.25
	Interest rate differential: $i_t^f - i_t^d$								
Mean	−3.51	−1.77	−0.07	0.03	−0.03	0.26	1.55	2.66	4.20
Std	0.36	0.36	0.21	0.39	0.49	0.40	0.31	0.49	0.41
	Excess return: $r_{j,t+1}^e$								
Mean	1.03	5.31	7.25	7.38	6.62	7.34	0.72	7.17	2.37
Std	10.65	11.32	10.41	9.20	10.42	9.18	8.38	14.35	15.11
	Panel III: After default of Lehman Brothers (77 observations)								
	FX return: $\Delta p_{j,t+1}$								
Mean	−54.96	16.64	48.64	27.65	70.82	27.34	67.74	85.46	74.11
Std	10.08	16.17	22.96	23.30	19.21	23.05	18.40	30.77	21.39
	Interest rate differential: $i_t^f - i_t^d$								
Mean	−1.98	−0.61	0.50	1.68	2.10	2.48	2.49	4.10	5.40
Std	0.25	0.12	0.18	0.16	0.18	0.30	0.14	0.17	0.14
	Excess return: $r_{j,t+1}^e$								
Mean	52.98	−17.26	−48.14	−25.97	−68.72	−24.85	−65.24	−81.36	−68.71
Std	10.11	16.20	23.01	23.39	19.33	23.31	18.45	30.73	21.37

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 monthly excess log-returns over UIP are shown.

Panel I gives results for the whole sample which contains 427 observations and ranges from March 8, 2007 to November 26, 2008. Summary statistics for two subsamples prior to and after the default of Lehman Brothers are reported in Panels II and III, respectively.

Table 6: Two-stage GMM estimation results prior to default of Lehman Brothers, USD as base currency (March 8, 2007 – September 13, 2008)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
δ_{AER}	11.43			4.47	8.66	4.34	4.30
	(7.26)			(5.90)	(5.90)	(11.36)	(8.08)
δ_{HML}	18.70			5.64		7.48	
	(13.08)			(18.93)		(35.93)	
δ_{HML^O}					4.69		−24.47
					(11.56)		(10.06)
δ_{CLS}		6.98		10.03	2.92		
		(1.25)		(3.03)	(0.54)		
$\delta_{CLS_{latent}}$			13.16			27.13	20.35
			(3.35)			(17.77)	(7.85)
b_{AER}	0.13			0.13	0.13	−0.03	0.00
	(0.05)			(0.06)	(0.06)	(0.06)	(0.07)
b_{HML}	0.05			−0.07		−0.16	
	(0.04)			(0.05)		(0.07)	
b_{HML^O}					0.00		−0.14
					(0.04)		(0.05)
b_{CLS}		1.37		2.11	0.60		
		(0.25)		(0.53)	(0.12)		
$b_{CLS_{latent}}$			0.26			0.75	0.40
			(0.07)			(0.24)	(0.13)
J-stat	0.0467	0.0359	0.0444	0.0272	0.0427	0.0349	0.0343
p-value	6.03%	24.91%	11.35%	29.98%	3.65%	14.14%	15.08%

Notes: This table reports two-stage GMM estimation results for the sample prior to the default of Lehman Brothers (March 8, 2007 – September 13, 2008) for various asset pricing models. The estimates corresponding to risk factors of seven different models are shown. Annualized excess returns of individual currencies are used as test assets for the moment conditions. The upper part of the table shows the market prices of risk while the lower part reports SDF factor loadings. Newey–West standard errors with 21 lags, accounting for overlapping observations are shown in parenthesis. USD is the base currency.

Table 7: Daily liquidity measures based on most busy trading hours

		EUR/CHF	EUR/JPY	EUR/USD	USD/CHF	USD/JPY
busy hours (GMT)		8am–5pm	1am–5pm	8am–8pm	8am–8pm	1am–8pm
return reversal	*mean*	-0.024	-0.037	-0.014	-0.017	-0.023
(in bps)	*median*	-0.020	-0.029	-0.011	-0.014	-0.021
	std	0.023	0.037	0.013	0.029	0.018
bid-ask spread	*mean*	2.16	2.21	1.08	2.56	1.55
(in bps)	*median*	1.80	1.86	0.96	2.20	1.43
	std	1.30	1.07	0.32	1.21	0.52
effective cost	*mean*	0.40	0.51	0.46	0.56	0.58
(in bps)	*median*	0.37	0.44	0.42	0.54	0.54
	std	0.15	0.29	0.10	0.14	0.19
volatility (in %,	*mean*	6.69	14.09	9.44	11.10	12.46
annualized)	*median*	5.34	10.33	7.55	9.59	10.74
	std	4.69	10.85	5.53	5.57	7.15
trade impact	*mean*	0.177	0.347	0.141	0.282	0.224
(in bps)	*median*	0.156	0.285	0.120	0.259	0.202
	std	0.080	0.204	0.071	0.090	0.099

Notes: This table shows summary statistics for various daily measures of liquidity, which are computed based on the most busy trading hours only. Return reversal is the robustly estimated coefficient of lagged order flow in a regression of one minute returns on contemporaneous and lagged order flow. Bid-ask spread denotes the average proportional bid-ask 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. Volatility for each trading day is estimated using TSRV. It is expressed in percent on an annual basis. Trade impact is the coefficient of contemporaneous order flow in the same regression as the one used to obtain return reversal. The sample, which starts on January 3, 2007 and ends on December 30, 2008, contains 488 observations.

Table 8: Daily FX liquidity measures based on five minute data and OLS regressions

		AUD/USD	EUR/CHF	EUR/GBP	EUR/JPY	EUR/USD	GBP/USD	USD/CAD	USD/CHF	USD/JPY
Panel I: Daily liquidity estimates based on five minute data (488 observations)										
return reversal	mean	-0.106	-0.034	-0.056	-0.050	-0.014	-0.062	-0.124	-0.021	-0.025
(in bps)	median	-0.079	-0.030	-0.049	-0.041	-0.012	-0.047	-0.103	-0.019	-0.022
	std	0.421	0.035	0.138	0.056	0.017	0.131	0.281	0.053	0.026
trade impact	mean	1.072	0.186	0.454	0.366	0.142	0.426	0.788	0.261	0.213
(in bps)	median	0.776	0.156	0.400	0.291	0.117	0.353	0.709	0.238	0.193
	std	1.072	0.096	0.272	0.222	0.069	0.308	0.440	0.098	0.091
Panel II: Daily liquidity estimates based on one minute data using OLS estimation (488 observations)										
return reversal	mean	-0.080	-0.027	-0.048	-0.035	-0.011	-0.060	-0.063	-0.011	-0.022
(in bps)	median	-0.052	-0.022	-0.040	-0.027	-0.009	-0.044	-0.057	-0.011	-0.020
	std	0.359	0.030	0.109	0.042	0.013	0.153	0.259	0.034	0.020
trade impact	mean	1.136	0.203	0.497	0.381	0.161	0.505	0.864	0.307	0.240
(in bps)	median	0.860	0.177	0.432	0.311	0.136	0.413	0.812	0.281	0.215
	std	1.012	0.096	0.260	0.234	0.080	0.338	0.395	0.101	0.107
Panel III: Daily liquidity estimates based on five minute data using OLS estimation (488 observations)										
return reversal	mean	-0.105	-0.036	-0.039	-0.044	-0.010	-0.054	-0.137	-0.015	-0.024
(in bps)	median	-0.071	-0.033	-0.035	-0.036	-0.010	-0.044	-0.115	-0.013	-0.023
	std	0.548	0.040	0.174	0.059	0.020	0.189	0.349	0.059	0.028
trade impact	mean	1.003	0.191	0.446	0.370	0.145	0.399	0.866	0.265	0.221
(in bps)	median	0.741	0.163	0.395	0.300	0.126	0.332	0.775	0.250	0.198
	std	1.189	0.097	0.290	0.225	0.065	0.307	0.545	0.099	0.098

Notes: In Panel I, return reversal is the robustly estimated coefficient of lagged order flow in a regression of five minute returns on contemporaneous and lagged order flow, whereas trade impact is the coefficient of contemporaneous order flow. Panels II and III show the coefficients of similar regression models estimated by OLS based on one minute (Panel II) and five minute (Panel III) return and order flow data, respectively.

The sample, which starts on January 3, 2007 and ends on December 30, 2008, contains 488 observations.

Table 9: Two-stage GMM estimation results prior to default of Lehman Brothers, CHF as base currency (March 8, 2007 – September 13, 2008)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
δ_{AER}	3.40			−19.62	−18.02	−9.92	−4.82
	(11.69)			(10.82)	(12.05)	(13.21)	(12.79)
δ_{HML}	5.08			−21.71		−9.91	
	(29.87)			(29.62)		(33.17)	
δ_{HML^O}					−31.93		−8.82
					(33.50)		(24.14)
δ_{CLS}		6.70		10.65	12.41		
		(2.33)		(3.57)	(3.29)		
$\delta_{CLS_{latent}}$			14.72			11.33	19.28
			(4.05)			(13.04)	(8.54)
b_{AER}	0.04			−0.17	−0.16	−0.17	−0.16
	(0.01)			(0.11)	(0.11)	(0.11)	(0.11)
b_{HML}	0.01			−0.13		−0.13	
	(0.10)			(0.08)		(0.08)	
b_{HML^O}					−0.10		−0.03
					(0.12)		(0.13)
b_{CLS}		1.32		2.28	2.41		
		(0.46)		(0.60)	(0.67)		
$b_{CLS_{latent}}$			0.29			0.44	0.43
			(0.08)			(0.11)	(0.13)
J-stat	0.0431	0.0408	0.0439	0.0246	0.0353	0.0435	0.0399
p-value	8.90%	11.29%	8.11%	37.56%	8.96%	5.50%	5.21%

Notes: This table reports two-stage GMM estimation results for the sample prior to the default of Lehman Brothers (March 8, 2007 – September 13, 2008) for various asset pricing models. The estimates corresponding to risk factors of seven different models are shown. Annualized excess returns of individual currencies are used as test assets for the moment conditions. The upper part of the table shows the market prices of risk while the lower part reports SDF factor loadings. Newey–West standard errors with 21 lags, accounting for overlapping observations are shown in parenthesis. CHF is the base currency.

Table 10: Two-stage GMM estimation results prior to default of Lehman Brothers, AUD as base currency (March 8, 2007 – September 13, 2008)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
δ_{AER}	−16.78			−19.39	−21.20	2.64	−11.95
	(9.91)			(7.85)	(6.18)	(13.87)	(10.38)
δ_{HML}	−21.44			−33.50		−3.98	
	(24.58)			(26.62)		(41.72)	
δ_{HML^O}					−54.61		−37.90
					(18.27)		(15.01)
δ_{CLS}		6.58		7.83	7.38		
		(1.21)		(2.88)	(2.42)		
$\delta_{CLS_{latent}}$			13.93			19.88	8.81
			(3.15)			(17.84)	(8.64)
b_{AER}	−0.20			−0.15	−0.16	−0.01	−0.17
	(−0.05)			(0.07)	(0.05)	(0.09)	(0.09)
b_{HML}	−0.05			−0.16		−0.17	
	(0.08)			(0.08)		(0.10)	
b_{HML^O}					−0.20		−0.20
					(0.07)		(0.08)
b_{CLS}		1.30		1.78	1.42		
		(0.24)		(0.46)	(0.49)		
$b_{CLS_{latent}}$			0.27			0.62	0.23
			(0.06)			(0.19)	(0.14)
J-stat	0.0448	0.0349	0.0446	0.0250	0.0318	0.0377	0.0314
p-value	7.38%	20.13%	7.52%	36.37%	13.28%	10.50%	13.86%

Notes: This table reports two-stage GMM estimation results for the sample prior to the default of Lehman Brothers (March 8, 2007 – September 13, 2008) for various asset pricing models. The estimates corresponding to risk factors of seven different models are shown. Annualized excess returns of individual currencies are used as test assets for the moment conditions. The upper part of the table shows the market prices of risk while the lower part reports SDF factor loadings. Newey–West standard errors with 21 lags, accounting for overlapping observations are shown in parenthesis. AUD is the base currency.

Table 11: One-stage GMM estimation results for weekly data prior to default of Lehman Brothers, USD as base currency (January 18, 2007 – September 13, 2008)

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
δ_{AER}	5.64			1.16	5.15	5.81	5.83
	(7.26)			(1.82)	(7.51)	(8.74)	(8.97)
δ_{HML}	7.38			1.42		6.98	
	(15.95)			(4.13)		(32.30)	
$\delta_{HML^{\perp}}$					4.00		-3.45
					(17.72)		(27.46)
δ_{CLS}		36.84		67.69	55.05		
		(26.41)		(23.39)	(31.06)		
$\delta_{CLS_{latent}}$			11.21			52.45	54.69
			(13.00)			(73.07)	(69.95)
b_{AER}	0.10			0.09	0.11	0.12	0.15
	(0.02)			(0.12)	(0.12)	(0.12)	(0.12)
b_{HML}	0.02			0.07		-0.02	
	(0.06)			(0.08)		(0.08)	
$b_{HML^{\perp}}$					0.03		-0.06
					(0.08)		(0.09)
b_{CLS}		0.25		0.47	0.38		
		(0.18)		(0.18)	(0.22)		
$b_{CLS_{latent}}$			0.08			0.09	0.10
			(0.10)			(0.11)	(0.11)
J-stat	0.9996	0.8714	0.9410	0.5735	0.0815	0.9264	0.0786
p-value	0.00%	0.00%	0.00%	0.00%	45.37%	0.00%	47.97%

Notes: This table reports one-stage GMM estimation results for weekly data (non-overlapping) prior to the default of Lehman Brothers (January 18, 2007 – September 13, 2008) for various asset pricing models. The estimates corresponding to risk factors of seven different models are shown. Annualized excess returns of individual currencies are used as test assets for the moment conditions. The upper part of the table shows the market prices of risk while the lower part reports SDF factor loadings. USD is the base currency.