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Global Liquidity Risk in the Foreign Exchange Market

Chiara Banti, Kate Phylaktis, and Lucio Sarno*

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Abstract

Using a broad data set of 20 US dollar exchange rates and order flow of institutional investors over 14 years, we construct a measure of global liquidity risk in the foreign exchange (FX) market. Our FX liquidity measure may be seen as the analogue of the well-known Pastor-Stambaugh liquidity measure for the US stock market. We show that this measure has reasonable properties, and that there is a strong common component in liquidity across currencies. Finally, we provide evidence that liquidity risk is priced in the cross-section of currency returns, and estimate the liquidity risk premium in the FX market around 4.7 percent per annum.

Keywords: foreign exchange; liquidity; order flow; microstructure.

JEL Classification: F31; F37; G12; G15.

*Banti, Chiara.Banti.1@cass.city.ac.uk, Cass Business School, City University, 106 Bunhill Row, London, EC1Y 8TZ, UK; Phylaktis, K.Phylaktis@city.ac.uk, Cass Business School, City University, 106 Bunhill Row, London, EC1Y 8TZ, UK, +44 (0)20 7040 8735; and Sarno, Lucio.Sarno@city.ac.uk, Cass Business School, City University, 106 Bunhill Row, London, EC1Y 8TZ, UK, +44 (0) 20 7040 8772, and Centre for Economic Policy Research (CEPR), London.

1 INTRODUCTION

The foreign exchange (FX) market is considered to be highly liquid. In terms of turnover, the average daily market activity in April 2010 was \$3.98 trillion (BIS, 2010). However, there are large differences across currencies: 66 percent of the FX market average daily turnover in April 2010 involves the six most traded pairs of currencies. In addition to the different liquidity levels in the cross section of currencies, liquidity also changes over time both intraday and across days (e.g. Bessembinder, 1994; Bollerslev and Melvin, 1994; Lee, 1994; Hsieh and Kleidon, 1996). In this paper, we shed light on several aspects of liquidity in the FX market and on the premium required by investors for holding less liquid currencies.

Using a unique data set comprising daily order flow for 20 exchange rates spanning 14 years, we build a measure of liquidity inspired by the Pastor and Stambaugh (2003) measure, which was originally developed for the US stock market. Analyzing the properties of the individual currency liquidity measures, we find that they are highly correlated, suggesting the presence of a common component across them. The presence of a common component is consistent with the notion that liquidity is largely driven by shocks that affect the FX market as a whole rather than individual currencies. We then construct a measure of innovations in global FX liquidity (unexpected liquidity) and show that it explains a sizeable share of liquidity fluctuations in individual currencies.

In the stock market literature, several papers find significant co-movement of liquidity cross-sectionally (e.g. Datar, Naif and Radcliffe, 1998; Chordia, Roll and Subrahmanyam, 2000, 2001; Hasbrouck and Seppi, 2001; Huberman and Halka, 2001; Lesmond, 2005). In contrast, the FX market has received much less attention. The presence of such co-movement in the FX market during the recent crisis period is documented in Melvin and Taylor (2009) and Mancini, Ranaldo and Wrampelmeyer (2011). However, to our knowledge, this is the first paper to study global FX liquidity covering a long sample period which includes both crisis and non-crisis periods and drawing on the behavior of both developed and emerging market currencies, where liquidity considerations are likely to be more prominent.

Next, taking the perspective of a US investor, we ask whether unexpected changes (innovations) in FX market liquidity affect exchange rate movements. In other words, we examine whether there is a systematic liquidity risk premium in the FX market.[1] Estimating systematic liquidity risk as the covariance of exchange rate returns and innovations in global liquidity risk, we identify a liquidity risk premium by employing standard empirical asset pricing tests and the portfolio construction techniques first applied to FX data by Lustig and Verdelhan (2007). These methods allow us to eliminate currency-specific sources of returns by taking into account the common component of the excess returns related to systematic liquidity risk. The empirical asset pricing results suggest the presence of a statistically and economically significant risk premium associated with global FX liquidity risk, estimated to be about 4.7 percent per annum. The market price of liquidity risk stays significant even after conditioning on other common risk factors in FX asset pricing analysis, and is robust to a number of tests including alternative weighting of currencies to calculate the global liquidity measure, different rebalancing horizons, and an alternative estimation method. Finally, we find that the liquidity risk premium associated with emerging markets currencies is significantly higher than that of major currencies, and that it increased substantially after the 2008 collapse of Lehman Brothers.

The paper is organized as follows. Section 2 provides an overview of the relevant literature. In Section 3 we describe the data set and provide some descriptive statistics. The methodology for the construction of the liquidity risk measure and the empirical asset pricing exercise are described in Section 4. The core empirical results are reported in Section 5, where we document the presence of a common component in liquidity across currencies, and estimate the liquidity risk premium. Section 6 contains some further analysis, including an extension of the liquidity risk definition, an analysis of liquidity risk employing two alternative liquidity measures, an investigation of currencies of emerging markets and less traded developed countries, and an additional study focusing on liquidity risk in the recent financial crisis following the Lehman Brothers collapse in September 2008. We report additional robustness checks in Section 7. Finally, Section 8 concludes.

[1] Adopting different proxies for liquidity, some studies find a relationship between changes in liquidity and expected stock returns, detecting a liquidity risk premium in the stock market (e.g. Pastor and Stambaugh, 2003; Acharya and Pederson, 2005; Chen, 2005; Korajczyk and Sadka, 2008; Hasbrouck, 2009; Lee, 2011). We are guided by these studies in designing the methodology used in this paper.

2 LITERATURE REVIEW

1 Liquidity and the FX market

In the FX market, dealers provide liquidity to the market and quote prices after receiving orders from customers and other dealers. With the increase in data availability, a literature analyzing the price impact of order flow has emerged in the last decade, documenting that order flow can successfully explain a sizable share of the movements in exchange rates (Evans and Lyons, 2002a).[2]

Due to the heterogeneity of market participants, the FX market is characterized by informational asymmetries, so that dealers gather disperse information from the orders placed by their customers (e.g. Lyons, 1997). Indeed, FX market practitioners' surveys highlight how order flow is seen as a preferred channel for dealers to obtain private and dispersed information from customers (Goodhart, 1988; Cheung and Chinn, 2001; Gehrig and Menkhoff, 2004). In this sense, the information channel works from the dealer's own customer order flow and from the aggregate market customer order flow, which can be inferred from the interdealer and brokered trading. As a consequence, the presence of asymmetric information in the market influences liquidity (Copeland and Galai, 1983; Kyle, 1985; Glosten and Milgrom, 1985; Admati and Pfleiderer, 1988). Dealers quote prices by balancing the expected total revenues from liquidity trading against the expected total losses from informed trading. Copeland and Galai (1983) suggest that liquidity decreases with greater price volatility in the asset being traded, with a higher asset price level, and with lower volume. In this respect, Bollerslev and Melvin (1994) find a significant positive relationship between the bid-ask spread and exchange rate volatility in the interbank market trading of Deutsche mark-US dollar (DM/USD).

Analyzing the intra-day trading of DM/USD in two interbank FX markets (London and

[2] Order flow reflects buying pressure for a currency and it is typically calculated as the sum of signed trades. The sign of a given transaction is assigned with respect to the aggressive party that initiates the trade. Evans and Lyons (2002a) provided the seminal evidence in this literature, showing how order flow is a significant determinant of two major bilateral exchange rates, and obtaining coefficients of determination substantially larger than the ones usually found using standard structural models of nominal exchange rates. Their results are found to be fairly robust by subsequent literature; e.g. see Payne (2003), Bjønnes and Rime (2005), Killeen, Lyons and Moore (2006). Moreover, Evans and Lyons (2006) argue that gradual learning in the FX market can generate not only explanatory, but also forecasting power in order flow, as documented, for example, in King, Sarno and Sojli (2010) and Rime, Sarno and Sojli (2010).

New York), Hsieh and Kleidon (1996) find that the volatility patterns in spreads and trading volume are not consistent with standard asymmetric information models. In fact, the observed shifts in transaction costs and trading volume (which can be viewed as proxies for liquidity) are not related to information flows. They suggest that the high volatility of these measures could be explained by inventory considerations. In his empirical analysis, Bessembinder (1994) finds that bid-ask spreads of major currency pairs widen with forecasts of inventory price risk and with a measure of liquidity costs. In addition, there is a seasonal pattern in changes in spreads: spreads widen before weekends and nontrading intervals. These observed patterns are related to inventory control conditions. A dealer with a larger currency inventory than desired will set a lower price to attract buyers, known as 'quote shading'. According to the theoretical model by Amihud and Mendelson (1980), the market maker's constraints on her inventory positions influence the level of liquidity of the market. Furthermore, liquidity will depend upon the factors that influence the risk of holding inventory (Stoll, 1978; Ho and Stoll, 1981). According to Grossman and Miller (1988), the provision of liquidity depends on the cost incurred by the market maker to maintain her presence in the market. In turn, this cost is inversely related to the number of market makers which are operating in the market. As a result, the larger the number of market makers, the lower is the cost for immediacy and the more liquid is the market, resulting in a lower price impact of trades. Brunnermeier and Pedersen (2009) extend the Grossman-Miller model to include the interaction of funding liquidity with the provision of liquidity by speculators. Under certain conditions, this interaction leads the market to a liquidity spiral: speculators' liquidity constraints reduce market liquidity, which will further tighten the constraints.

In an empirical analysis of a dealer's trading activity in the DM/USD market, Lyons (1995) finds positive evidence of the effects of both the inventory control and the informational asymmetry channels. Specifically, running a regression of the changes in the exchange rate on incoming orders, the dealer's inventory at the beginning of the period and other variables, Lyons reports positive and significant coefficients associated with the two variables of interest, transaction orders and inventory at the beginning of the period. Similarly, Bjønnes and Rime (2005) document a strong information effect on the trading activity of four dealers from a large Scandinavian bank. They find these results both taking into account the size of the orders and the direction of trades.

2 Measures of liquidity

The bid-ask spread is the most widely used measure of liquidity in the literature. In this respect, Stoll (1989) determines the relative importance of each of the three components of the spread (order processing costs, inventory control cost and adverse selection costs) from the covariance of transaction returns. In the FX market, much research has been carried out on the bid-ask spread; e.g. see Bessembinder (1994), Bollerslev and Melvin (1994), Lee (1994), and Hsieh and Kleidon (1996). However, Grossman and Miller (1988) highlight a key limitation of the bid-ask spread as a measure for liquidity: this method gives the cost of providing immediacy of the market maker in the case of a contemporaneous presence of buy and sell transactions. In reality, this is almost never the case.

Apart from measures related to transaction costs, other liquidity measures were developed to proxy the price impact of transactions. Pastor and Stambaugh (2003) propose a liquidity measure based on the temporary price change, in terms of expected return reversal, due to signed transaction volume. This measure is based on the intuition that lower liquidity is accompanied by a higher volume-related return reversal.[3] Furthermore, Amihud (2002)'s illiquidity ratio measures the elasticity of liquidity. This is calculated as the daily measure of absolute asset returns to dollar volume, averaged over some period.

These liquidity measures have been developed and tested mainly for the stock market (e.g. see Naes, Skjeltorp and Ødegaard, 2010). In fact, their application to the FX market can be quite problematic due to its specific characteristics and the difficulty of gathering order flow and volume data. As a result, liquidity in the FX market has been investigated in only a few papers. However, two studies are worth noting. Evans and Lyons (2002b) study time-varying liquidity in the FX market using the slope coefficient in a contemporaneous regression of FX returns on order flow as a proxy for liquidity, in the spirit of Kyle (1985) model. More

[3] Another measure of this kind is the market depth measure of Kyle (1985)'s model, which in its empirical counterpart relies on the contemporaneous relationship between FX returns and order flow (see Evans and Lyons, 2002b). The specific rationale is discussed later in the paper.

recently, Mancini, Ranaldo and Wrampelmeyer (2011) apply a modified version of Pastor and Stambaugh's measure to the FX market by building a daily measure of liquidity for about one year of order flow data during the recent financial crisis. In our paper, we also apply the Pastor and Stambaugh's measure of liquidity but we can rely on 14 years of order flow data and 20 exchange rates.

3 Liquidity risk premium

The literature on liquidity risk premia is virtually non-existing in the FX market, with most studies focusing on stock markets and some on bond markets. Starting from the seminal paper by Amihud and Mendelson (1986), several papers model and empirically test the relationship between liquidity and expected stock returns (Brennan and Subramahmanyan, 1996; Brennan, Chordia and Subrahmanyam, 1998; Datar, Naif and Radcliffe, 1998), showing that a higher return is demanded by traders when liquidity is lower and transaction costs are higher.[4] The same result holds true for other assets: Amihud and Mendelson (1991), for example, find a significant spread in the yields of Treasury notes and bills due to a liquidity risk premium.

Some studies also focus on the time variation of liquidity and on its co-movements cross-sectionally. Chordia, Roll and Subrahmanyam (2000) analyze the correlation in movements in liquidity both at industry and market level. After controlling for determinants of liquidity such as volatility, prices and volume, they document significant commonality in liquidity across stocks. Similar conclusions are reached also by other authors. Huberman and Halka (2001) find that there is a systematic and time-varying component in stock market liquidity. A less clear-cut conclusion is reached by Hasbrouck and Seppi (2001), who find evidence of weak co-movement in stock market liquidity measures constructed from intra-day data. Employing a longer data set of intra-day stock market data, Chordia, Roll and Subrahmanyam (2001) confirm the presence of a common component in stock market liquidity, and then present an investigation of the possible determinants of the observed variation in market liquidity and trading activity over time.[5]

[4]Most of these papers study the US stock market, but the same result is documented by Bekaert, Harvey and Lundblad (2007) for emerging markets.

[5]The determinants considered are inventory control variables (such as daily returns and volatility) and

Finally, some studies examine the implications of the documented time-variation in common liquidity for asset returns, controlling for the presence of a priced liquidity risk in the stock market. In their analysis, Pastor and Stambaugh (2003) find that the sensitivities of stock returns to common liquidity innovations are priced. Acharya and Pedersen (2005) broaden the analysis and generalize the Pastor-Stambaugh liquidity measure. In doing so, they develop a liquidity-adjusted Capital Asset Pricing Model (CAPM) and find empirical support for the presence of a priced liquidity risk. In an empirical application of Acharya and Pedersen's (2005) liquidity-adjusted CAPM, Lee (2011) identifies a systematic liquidity risk premium in stock returns. In particular, he finds a premium related both to the commonality in liquidity, and the covariance of individual stocks' liquidity and the stock market return. Similarly, defining systematic liquidity risk as the common component of different liquidity measures, Chen (2005), Korajczyk and Sadka (2008) and Hasbrouck (2009) provide evidence that systematic liquidity risk is priced in stock markets.

This is the key subset of the literature on which we build to design an empirical strategy to construct a global liquidity risk measure for the FX market and to test whether liquidity risk is priced in currency markets.

3 DATA

1 Description of the data

The main data set analyzed in this paper comprises daily data for 20 exchange rates and their order flow for a time period of 14 years, from April 14, 1994 to July 17, 2008. Its distinctive feature is the availability of order flow for a wide cross section of currencies available for a long time period, including a number of emerging markets. Of the 20 currencies in the data set, 10 are of developed economies (Australian dollar, Canadian dollar, Danish krone, euro, Great Britain pound, Japanese yen, New Zealand dollar, Norwegian kroner, Swedish krona, and Swiss franc) and 10 are of emerging markets (Brazilian real, Chilean peso, Czech koruna, Hungarian forint, Korean won, Mexican peso, Polish zloty, Singaporean dollar, South African

informed trading variables (such as dummies for macroeconomic announcement dates).

rand, and Turkish lira). The abbreviations for these currencies used in the paper are given in Appendix A.[6]

Log returns are calculated from the FX spot exchange rates of the US dollar versus these currencies and are obtained from Datastream. They are the WM/Reuters Closing Spot Rates, provided by Reuters at around 16 GMT. Log-exchange rate returns are calculated as:

$$r_t = \ln(S_t) - \ln(S_{t-1}) \tag{1}$$

where S_t is the FX spot rate of the US dollar versus the currency.

In order to calculate FX excess returns, one month forward exchange rates are obtained from Datastream and provided by WM/Reuters. Excess returns are calculated as follows:

$$er_t = \ln(S_{t+1}) - \ln(F_t) \tag{2}$$

where F_t is the one-month forward exchange rate.[7]

Turning to order flow, the FX transaction data is obtained from State Street Corporation (SSC). As one of the world's largest custodian institutions, SSC counts about 10,000 institutional investor clients with about 12 trillion US dollars under custody. SSC records all the transactions in these portfolios, including FX operations. The data provided by SSC is the daily order flow aggregated per currency traded. Order flow data is defined by SSC as the overall buying pressure on the currency and is expressed in millions of transactions (number of buys minus number of sells in a currency).

The measures of investor behavior developed at SSC reflect the aggregate flows (and holdings) of a fairly homogenous group of the world's most sophisticated institutional investors and represent approximately 15 percent of tradable securities across the globe. The data are used by SSC for the construction of the Foreign Exchange Flow Indicator (FXFI), an indicator of net buying pressure for currencies. The FXFI data available to us is the net flow

[6] The classification in developed and emerging countries above does not correspond to the IMF classification, but follows instead common practice in the FX market.

[7] This definition of excess returns assumes the validity of covered interest parity, implying that interest rate differentials are identical to forward premia under no-arbitrage. This condition is generally valid in FX markets at the frequency used in this paper (see Akram, Rime and Sarno, 2008).

for 20 currencies, derived from currency-level transactions and aggregated to ensure client confidentiality. The data is therefore not derived from broker/intermediary flow. However, it is important to note that the FXFI is not exactly the raw net of buy and sell number of transactions (net flow), but is the net flow filtered through a 'normalization' designed to increase comparability across currencies and through time as well as to reflect the SSC commitment to client confidentiality. The raw flows are the same as those used in Froot and Ramadorai (2005), who also normalize the SSC data in their empirical work by dividing the flow by its standard deviation.[8]

The sample period is generally from April 14, 1994 to July 17, 2008. For a group of currencies the sample for the liquidity analysis is shorter due to limited data availability from the providers. Specifically, the sample period for CZK starts on December 12, 1994; CLP on October 4, 1995; HUF on September 30, 1994; and PLN on August 22, 1995. In addition, BRL is considered from January 15, 1999, when the real was introduced as the national currency and Brazil adopted a floating exchange rate system, and EUR starts on December 31, 1998 when the EMU was established. Furthermore, for the portfolio analysis and the following asset pricing exercise the sample period is from January 1, 1997 to July 17, 2008, when the one-month forward exchange rate became available from Datastream.[9]

2 Descriptive statistics

Table 1 presents some descriptive statistics of the log FX returns, grouped in developed and emerging countries. In general, emerging markets' currencies present a higher standard deviation than developed countries' currencies. Furthermore, log returns of developed currencies present low first- and second-order autocorrelation. In contrast, most of the emerging markets' currencies exhibit positive significant first-order autocorrelation and negative significant

[8]While a strength of the SSC data is that it covers a large fraction of the FX market, we do not have information on different segments of the investors included in the data set. This prevents us from distinguishing between different types of institutional investors and explore questions related to heterogeneous impact on prices or differences in the degree of informed trading across different investors. For an analysis of this kind, see e.g. Menkhoff, Osler and Schmeling (2010).

[9]However, the sample period is shorter due to limited data availability from Datastream for the following currencies: BRL (from March 29, 2004), HUF (from October 27, 1997), KRW (from February 11, 2002), and PLN (from February 11, 2002).

second-order autocorrelation.

[Insert Table 1 about here]

Table 2 shows some descriptive statistics for the order flow data. It is useful to recall that, because of the normalization carried out by SSC on these data, it is not possible to offer a clear-cut interpretation of the average values of the flows. The order flow time series for emerging markets generally present a higher standard deviation than for developed countries, and also much stronger evidence of non-normality, as evidenced by the 1st and 99th percentiles. Furthermore, the order flow data exhibit strong autocorrelation for all currencies in the sample. In the last column we report the correlation between order flow and the log return of the US dollar versus the currency. The correlation is significant for most of the currencies, and is higher for the currencies of advanced economies in the sample. All the correlations are positive, as expected: a positive order flow indicates buying pressure for the currency, which should cause the currency to appreciate. All these preliminary statistics are comparable to the ones reported by Froot and Ramadorai (2005), who use a similar data set from the same source over a shorter sample.[10]

[Insert Table 2 about here]

4 METHODOLOGY

1 *Construction of the liquidity measure*

Starting from Evans and Lyons (2002a), several papers document that order flow is a statistically powerful determinant of FX returns. Running the simple Evans-Lyons regression of log returns on contemporaneous order flow:

$$r_{i,t} = \alpha_i + \beta_i \Delta x_{i,t} + \varepsilon_{i,t}, \tag{3}$$

[10] However, note that order flow in Froot and Ramadorai (2005) is measured in hundreds of millions of dollars, whereas our order flow series is defined as in the majority of papers since Evans and Lyons (2002a), in terms of net number of transactions. Nevertheless, the descriptive statistics suggest that the properties of the data are qualitatively the same. This seems consistent with Jones, Gautam and Lipson (1994), who show that the size of trades (volume) has no additional information content beyond that contained in the number of transactions. Similar results are recorded for FX order flow by Bjønnes and Rime (2005).

we expect to find a positive coefficient associated with the contemporaneous order flow Δx. A positive order flow causes the currency to appreciate, which leads to an increase in the exchange rate quoted as US dollar versus the foreign currency. Also, Evans and Lyons (2002b) use the above regression to investigate time-varying liquidity in the FX market, allowing the slope coefficient to vary over time.

Following Pastor and Stambaugh (2003), we measure liquidity as the expected return reversal accompanying order flow. Pastor and Stambaugh's measure is based on the theoretical insights of Campbell, Grossman and Wang (1993). Extending the literature relating time-varying stock returns to non-informational trading (e.g. De Long, Shleifer, Summers and Waldmann, 1990), Campbell, Grossman and Wang develop a model relating the serial correlation in stock returns to trading volume. A change in the stock price can be caused by a shift in the risk-aversion of non-informed (or liquidity) traders or by bad news about future cash flows. While the former case will be accompanied by an increase in trading volume, the latter will be characterized by low volume, as risk-averse market makers will require an increase in returns to accommodate liquidity traders' orders. The serial correlation in stock returns should be directly related to trading volume. The Pastor-Stambaugh measure of liquidity captures the return reversal due to the behavior of risk-averse market makers. While Pastor and Stambaugh use signed trading volume as a proxy for order flow, we employ actual order flow.

To estimate the return reversal associated with order flow, we extend regression (3) above to include lagged order flow:

$$r_{i,t} = \alpha_i + \beta_i \Delta x_{i,t} + \gamma_i \Delta x_{i,t-1} + \varepsilon_{i,t}. \tag{4}$$

We estimate this regression using daily data for every month in the sample, and then take the estimated coefficient for γ to be our proxy for liquidity. Thus, the monthly proxy for liquidity of a specific exchange rate is:

$$L_{i,m} = \widehat{\gamma}_{i,m}, \tag{5}$$

where the subscript m refers to the monthly frequency of the series. If the effect of the lagged order flow on the returns is indeed due to illiquidity, γ_i should be negative and reverse a portion of the impact of the contemporaneous flow, since β_i is expected to be positive. In other words, contemporaneous order flow induces a contemporaneous appreciation of the currency in net demand ($\beta_i > 0$), whereas lagged order flow partly reverses that appreciation ($\gamma_i < 0$).

Other methodologies have been used in the literature to empirically estimate liquidity using regression analysis applied to order flow data. In particular, in Evans and Lyons (2002b) the contemporaneous impact, changed of sign, corresponds to the measure of market depth from Kyle (1985)'s model. Pastor and Stambaugh (2003) estimate liquidity from a regression of returns on lagged order flow, including lagged returns to account for serial correlation. We specify our regression not including the lagged returns but including contemporaneous order flow instead. It is clear that each of these regressions reflects some degree of arbitrariness. However, later in the paper, we will apply these other methodologies for robustness.

2 *Estimation of a common liquidity measure*

Next, we construct a measure of common liquidity (DL_m) by averaging across currencies the individual monthly liquidity measures (e.g. Chordia, Roll and Subrahmanyam, 2000; Pastor and Stambaugh, 2003), excluding the two most extreme observations:

$$DL_{i,m} = (L_{i,m} - L_{i,m-1}) \tag{6}$$

$$DL_m = \frac{1}{N}\sum_{i=1}^{N} DL_{i,m}. \tag{7}$$

In order to account for potential autocorrelation of some of the individual liquidity series and isolate liquidity innovations, the unexpected component of common liquidity (DL_m^C) is obtained as the residual of an AR(1) model of the common liquidity measure.[11] In other words, we estimate:

$$DL_m = \rho_0 + \rho_1 DL_{m-1} + \varepsilon_m \tag{8}$$

and set $DL_m^C = \widehat{\varepsilon}_m$.

Following Chordia, Roll and Subrahmanyam (2000), we then regress the individual liquidity measures ($DL_{i,m}$) on global FX liquidity risk (DL_m^C) to further investigate the commonality in the liquidity innovations across currencies:

$$DL_{i,m} = \delta_{0i} + \delta_{1i} DL_m^C + \epsilon_{i,m}. \tag{9}$$

A statistically significant value for δ_1 would imply that global FX liquidity risk is related to fluctuations in liquidity of individual currencies.

3 Liquidity-sorted portfolios

A key empirical question is whether global liquidity risk is priced in FX returns. In order to investigate this issue, we construct four portfolios for each year based on the ranking of the historical sensitivities of currency returns to global liquidity risk.[12] Linking the excess return of each of the four portfolios year after year, the excess returns of the portfolios are then compared, and we expect the portfolios more sensitive to liquidity risk to have a higher excess return than the less sensitive portfolios.

The analysis starts from January 1997 to account for the start date of the forward rate data from Datastream and it is conducted at every year-end. For each currency, the liquidity measure is estimated by the coefficient associated with the lagged order flow from regression (4), run with the past observations available at each year-end starting from January 1999, to allow for at least two years of past data in the estimations. At each year-end, the monthly series of common liquidity for the past available period is also calculated according to equations

[11] An AR(1) model is enough to eliminate serial correlation in the residuals. Also note that we use the term 'common', 'systematic' and 'aggregate' liquidity interchangeably in this paper.

[12] In other words, we estimate the sensitivity to global liquidity risk for each exchange rate using non-overlapping years, and this gives us an estimate of the sensitivity per year for each exchange rate. Then, we sort currencies on the basis of the estimated sensitivities into four portfolios, which are rebalanced yearly.

(6) to (8).

Then, the sensitivity of each currency's return to global liquidity risk is estimated with a regression of monthly returns on the global liquidity risk measure estimated at each year end:

$$r_{i,m} = \zeta_{0i} + \zeta_{1i} DL_m^C + \varepsilon_{i,m}. \tag{10}$$

At this point, the currencies are sorted according to the estimated parameter ζ_1, which captures the sensitivity to global liquidity risk. Based on this ranking, four portfolios are constructed with five equally-weighted currencies at each year-end: the first portfolio containing the least sensitive currencies to liquidity risk and the fourth comprising the most sensitive ones. The excess return of each portfolio for the following year is then calculated from the excess returns of each of the five equally-weighted currencies. For each portfolio an excess return series is obtained by linking the excess return calculated in each year. Having constructed the portfolios based on their sensitivity to our liquidity measure (liquidity-sorted portfolios), we expect the most sensitive portfolio to be associated with a higher return in compensation for the higher liquidity risk related to it.

4 Empirical asset pricing and the FX liquidity risk premium

Following the comparison of the liquidity-sorted portfolios' excess returns, we investigate whether systematic liquidity risk is priced in the cross-section of excess returns of the portfolios. We are specifically interested in quantifying the FX liquidity risk premium.

In order to establish whether systematic liquidity risk is priced, we conduct a standard Fama-MacBeth (1973) analysis. Taking the perspective of a US investor, we test whether our global liquidity risk factor prices the excess returns of the liquidity-sorted portfolios. We test the significance of liquidity risk also conditioning on other factors, i.e. we check whether the systematic liquidity risk factor remains priced when accounting for other sources of systematic risk, such as those proposed by Lustig, Roussanov and Verdelhan (2011).

Applying the standard Fama-MacBeth procedure, we begin by estimating the sensitivities of the portfolios' excess returns to global liquidity and some common risk factors through a time-series regression of the form:

$$er_{j,m} = \alpha_j + \beta_j^{LIQ} f_m^{LIQ} + \beta_j^{other} f_m^{other} + \epsilon_{j,m} \qquad \text{for } j = 1, ..., 4 \tag{11}$$

where f_m^{LIQ} is the proposed liquidity risk factor DL_m^C, and f_m^{other} is an additional risk factor. This could be either the carry risk factor, developed as the difference in the excess returns of the high-interest currencies portfolio and the low-interest currencies portfolio, or the dollar risk factor, constructed as the cross-sectional average of the portfolios excess returns.

At this point, we proceed to determine the cross-sectional impact of the sensitivities on the FX excess returns. A cross-sectional regression of the excess returns on the sensitivities is run at each point in time as follows:

$$er_{j,m} = \beta_j^{LIQ} \lambda_m^{LIQ} + \beta_j^{other} \lambda_m^{other} + \varepsilon_{j,m} \qquad \text{for } m = 1, ..., M \tag{12}$$

where λ_m is the market price of a specific risk factor at time m and the βs are calculated from the first step presented above. The market price of risk is the average of the λs estimated at each point in time. The same applies to the pricing errors, as follows:

$$\widehat{\lambda^{LIQ}} = \frac{1}{M} \sum_{m=1}^{M} \lambda_m^{LIQ} \tag{13}$$

$$\widehat{\lambda^{other}} = \frac{1}{M} \sum_{m=1}^{M} \lambda_m^{other} \tag{14}$$

$$\widehat{\varepsilon_j} = \frac{1}{M} \sum_{m=1}^{M} \varepsilon_{j,m}. \tag{15}$$

In order to validate the hypothesis that liquidity risk is a priced factor in the FX market, we require the market price to be positive and significant. Furthermore, we expect the price to stay significant once other factors are controlled for in the analysis.[13]

[13] When calculating the standard errors, we also employ the Shanken (1992) adjustment.

5 EMPIRICAL RESULTS

1 The FX liquidity measure

Table 3 reports the results from estimating regression (4), where FX returns are regressed on contemporaneous and lagged order flow; the estimation is carried out by OLS and with standard errors calculated following Newey and West (1987). The coefficients associated with contemporaneous order flow are generally positive and highly significant, as expected.[14] In contrast, the coefficients of lagged order flow are negative and generally significant, which is consistent with the rationale of regression (4) since they capture the return reversal. For the currencies of advanced economies, the regressions have particularly high explanatory power, exceeding 18 percent for CHF.

[Insert Table 3 around here]

Running the same regression for each independent month in the sample period gives a time series of monthly γs for each currency. These series represent our monthly proxies of liquidity for the currencies considered.[15] We then calculate a systematic (or aggregate) liquidity measure from the liquidity measures of individual currencies, as in equations (6)-(8). Indeed, given that there is a common component in the cost of providing liquidity in the FX market, it seems reasonable to expect the time-variation in liquidity to be correlated across currencies. In fact, Melvin and Taylor (2009) show a substantial shift in trading costs common across currencies during the last financial crisis. Similarly, focusing on the years of the last financial crisis (2007-2008), Mancini, Ranaldo, and Wrampelmeyer (2011) analyze common liquidity across nine exchange rates and find strong positive correlation in liquidity cross-sectionally. Given the particular market conditions in which the co-movement has been found, it does not follow that the same result can be generalized to normal market conditions. Since the data set analyzed here includes both crisis and non-crisis periods, an answer to

[14] The only exception is the MXN. Even though formally considered a floating system, the Mexican peso arrangement might be affected by the movements in FX reserves which are particularly strong due to the accumulation in US dollar deposits of the revenues from oil exports (Frankel and Wei, 2007). Another possible explanation is that SSC may only handle a small fraction of the daily volume in MXN.

[15] Overall, across currencies, 79% of the betas are correctly signed, and 76% of the gammas are correctly signed.

this question can be given irrespective of market conditions. Furthermore, our large number of currencies, including both developed and emerging countries, allows us to establish fairly robust and general results.

At this point, we construct the common liquidity measure using equations (6)-(8).[16] The proxy captures the innovation in common liquidity across currencies. It presents a mean of -0.004 percent and a standard deviation of 0.219 percent. Furthermore, the proxy has an autocorrelation of about -13 percent. In Figure 1 we show the evolution over time of both the level of systematic liquidity and its innovation. Regression (9) is run to investigate the ability of the proxy to capture systematic liquidity across currencies. The regression is estimated by OLS and the standard errors are adjusted according to Newey and West (1987). The results are highly supportive of the presence of commonality (see Table 4). All the coefficients are positive and statistically significant, except for CAD, BRL, and TRY. Furthermore, about 70 percent of the regressions have an R^2 in excess of 5 percent. Hence, the common liquidity proxy does generally explain a non-trivial proportion of the movements in individual currencies' liquidity.

[Insert Table 4 around here]

[Insert Figure 1 around here]

2 *Is there a liquidity risk premium?*

Next, we build four portfolios based on the ranking of the sensitivities of the currencies' returns to the global liquidity risk measure. This exercise reveals that portfolios with higher sensitivity dominate the ones with lower sensitivity to liquidity risk, as one would expect. Table 5 (Panel A) shows some descriptive statistics for the excess returns of the four liquidity-sorted portfolios. It includes in the last column the return of a strategy that goes long in the most sensitive portfolio and short in the least sensitive one. The spread in average returns is substantial and gives empirical support to the presence of a systematic liquidity risk premium.

[Insert Table 5 around here]

[16] A preliminary analysis of the correlations between the individual liquidity innovation measures shows that in general the series are strongly positively correlated. This is a first sign of the presence of a common liquidity component.

In order to check whether the results of this analysis are driven by the Turkish lira's extreme behavior during the 2001 crisis, we cap the monthly excess returns to +/- 10 percent.[17] Table 5 (Panel B) shows that the most sensitive portfolios still generate higher excess returns on average. This is also evident from the graphical analysis of the cumulative excess returns of the four portfolios in Figure 2.[18]

[Insert Figure 2 around here]

Analyzing the composition of the portfolios, we concentrate our attention on the portfolios of our long/short strategy, i.e. the portfolio comprising the currencies with higher sensitivities, which tend to perform well in good liquidity states and depreciate the most in response to a bad liquidity shock (Portfolio 4), and the portfolio containing the currencies with the lower sensitivities, which tend to depreciate the least or appreciate in response to a bad liquidity shock (Portfolio 1). The portfolios present a fairly low turnover of 26 percent, measured as the percentage of currencies exiting from a portfolio over the period. The currencies more frequently in Portfolio 4 are BRL and NZD, and to a lesser extent TRY, CLP, KRW and AUD; the currencies more frequently in Portfolio 1 are NOK and CAD. The difference between the average sensitivity (ζ_1 in regression (10)) of the currencies included in Portfolio 4 and the average sensitivity of the currencies included in Portfolio 1 is about 3.7 (specifically, -1.05 is the average sensitivity for the currencies included in Portfolio 1, and the corresponding number for the currencies in Portfolio 4 is 2.65). Emerging market currencies feature both in the long and short portfolios.

[17] During 2001 and part of 2002, the Turkish crisis led to a collapse of the Turkish lira, that experimented massive returns. Indeed, during the year 2001, the monthly excess return of the USD/TRY was in excess of -50%.

[18] It is intriguing that all Portfolios 1 to 4 generated low or negative returns at the beginning of the sample, before starting to trend upwards in 2002. This may reflect the fact that the US dollar (the short position in each of the four portfolios) appreciated against most currencies from 1999 to 2000 especially, when the Federal Reserve raised interest rates aggressively (six times) and the US economy was booming. During the stock market crash and recession of 2000-2001, this appreciation moderated but did not stop until early 2002. This dollar effect is not relevant, however, for the long-short strategy discussed below since the latter is dollar neutral.

3 Liquidity risk: a priced common risk factor

Table 6 shows the results of the Fama-MacBeth procedure with different regression specifications. Panel A reports the analysis where we test whether the global liquidity risk factor is priced in our cross-section of currency excess returns. The λ coefficient associated with systematic liquidity risk is positive and strongly statistically significant. In particular, we estimate an annualized liquidity risk premium of about 4.7 percent.

[Insert Table 6 around here]

What happens to the market price of liquidity risk when other common risk factors are included in the analysis? Panels B and C show the results with the inclusion of the dollar risk and the carry risk factors, respectively. In both cases, the λ associated with the systematic liquidity risk remains statistically significant and does not change much in magnitude.

In Panel B, note that the dollar risk factor is significant, unlike in Lustig, Roussanov and Verdelhan (2011), where the dollar risk factor does not explain any of the cross-sectional variation of the portfolios' excess returns. However, as Lustig, Roussanov and Verdelhan (2011), we also find that the sensitivities of the portfolios' excess returns to the dollar risk factor are not different from one, so the inclusion of a constant in the cross-sectional regression is not appropriate.[19] Moreover, Panel C shows that the carry risk factor is not statistically significant in explaining the cross-sectional variation of the liquidity-sorted portfolios' excess returns, once introduced in the analysis together with the liquidity risk factor. In short, we confirm that systematic liquidity risk is priced in the FX market.[20]

In their analysis of liquidity across 9 developed countries' currencies during the recent financial crisis, Mancini, Ranaldo and Wrampelmeyer (2011) identify a liquidity risk premium as high as 20 percent. Our lower estimate of the liquidity risk premium can be explained by the inclusion in our sample of both crisis and non-crisis periods. From this comparison, we argue that the FX liquidity risk premium is time-varying. Following the theoretical model

[19] These results are confirmed in the analysis of Menkhoff, Sarno, Schmeling and Schrimpf (2012) for carry trade portfolios.

[20] We also considered global FX volatility risk as a potential common risk factor. We construct this factor as the absolute value of currency returns following Menkhoff, Sarno, Schmeling and Schrimpf (2012). However, we find that global FX volatility risk is not statistically significant in explaining our cross section of excess returns.

developed by Vayanos (2004), the liquidity risk premium is time-varying due to changes in investors' liquidity preferences. In other words, during a financial crisis, investors' desire to liquidate their assets leads to a higher liquidity risk premium. However, our results show that a liquidity risk premium is present and significant in the FX market irrespective of market conditions, and hence also in normal times.

6 FURTHER ANALYSIS

1 Liquidity risk premium: extension

Adjusting the CAPM to account for liquidity risk, Acharya and Pedersen (2005) extend the definition of liquidity risk to include the covariance of individual asset liquidity and market liquidity, and the covariance of individual asset liquidity and the market return, in addition to the covariance of an asset return and market liquidity already presented by Pastor and Stambaugh (2003). In essence, the Acharya-Pedersen liquidity measure is a generalization of the Pastor-Stambaugh measure. Following Acharya and Pedersen (2005), we extend our analysis to estimate liquidity risk as both the covariance of individual currency returns and market liquidity, and the covariance of individual currencies' liquidity and market liquidity.[21] The rationale is that an investor requires a premium to hold a currency that is illiquid when the market as a whole is illiquid. As a consequence, expected currency returns will be negatively correlated with the covariance of individual currencies liquidity and market liquidity.

Thus, the βs measuring systematic liquidity risk are estimated using the following regressions:

$$er_{j,m} = \alpha_j + \beta_j^1 DL_m^C + \varepsilon_{j,m} \tag{16}$$

$$DL_{j,m} = \alpha_j' + \beta_j^2 DL_m^C + \varepsilon_{j,m}'. \tag{17}$$

The first regression is the equivalent of regression (11), with innovations in global liquidity

[21] We thus leave out the component given by the covariance of innovations of individual liquidity with the market return, since there is no stock market return equivalent for the FX market.

as the only common risk factor. In addition, we run the second regression in order to estimate the Acharya and Pedersen (2005) additional measure of liquidity risk, given by the regression of innovations in individual liquidity on innovations in global liquidity.

Hence, the 'net' βs measuring systematic liquidity risk are given by:

$$\widehat{\beta}_j = \widehat{\beta}_j^1 - \widehat{\beta}_j^2. \tag{18}$$

At this point, we conduct the same empirical asset pricing analysis as above in equation (12). The results of this analysis are not reported in full since they are very close to the results of the core analysis. Specifically, for liquidity-sorted portfolios, the λ coefficient is still positive and significant and the estimated annualized liquidity premium is about 4.7 percent, with a t-statistic of 3. In short, the results are qualitatively unchanged when allowing for the additional effects in the definition of liquidity risk in Acharya and Pedersen (2005).

2 *Alternative liquidity measures*

We extend the analysis of liquidity by building the proxy for liquidity on Kyle (1985)'s theoretical model, as done e.g. by Evans and Lyons (2002b). In this setting, the contemporaneous impact of order flow on the exchange rate can be explained as the information discovery process of the dealer, who updates her quotes after receiving orders from her clients and other dealers. Nevertheless, the slope coefficient in the regression does not only reflect information arrival, but also the level of market liquidity. In fact, the contemporaneous coefficient, changed of sign, corresponds to the measure of market depth in Kyle (1985) model. So, we consider this proxy as an alternative liquidity measure to the one in the main analysis.

Estimating regression (3) for every currency and every month in the sample, we take the estimated coefficient for β changed of sign as our new measure of liquidity:

$$L_{i,m} = -\widehat{\beta}_{i,m}. \tag{19}$$

Intuitively, the rationale behind this proxy is that the more liquid a market, the lower the impact of transactions on asset prices. We change the sign of β to take $L_{i,m}$ as a measure of liquidity and make it comparable to the others in the paper. We then calculate the innovation to common liquidity from the individual liquidity measures, following the same steps as in the core analysis.

Table 7 shows the results of the portfolio and empirical asset pricing analysis conducted as above, based on this new liquidity measure. Panel A reports some descriptive statistics of excess returns of the portfolios constructed from the ranking of the sensitivities of currencies to innovations in market liquidity. The results are qualitatively similar to the ones obtained in the main results. This is also true for the liquidity risk premium, estimated to be about 4.6 percent (Panel B). However, the χ^2 test suggests that the pricing errors are statistically significantly different from zero, and hence our liquidity measure proposed in the core analysis performs better in pricing the cross-section of currency excess returns.

[Insert Table 7 around here]

In the core analysis, we have estimated liquidity as the return reversal associated with order flow. Practically, we have estimated liquidity as the impact of lagged order flow on currency returns, conditioning on current order flow. In this section, following Pastor and Stambaugh (2003) we add lagged returns as an independent variable in the regression, to account for potential serial correlation in currency returns. Thus we run the following regression using daily data for every month in the sample:

$$r_{i,t} = \alpha_i + \beta_i \Delta x_{i,t} + \gamma_i \Delta x_{i,t-1} + \delta_i r_{i,t-1} + \varepsilon_{i,t}. \tag{20}$$

We take the estimated coefficient for γ to be a proxy for liquidity and construct a monthly liquidity series for each currency i:

$$L_{i,m} = \widehat{\gamma}_{i,m}. \tag{21}$$

Next, we use these new estimates of liquidity to calculate the innovation in common liquidity from equations (6)-(8) and conduct the same portfolio and empirical asset pricing analysis as in the core results. The results of this analysis are reported in Table 8, which shows that there still exists a substantial spread between the portfolios that contain the least and most sensitive currencies to innovations in global liquidity risk (Panel A). Furthermore, the empirical asset pricing exercise confirms the presence of a statistically significant liquidity risk premium, although its magnitude is estimated to be smaller than in the core analysis, just above 3 percent (Panel B).

[Insert Table 8 around here]

3 Emerging market currencies

In the FX market most of the trading happens between the currencies of the most developed countries. If the currencies of emerging markets are less traded, it is reasonable to expect the liquidity risk premium to be higher for these currencies.

Since our data set includes a number of emerging market and less traded currencies, it is interesting to conduct our analysis excluding the most traded currencies (AUD, CAD, CHF, GBP, EUR, JPY, NZD, and SEK). In this section we report the results of the portfolio analysis and empirical asset pricing exercise limiting the currencies included in the data set to BRL, CLP, CZK, DKK, HUF, KRW, MXN, NOK, PLN, SGD, TRY, and ZAR. In detail, we group the 12 currencies in 4 portfolios with 3 currencies in each one and conduct the same steps as in the core analysis.[22]

As expected, the spread between the excess return of the portfolios is higher once the most traded currencies are excluded from the sample (Table 9, Panel A). Furthermore, the liquidity risk premium associated with this sample is significantly higher, exceeding 7 percent (Table 9, Panel B). In short, liquidity is more important in pricing the cross-section of currency returns of emerging markets and less traded developed currencies.

[Insert Table 9 around here]

4 Crisis period

In this section we extend the analysis to the recent financial crisis period, focusing our attention on the period after the Lehman Brothers collapse in September 2008. Our transaction data set

[22] We have 10 emerging markets in the data set, but preferably need 12 currencies to form 4 portfolios. Hence, we add NOK and DKK to this currency universe.

does not allow us to analyze this period since it ends in July 2008, so we employ a different data set. We use order flow data from proprietary daily transactions between end-user segments and UBS, one of the world's largest player in the FX market. The data includes daily transaction data of UBS across a variety of different clients, including both financial and non-financial institutions. At the end of each business day, transactions registered at any worldwide office are aggregated across segments. The order flow data measures the imbalance between the value of purchase and sale orders for foreign currency initiated by clients; in essence it is the raw net flow for each currency, expressed in billions of US dollars. In detail, it includes the transactions against the USD of AUD, CAD, CHF, EUR, GBP, JPY, NOK, NZD, SEK, in addition to the emerging market currencies BRL, KRW, MXN, SGD, and ZAR. The sample period for which we have data for all currencies spans from January 1, 2005 until May 27, 2011.

The order flow data analyzed in this section is different from the SSC data used in the main analysis in several respects. It includes a more limited part of the FX market, namely clients of UBS. Moreover, the data set covers less currencies since it includes the transactions of 9 developed countries and 5 emerging markets. As a result, the measure of market liquidity calculated from this sample will be more limited in its breadth compared to the global FX measure built in the main analysis. Moreover, the UBS data covers a more heterogeneous group of FX clients and, for example, some are not FX speculators. However, this data set gives us a raw, unfiltered measure of order flow, and covers the recent financial crisis, which enables us to conduct a portfolio analysis to investigate the presence of a liquidity risk premium during the crisis.

We start from calculating the measure of global liquidity risk following exactly the same steps as in the core analysis, and report a graph of this measure obtained using the UBS data in Figure 3 (Panel A). We note that, after the collapse of Lehman Brothers, a significant shock to liquidity in the FX market took place together with a subsequent increase in volatility. Furthermore, there is strong evidence of a sharp increase in the spread in excess returns between the portfolios containing the three least and three most sensitive currencies to innovations in global liquidity after the collapse of Lehman Brothers. Table 10 reports the descriptive statistics of the excess returns of the portfolio containing the three least sensitive currencies to innovation in global liquidity and the portfolio containing the three most sensitive ones. The average excess returns and the Sharpe ratios suggest that the liquidity risk premium is substantial. However, the relatively small sample size and cross section – there are now only 3 currencies in each portfolio and about 6 years of monthly observations – prevent us from conducting a statistically meaningful asset pricing test, and hence we cannot estimate the liquidity risk premium using the same methods as in the core analysis. Nevertheless, the difference in excess returns across liquidity-sorted portfolios is very apparent and can be seen even more clearly in the graphical analysis of the cumulative excess returns of the two portfolios used in the long-short strategy, in Panel B of Figure 3. This shows that there is an evident widening in the spread of the two portfolio returns after the Lehman collapse, consistent with an increased premium required for liquidity risk and with the evidence described in Melvin and Taylor (2009) and Mancini, Ranaldo and Wrampelmeyer (2011).

[Insert Table 10 around here]

[Insert Figure 3 around here]

Analyzing the composition of the portfolios of the long/short strategy, for example, we note that in the last year the three currencies selected in the long portfolio are ZAR, KRW and AUD, whereas the currencies selected in the short portfolio are JPY, CHF, and GBP. The difference between the average sensitivity (ζ_1 in regression (10)) of the currencies included in the long portfolio and the average sensitivity of the currencies included in the short portfolio is about 1.37 (specifically, -0.55 is the average sensitivity for the currencies included in the short portfolio, and the corresponding number for the currencies in the long portfolio is 0.82).

In conclusion, this section provides some evidence of an increase in the liquidity risk premium during the latest financial crisis period. Even though we are not able to quantify the premium due to the small size of the sample, the portfolio analysis gives empirical support to a dramatic widening in the spread in excess returns between the portfolio less exposed to liquidity risk and the one most exposed, following the Lehman collapse.

7 ROBUSTNESS CHECKS

1 Volume-weighted common liquidity

In the calculation of a common component in liquidity across currencies, we have taken the average of equally weighted currencies. In this section we calculate the common component in liquidity across currencies by weighting the currencies based on their share of market turnover. We take the monthly weights as the annual percentages of the global FX market turnover by currency pair reported in the Triennial reports of the BIS for various years (1995, 1998, 2001, 2004, 2007, and 2010). We calculate the weights for the years not covered by the reports by interpolation. Furthermore, for the currencies not individually included in the reports, we take the value of "other currencies versus the USD" and evenly distribute it among these currencies.[23] Then we proceed to estimate the innovation in market liquidity running regression (8).

The new measure of innovation in market liquidity presents a correlation of 67 percent with the one from the core analysis. Then, we conduct the usual portfolio analysis in order to investigate whether there is still a spread in the excess returns of liquidity-sorted portfolios. The results show the presence of a high spread between the excess returns of the portfolios with lower and higher sensitivities to innovation in market liquidity (Table 11), confirming qualitatively the core results. Thus, the results for the analysis of liquidity-sorted portfolios do not qualitatively change once the new weighting is introduced in the calculation of market liquidity.

[Insert Table 11 around here]

2 Different rebalancing horizons

Our portfolio analysis results are based on a yearly rebalancing of the portfolios. In this section, we rebalance the portfolios at higher frequencies, namely 3 months and 1 month. In

[23] Specifically, taking the measures of changes in liquidity of individual currencies $DL_{i,m}$ from equation (6), the new measure of changes in market liquidity DL_m is calculated as $DL_m = \frac{1}{N}\sum_{i=1}^{N} w_{i,m} DL_{i,m}$, where $w_{i,m}$ is the weight associated with currency i in month m. On average, the currencies with the highest weights are EUR (37%), JPY (20%) and GBP (12%). AUD, CAD, and CHF have weights of around 5% each. All other currencies have lower weights.

Table 12 we report the results of the same analysis conducted with a different rebalancing period. We rank the currencies at every end of a 3-month or 1-month period based on their historical sensitivity to innovations in market liquidity. After grouping the currencies in 4 portfolios according to this ranking, we construct a series of excess returns for the portfolios over the following 3-month or 1-month period. Table 12 shows that the portfolio analysis does not change dramatically once the rebalancing is conducted at higher frequencies (Panel A and Panel C). In other words, the portfolio containing the most sensitive currencies displays higher excess returns than the one containing the least sensitive currencies. Furthermore, the annualized liquidity risk premium stays around 4 percent for both rebalancing frequencies (Panel B and Panel D). In short, we can conclude that our results are not due to a specific rebalancing period and that there is no gain in rebalancing more frequently.

[Insert Table 12 around here]

3 GMM alternative estimation

In the main section we estimate the premium associated with our liquidity risk factor using the Fama-MacBeth procedure. In this section, we conduct the same exercise via the General Method of Moments (GMM) procedure as a robustness check of the results. We conduct a two-step GMM estimation with an identity matrix as our first-step weighting matrix and six moment conditions.

The results indicate that the liquidity risk premium estimated via GMM is lower than the one recorded earlier at around 3 percent but still strongly statistically significant with a t-statistic of 8.36. Furthermore, the loading associated with the liquidity risk factor is also statistically significant, with a t-statistic of 2.46. In short, the core results are qualitatively unchanged using GMM for the asset pricing test.

8 CONCLUSIONS

In this paper, we study liquidity in the FX market of 20 US dollar exchange rates over 14 years using order flow data from a large custodian bank. Defining liquidity as the expected return reversal associated with order flow, the well-known Pastor-Stambaugh measure for stocks, we estimate individual currency liquidity measures. As for the stock market, we find the presence of a strong common component in liquidity across currencies, which is consistent with the literature that identifies the dealers' inventory control constraints and preferences as significant channels influencing price formation. In other words, the dealers' response to incoming orders of different currencies has a common part dictated by inventory considerations. Furthermore, the commonality can be explained by the need for funding liquidity on the side of traders. In this sense, changes in funding conditions affect the provision of liquidity in all the currencies in which an investor trades.

The global FX liquidity measure proposed exhibits strong variation through time. Our focus in this paper is on the unexpected component in FX aggregate liquidity, or global FX liquidity risk. In this sense, the paper's main contribution is the identification and estimation of a systematic liquidity risk premium that significantly explains part of the cross-sectional variation in FX excess returns. If there is a liquidity risk premium in the FX market, an investor will require a higher return to hold a currency more sensitive to liquidity innovations. The higher is the sensitivity of a currency to innovations in liquidity, the greater is the premium for holding that currency. Taking the perspective of a US investor, we group the currencies in four portfolios based on the historical sensitivities to the liquidity measures. Comparing the returns of the portfolios, we find that the returns are higher for the portfolios containing the more sensitive currencies. Applying standard asset pricing methods, we estimate an annualized liquidity risk premium of about 4.7 percent, which is both statistically and economically significant.

We also find that liquidity risk is especially important in explaining the cross-section of emerging market currencies. Indeed, excluding the most traded currencies from the portfolio analysis, the liquidity risk premium reaches 7 percent, which is significantly higher than the one for the whole data set. Finally, employing a different proprietary data set for order flow from a large investment bank, we provide empirical evidence that the magnitude of the liquidity risk premium increased substantially after the collapse of Lehman Brothers in the recent financial crisis.

A Appendix: ABBREVIATIONS

List of the abbreviations used in the paper for currencies:

AUD: Australian dollar

BRL: Brazilian real

CAD: Canadian dollar

CHF: Swiss franc

CLP: Chilean peso

CZK: Czech koruna

DKK: Danish krone

DM: Deutsche mark

EUR: euro

GBP: UK pound sterling

HUF: Hungarian forint

JPY: Japanese yen

KRW: Korean won

MXN: Mexican peso

NOK: Norwegian kroner

NZD: New Zealand dollar

PLN: Polish zloty

SEK: Swedish krona

SGD: Singaporean dollar

TRY: Turkish lira

USD: US dollar

ZAR: South African rand

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Table 1: **Descriptive statistics of log returns**

Curr	Mean (*100)	Median (*100)	St dev (*100)	Skew	Kurt	AC(1)	pAC(2)
			Developed countries				
USD/AUD	0.008	0.027	0.643	-0.309	7.101	0.023	-0.041*
USD/CAD	0.009	0.000	0.426	-0.050	5.086	-0.006	-0.018
USD/CHF	0.009	-0.012	0.651	0.263	4.705	-0.013	0.006
USD/DKK	0.010	0.000	0.573	0.204	4.330	0.004	0.002
USD/EUR	0.009	0.000	0.564	0.187	4.342	0.004	0.005
USD/GBP	0.008	0.009	0.483	0.006	4.240	0.016	-0.004
USD/JPY	0.000	-0.015	0.680	0.578	8.081	0.018	0.008
USD/NOK	0.010	0.000	0.616	0.007	5.982	0.037*	-0.006
USD/NZD	0.008	0.022	0.689	-0.386	6.724	0.031	-0.048*
USD/SEK	0.008	0.004	0.602	0.078	4.171	0.037*	-0.021
			Emerging markets				
USD/BRL	-0.014	0.000	0.903	-0.588	31.004	0.103*	-0.079*
USD/CLP	-0.004	0.000	0.506	-0.182	7.470	0.044*	-0.040*
USD/CZK	0.018	0.000	0.641	-0.441	11.767	0.044*	-0.025
USD/HUF	-0.009	-0.018	0.631	-0.385	7.882	0.045*	-0.002
USD/KRW	-0.006	0.000	0.867	0.766	140.078	0.163*	-0.064*
USD/MXN	-0.030	0.000	0.956	-3.378	113.929	-0.084*	-0.056*
USD/PLN	0.005	0.000	0.586	-0.409	6.765	0.082*	0.018
USD/SGD	0.004	0.000	0.345	0.810	18.775	-0.034*	0.008
USD/TRY	-0.094	-0.082	1.186	-8.967	297.445	0.086*	-0.138*
USD/ZAR	-0.020	0.000	0.880	-0.135	10.089	0.032	-0.050*

Notes: The sample period is generally from April 14, 1994 to July 17, 2008. For some currencies the sample period is shorter due to availability of the spot rates from Datastream: for the Brazilian real observations start on July 05, 1994, for the Czech koruna on December 12, 1994, and for the Polish zloty on January 4, 1995. The first two columns show the mean and the median of the log exchange rate returns. The third, fourth and fifth columns report the daily standard deviation, the skewness, and the kurtosis of the log returns. The sixth and seventh columns show the autocorrelation and the second-order partial autocorrelation of the data. * indicates statistical significance at the 5% significance level.

Table 2: Descriptive statistics of order flow data

Curr	Mean	Median	1^{st} perc	99^{th} perc	St dev	Skew	Kurt	AC(1)	pAC(2)	Corr(r,f)
					Developed countries					
AUD	0.038	0.049	-1.265	1.116	0.465	-0.268	1.042	0.760*	-0.016	0.248*
CAD	0.028	0.024	-1.126	1.394	0.498	0.914	6.307	0.792*	0.078*	0.179*
CHF	-0.004	-0.025	-1.373	1.407	0.562	0.152	1.017	0.843*	0.017	0.248*
DKK	-0.043	-0.012	-2.152	1.450	0.694	-3.194	29.454	0.847*	0.057*	0.126*
EUR	-0.004	-0.008	-1.196	1.163	0.475	0.055	1.039	0.817*	0.113*	0.220*
GBP	-0.013	0.017	-1.322	1.143	0.497	-0.202	0.859	0.832*	0.004	0.195*
JPY	0.000	-0.002	-1.267	1.301	0.496	-0.013	0.958	0.783*	0.116*	0.264*
NOK	-0.007	0.000	-2.399	2.480	0.832	0.341	6.932	0.855*	-0.018	0.122*
NZD	-0.003	0.014	-2.235	1.817	0.656	-0.675	7.264	0.818*	-0.027	0.171*
SEK	0.004	0.013	-1.257	1.212	0.513	-0.271	2.541	0.822*	0.020	0.199*
					Emerging markets					
BRL	-0.049	0.015	-7.092	4.348	1.977	-4.959	57.035	0.880*	0.013	0.035
CLP	0.282	0.005	-9.095	13.084	4.509	4.464	67.590	0.888*	0.041*	0.102*
CZK	0.012	0.002	-3.327	3.310	1.410	4.885	72.394	0.836*	0.112*	0.049*
HUF	0.052	0.023	-4.401	4.961	1.416	0.187	10.050	0.839*	0.110*	0.029
KRW	-0.037	0.003	-6.965	6.357	2.411	-5.275	87.355	0.881*	0.145*	0.046*
MXN	-0.008	-0.006	-4.265	4.720	1.361	1.819	21.037	0.835*	0.082*	0.015
PLN	0.185	0.002	-4.715	8.858	2.067	3.649	33.211	0.863*	0.082*	0.096*
SGD	0.017	0.040	-2.195	1.990	0.737	-0.492	5.712	0.803*	0.097*	0.036*
TRY	0.222	0.001	-5.394	7.975	3.597	12.102	204.278	0.893*	0.076*	0.087*
ZAR	-0.026	0.003	-4.451	3.106	1.094	-0.842	10.575	0.823*	0.038*	0.094*

Notes: Order flow data are defined as the net buying pressure on the currency, expressed as number of buys minus number of sells in a currency; see the text in Section 3 for a more precise definition. The sample period is generally from April 14, 1994 to July 17, 2008. For some currencies the sample period is shorter due to availability of data from the provider: for the Chilean peso observations start on October 04, 1995, for the Hungarian forint on September 30, 1994, and for the Polish zloty on August 22, 1995. The first two columns show the mean and the median of the order flow. The third and fourth columns report the 1st and 99th percentiles of the data. The fifth, sixth and seventh columns report the daily standard deviation, the skewness, and the kurtosis. The eighth and ninth columns report the first-order autocorrelation and the partial second-order autocorrelation of the data. The tenth column reports the correlation between the log returns of the US dollar against the currency and the currency's order flow. * indicates statistical significance at the 5% significance level.

Table 3: Regression of returns on order flow

Curr	β	γ	R^2	DW	LM	Curr	β	γ	R^2	DW	LM
	Developed countries						*Emerging markets*				
AUD	0.0082	-0.0063	0.15	1.89	11.62	**BRL**	0.0029	-0.0028	0.03	1.79	24.99
	(17.23)	(-15.10)					(4.37)	(-3.99)			
CAD	0.0041	-0.0032	0.08	1.97*	0.89*	**CLP**	0.0013	-0.0010	0.02	1.92*	4.12*
	(11.49)	(-9.87)					(4.78)	(-3.82)			
CHF	0.0092	-0.0075	0.18	2.04*	1.27*	**CZK**	0.0017	-0.0016	0.02	1.92*	4.44*
	(20.46)	(-17.49)					(5.93)	(-5.60)			
DKK	0.0035	-0.0029	0.05	1.95*	2.45*	**HUF**	0.0004	-0.0004	0.00	1.9	8.31
	(7.85)	(-7.61)					(2.64)	(-2.39)			
EUR	0.0074	-0.0057	0.14	1.96*	1.04*	**KRW**	0.0012	-0.0011	0.01	1.86	13.21
	(12.93)	(-10.37)					(4.15)	(-3.85)			
GBP	0.0061	-0.0051	0.12	1.96*	1.85*	**MXN**	-0.0002	0.0003	0.00	2.19	42.96
	(17.48)	(-15.60)					(-0.59)	(0.86)			
JPY	0.0085	-0.0062	0.15	1.96*	1.61*	**PLN**	0.0010	-0.0004	0.01	1.83	15.21
	(15.26)	(-12.58)					(2.36)	(-1.24)			
NOK	0.0035	-0.0030	0.06	1.87	15.03	**SGD**	0.0004	-0.0003	0.00	2.07*	4.66*
	(10.21)	(-8.85)					(3.13)	(-2.49)			
NZD	0.0055	-0.0045	0.09	1.87	16.48	**TRY**	0.0037	-0.0029	0.02	1.81	17.42
	(11.87)	(-10.53)					(5.41)	(-3.97)			
SEK	0.0068	-0.0055	0.11	1.87	16.58	**ZAR**	0.0023	-0.0019	0.03	1.94*	3.54*
	(15.21)	(-13.16)					(7.69)	(-6.46)			

Notes: Regression (4):

$$r_{i,t} = \alpha_i + \beta_i \Delta x_{i,t} + \gamma_i \Delta x_{i,t-1} + \varepsilon_{i,t}$$

is estimated for each currency i in the data set. t-statistics are calculated according to Newey and West (1987) and are reported in parenthesis under the coefficients. The Durbin-Watson and the LM test statistics are reported in the last two columns. * indicates statistical significance at the 5% significance level.

Table 4: **Regression of currencies' liquidity on common liquidity**

Curr	δ_1	R^2	DW	LM	Curr	δ_1	R^2	DW	LM
	Developed countries					*Emerging markets*			
AUD	0.768	0.08	2.19*	1.52*	**BRL**	0.574	0.02	2.09*	0.35*
	(3.57)					(1.83)			
CAD	0.352	0.02	2.28*	3.45*	**CLP**	1.373	0.08	1.91*	0.18*
	(1.46)					(3.10)			
CHF	0.907	0.08	1.96*	0.02*	**CZK**	1.175	0.07	2.18*	1.41*
	(3.37)					(3.50)			
DKK	1.157	0.15	2.13*	0.72*	**HUF**	0.449	0.03	2.16*	1.23*
	(5.83)					(2.33)			
EUR	0.945	0.11	2.15*	1.15*	**KRW**	0.817	0.05	2.19*	1.58*
	(5.29)					(3.56)			
GBP	0.604	0.05	2.18*	1.40*	**MXN**	1.499	0.09	2.23*	2.26*
	(2.90)					(2.90)			
JPY	1.178	0.14	2.20*	1.81*	**PLN**	0.653	0.04	2.10*	0.49*
	(5.19)					(2.66)			
NOK	0.801	0.07	2.09*	0.35*	**SGD**	0.337	0.06	2.07*	0.30*
	(2.96)					(3.25)			
NZD	1.063	0.12	2.02*	0.02*	**TRY**	1.187	0.02	2.20*	1.65*
	(5.42)					(1.77)			
SEK	1.390	0.19	2.16*	1.68*	**ZAR**	0.930	0.04	2.07*	0.41*
	(6.44)					(2.38)			

Notes: Regression (9):

$$DL_{i,t} = \delta_{0i} + \delta_{1i} DL_t^C + \varepsilon_{i,t}$$

is estimated for each currency i in the data set. t-statistics are calculated according to Newey and West (1987) and are reported in parenthesis under the coefficients. The Durbin-Watson and the LM test statistics are reported in the last two columns. * indicates statistical significance at the 5% significance level.

Table 5: Descriptive statistics of the portfolios

Panel A					
Portfolio	***1***	***2***	***3***	***4***	***4–1***
mean	-0.1348	0.0360	0.0338	0.0835	0.2184
median	-0.0221	0.0137	0.0208	0.1335	0.1022
st dev	0.1853	0.0693	0.0754	0.0958	0.1782
sharpe ratio	-0.7274	0.5195	0.4482	0.8719	1.2255
Panel B					
Portfolio	***1***	***2***	***3***	***4***	***4–1***
mean	0.0177	0.0278	0.0466	0.0871	0.0694
median	0.0078	-0.0028	0.0286	0.1214	0.0358
st dev	0.0809	0.0645	0.0729	0.0842	0.0746
sharpe ratio	0.2185	0.4317	0.6389	1.0342	0.9297

Notes: The portfolios are constructed by sorting the currencies according to the sensitivity of their returns to systematic liquidity risk. Each portfolio contains 5 currencies. The first four columns in Panel A report the annualized descriptive statistics for the excess returns of the individual portfolios. The fifth column shows the annualized descriptive statistics of the excess returns of the portfolio constructed by taking a short position on the first portfolio and long on the fourth portfolio. Portfolio 1 contains the currencies with the lowest sensitivities to liquidity risk, while Portfolio 4 contains the currencies with the highest sensitivity. Panel B shows the results of the same analysis with a cap on the individual currency monthly excess returns of +/- 10%.

Table 6: Results of the cross-sectional pricing analysis

	Panel A			
	LIQ	*constant*	$\chi 2$	
λ	0.0465	-	0.7813	
t-stat (SH)	*(2.7003)*			
	Panel B			
	LIQ	*AVE*	$\chi 2$	
λ	0.0372	0.0440	0.1623	
t-stat (SH)	*(2.7016)*	*(1.9846)*		
	Panel C			
	LIQ	*HML*	*constant*	$\chi 2$
λ	0.0413	-0.0566	-	0.2325
t-stat (SH)	*(2.9407)*	*(-0.5691)*		

Notes: Estimations are obtained via the Fama-MacBeth procedure. LIQ indicates the systematic liquidity risk factor. AVE is the dollar risk factor and is calculated as the average of the cross-sectional portfolios' monthly excess returns. HML refers to the carry risk factor, which is the return of a strategy long in the high-interest rate portfolio and short in the low-interest rate portfolio. The estimated coefficients reported are annualized. t-statistics corrected with the Shanken (1992) adjustment are reported in parenthesis below the estimated coefficients. The p-values of the $\chi 2$ test for the null hypothesis of zero pricing errors are adjusted according to Shanken (1992). A constant is included in the cross-sectional regressions, but it is only reported when statistically significant. However, as in Lustig, Roussanov, and Verdelhan (2011), we find that the sensitivities of the portfolios' excess returns to the dollar risk factor are not different from one, so we do not include a constant in the cross-sectional regression of Panel B.

Table 7: **Alternative liquidity measure: Kyle's lambda**

		Panel A			
Portfolio	***1***	***2***	***3***	***4***	***4–1***
mean	0.0380	0.0033	0.0493	0.0801	0.0421
median	0.0364	0.0072	0.0424	0.1055	0.0295
st dev	0.0765	0.0835	0.0645	0.0720	0.0601
sharpe ratio	0.4964	0.0393	0.7650	1.1128	0.7002
		Panel B			
	LIQ	*constant*	$\chi 2$		
lambda	0.0458	-	0.0000		
t-stat (SH)	*(3.9625)*				

Notes: Liquidity is estimated as the coefficient on contemporaneous order flow on currency returns, from Kyle (1985)'s liquidity definition. The portfolios are constructed by sorting the currencies according to the sensitivity of their returns to systematic liquidity risk. Each portfolio contains 5 currencies. The first four columns in Panel A report the annualized descriptive statistics for the excess returns of the individual portfolios. The fifth column shows the annualized descriptive statistics of the excess returns of the portfolio constructed by taking a short position on the first portfolio and long on the fourth portfolio. Portfolio 1 contains the currencies with the lowest sensitivities to liquidity risk, while Portfolio 4 contains the currencies with the highest sensitivity. Panel B shows the results of the empirical asset pricing exercise. Estimations are obtained via the Fama-MacBeth procedure. LIQ indicates the systematic liquidity risk factor. The estimated coefficient reported is annualized. t-statistics corrected with the Shanken (1992) adjustment are reported in parenthesis below the estimated coefficients. The p-values of the $\chi 2$ test for the null hypothesis of zero pricing errors are adjusted according to Shanken (1992). A constant is included in the cross-sectional regressions, but it is only reported when statistically significant.

Table 8: **Alternative liquidity measure: accounting for serial correlation in returns**

		Panel A			
Portfolio	***1***	***2***	***3***	***4***	***4–1***
mean	0.0112	0.0608	0.0391	0.0538	0.0426
median	0.0183	0.0397	0.0169	0.0801	0.0253
st dev	0.0777	0.0689	0.0810	0.0788	0.0745
sharpe ratio	0.1444	0.8816	0.4824	0.6824	0.5710
		Panel B			
	LIQ	*constant*	$\chi 2$		
lambda	0.0314	-	0.1610		
t-stat (SH)	*(2.0906)*				

Notes: Liquidity is estimated as the impact of lagged order flow on currency returns in a regression where lagged currency returns are also included as an independent variable as in regression (20). The portfolios are constructed by sorting the currencies according to the sensitivity of their returns to systematic liquidity risk. Each portfolio contains 5 currencies. The first four columns in Panel A report the annualized descriptive statistics for the excess returns of the individual portfolios. The fifth column shows the annualized descriptive statistics of the excess returns of the portfolio constructed by taking a short position on the first portfolio and long on the fourth portfolio. Portfolio 1 contains the currencies with the lowest sensitivities to liquidity risk, while Portfolio 4 contains the currencies with the highest sensitivity. Panel B shows the results of the empirical asset pricing exercise. Estimations are obtained via the Fama-MacBeth procedure. LIQ indicates the systematic liquidity risk factor. The estimated coefficient is annualized. t-statistics corrected with the Shanken (1992) adjustment are reported in parenthesis below the estimated coefficients. The p-values of the $\chi 2$ test for the null hypothesis of zero pricing errors are adjusted according to Shanken (1992). A constant is included in the cross-sectional regressions, but it is only reported when statistically significant.

Table 9: **Portfolio for emerging markets and less traded developed countries**

	Panel A				
Portfolio	***1***	***2***	***3***	***4***	***4–1***
mean	0.0342	0.0019	0.0664	0.1768	0.1426
median	0.0411	0.0150	0.0692	0.1900	0.1306
st dev	0.0858	0.0952	0.0809	0.0878	0.1024
sharpe ratio	0.3988	0.0202	0.8208	2.0135	1.3925
	Panel B				
	LIQ	*constant*	*$\chi 2$*		
lambda	0.0718	-	0.1310		
t-stat (SH)	*(5.4959)*				

Notes: The portfolio analysis and the cross-sectional pricing analysis are conducted excluding the most traded currencies. The sample includes here emerging market currencies and developed less traded ones. The portfolios are constructed by sorting the currencies according to the sensitivity of their returns to systematic liquidity risk. Each portfolio contains 3 currencies. The first four columns in Panel A report the annualized descriptive statistics for the excess returns of the individual portfolios. The fifth column shows the annualized descriptive statistics of the excess returns of the portfolio constructed by taking a short position on the first portfolio and long on the fourth portfolio. Portfolio 1 contains the currencies with the lowest sensitivities to liquidity risk, while Portfolio 4 contains the currencies with the highest sensitivity. Panel B shows the results of the empirical asset pricing exercise. Estimations are obtained via the Fama-MacBeth procedure. LIQ indicates the systematic liquidity risk factor. The estimated coefficient reported is annualized. t-statistics corrected with the Shanken (1992) adjustment are reported in parenthesis below the estimated coefficients. The p-values of the $\chi 2$ test for the null hypothesis of zero pricing errors are adjusted according to Shanken (1992). A constant is included in the cross-sectional regressions, but it is only reported when statistically significant.

Table 10: **Crisis period: portfolio analysis**

Portfolio	***1***	***2***	***2–1***
mean	-0.0079	0.0730	0.0808
median	0.0566	0.1355	0.1187
st dev	0.1002	0.1445	0.1095
sharpe ratio	-0.0787	0.5048	0.7386

Notes: The portfolio analysis is conducted with the UBS order flow data set for the time period from January 1, 2005 to May 27, 2011. The portfolios are constructed by sorting the currencies according to the sensitivity of their returns to systematic liquidity risk. Each portfolio contains 3 currencies. The first two columns report the annualized descriptive statistics for the excess returns of the individual portfolios. The third column shows the annualized descriptive statistics of the excess returns of the portfolio constructed by taking a short position on the first portfolio and long on the second portfolio. Portfolio 1 contains the currencies with the lowest sensitivities to liquidity risk, while Portfolio 2 contains the currencies with the highest sensitivity.

Table 11: **Analysis with volume-weighted currencies**

Portfolio	***1***	***2***	***3***	***4***	***4–1***
mean	0.0380	0.0033	0.0493	0.0801	0.0421
median	0.0364	0.0072	0.0424	0.1055	0.0295
st dev	0.0765	0.0835	0.0645	0.0720	0.0601
sharpe ratio	0.4964	0.0393	0.7650	1.1128	0.7002

Notes: Market liquidity is estimated as the weighted average of the currencies liquidity measures. The weights assigned to the currencies are volume-related and are taken from the BIS Triennial reports of various years. The weights for the years not covered by the reports are calculated by interpolation. The weights of the currencies not specifically covered by the reports are assigned by equally distributing the percentage associated with the item "other currencies versus the USD". The portfolios are constructed by sorting the currencies according to the sensitivity of their returns to systematic liquidity risk. Each portfolio contains 5 currencies. The first four columns in Panel A report the annualized descriptive statistics for the excess returns of the individual portfolios. The fifth column shows the annualized descriptive statistics of the excess returns of the portfolio constructed by taking a short position on the first portfolio and long on the fourth portfolio. Portfolio 1 contains the currencies with the lowest sensitivities to liquidity risk, while Portfolio 4 contains the currencies with the highest sensitivity.

Table 12: Analysis with 1-month and 3-month rebalancing

		Panel A			
Portfolio	***1***	***2***	***3***	***4***	***4–1***
mean	0.0290	0.0212	0.0544	0.0871	0.0582
median	0.0333	0.0127	0.0311	0.1048	0.0352
st dev	0.0787	0.0692	0.0711	0.0824	0.0737
sharpe ratio	0.3681	0.3063	0.7658	1.0580	0.7900
		Panel B			
	LIQ	*constant*	$\chi 2$		
lambda	0.0432	-	0.3384		
t-stat (SH)	*(2.9940)*				
		Panel C			
Portfolio	***1***	***2***	***3***	***4***	***4–1***
mean	0.0224	0.0313	0.0557	0.0763	0.0539
median	0.0312	0.0235	0.0614	0.0792	0.0398
st dev	0.0786	0.0647	0.0767	0.0815	0.0751
sharpe ratio	0.2850	0.4844	0.7254	0.9359	0.7173
		Panel D			
	LIQ	*constant*	$\chi 2$		
lambda	0.0396	-	0.2925		
t-stat (SH)	*(2.7476)*				

Notes: The portfolios are constructed by sorting the currencies according to the sensitivity of their returns to systematic liquidity risk. The estimation of the sensitivities and the subsequent ranking of them and rebalancing of the portfolios are conducted at each end of a 3-month period in Panels A and B and a 1-month period in Panels C and D. Each portfolio contains 5 currencies. The first four columns in Panels A and C report the annualized descriptive statistics for the excess returns of the individual portfolios. The fifth column shows the annualized descriptive statistics of the excess returns of the portfolio constructed by taking a short position on the first portfolio and long on the fourth portfolio. Portfolio 1 contains the currencies with the lowest sensitivities to liquidity risk, while Portfolio 4 contains the currencies with the highest sensitivity. Panels B and D show the results of the empirical asset pricing exercises. Estimations are obtained via the Fama-MacBeth procedure. LIQ indicates the systematic liquidity risk factor. The estimated coefficient reported is annualized. t-statistics corrected with the Shanken (1992) adjustment are reported in parenthesis below the estimated coefficients. The p-values of the $\chi 2$ test for the null hypothesis of zero pricing errors are adjusted according to Shanken (1992). A constant is included in the cross-sectional regressions, but it is only reported when statistically significant.

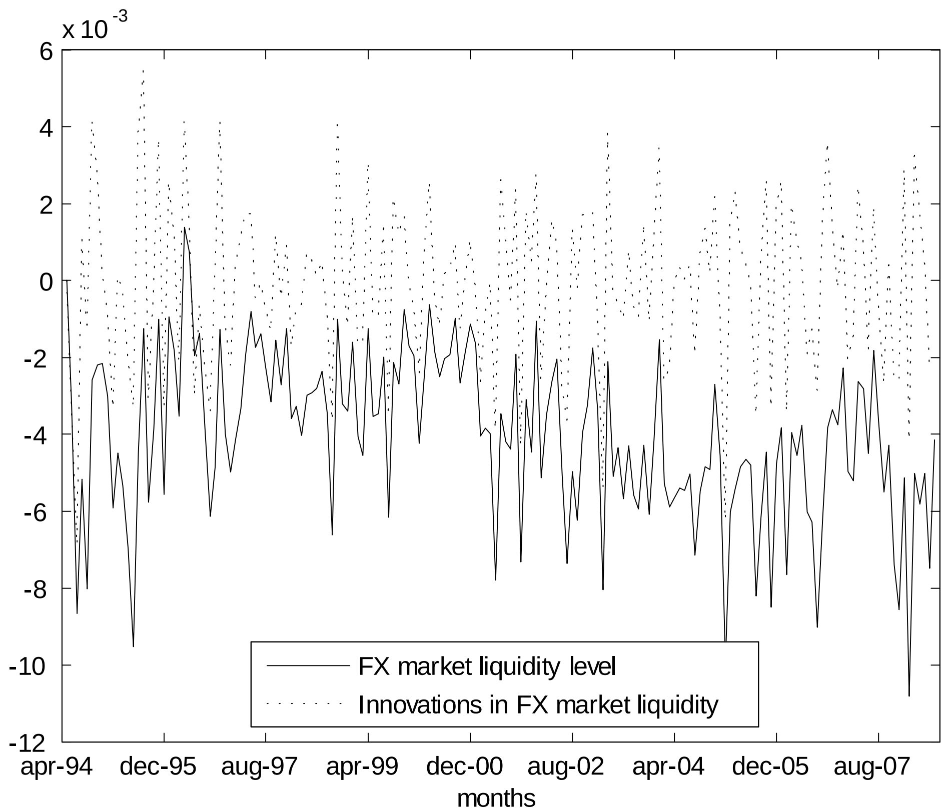

Figure 1: FX market liquidity level and its innovations.

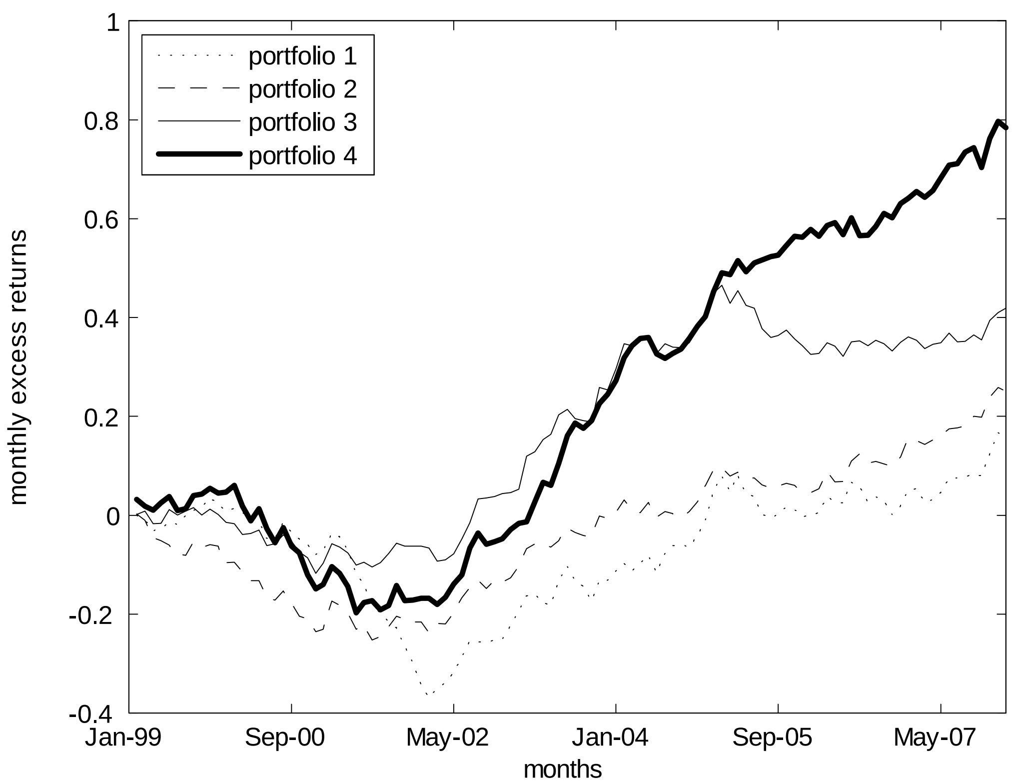

Figure 2: **Cumulative excess returns of portfolios.**
Notes: Portfolio 1 contains the currencies with the lowest sensitivities to liquidity risk, while Portfolio 4 contains the currencies with the highest sensitivities.

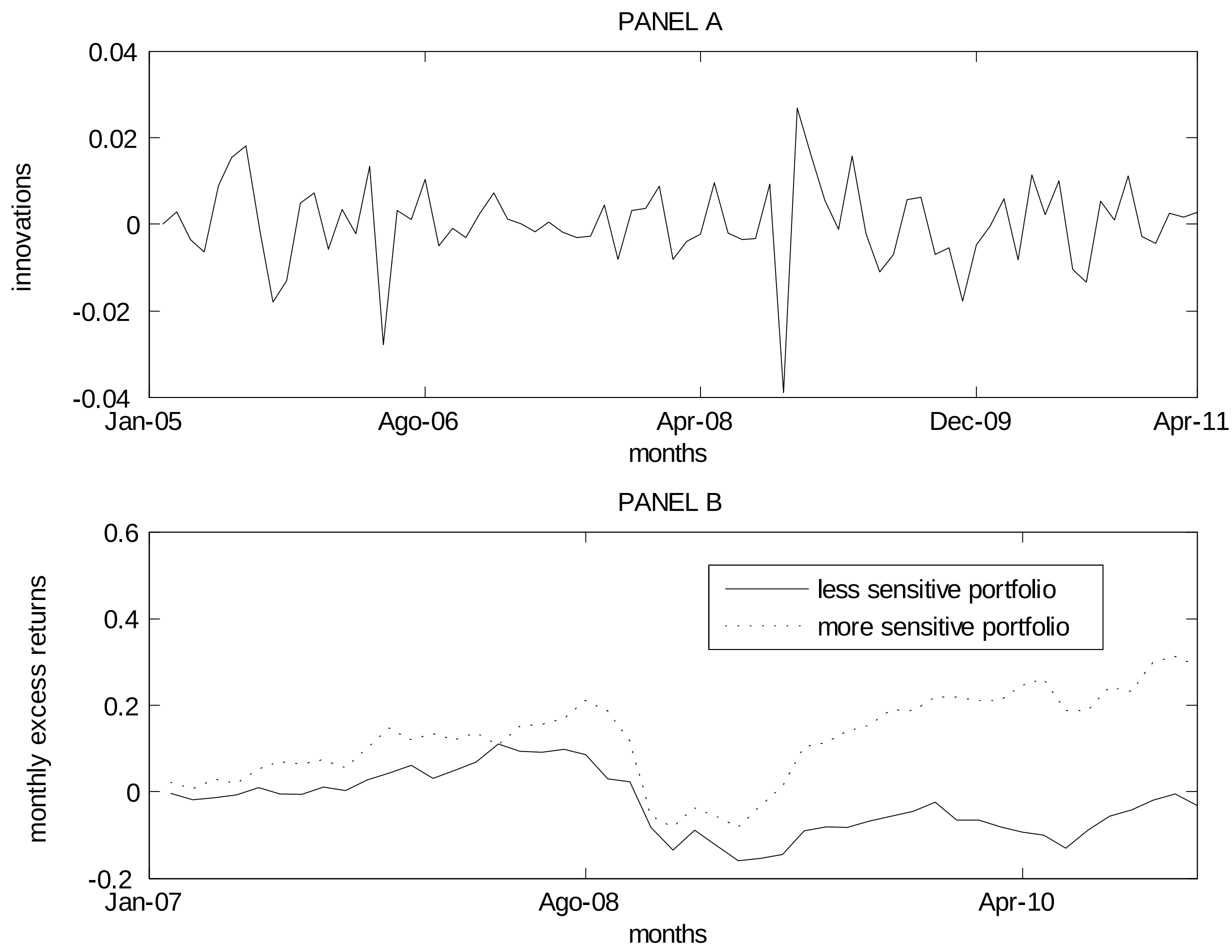

Figure 3: **Crisis period analysis: Innovation in common liquidity and cumulative excess returns of portfolios.**

Notes: Crisis period analysis conducted with an alternative data set comprising the recent crisis period (years 2005-2011). Panel A shows the innovation in common liquidity estimated during this period. Panel B reports the cumulative excess returns of the portfolio containing the least sensitive currencies to innovation in common liquidity and the portfolio containing the most sensitive ones.