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ESSAYS IN FX MARKET MICROSTRUCTURE

Chiara Banti

A Thesis submitted for the degree of Doctor of Philosophy in Finance

Cass Business School
City University London

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Declaration

I grant powers of discretion to the University Librarian to allow the thesis to be copied in whole or in part without further reference to me. This permission covers only single copies made for study purposes, subject to normal conditions of acknowledgement.

I declare that the first paper included in the main body of the thesis, ‘Global Liquidity Risk in the Foreign Exchange Market’, is co-authored with my PhD supervisors Prof. Kate Phylaktis and Prof. Lucio Sarno and published in the Journal of International Money and Finance. I also declare that the second paper, ‘FX Market Illiquidity and Funding Liquidity Constraints’, is co-authored with my PhD supervisor Prof. Kate Phylaktis.

Abstract

The thesis presents three papers in the field of international finance and provides a study of the foreign exchange (FX) market from a microstructure perspective. From the empirical identification of a common component in liquidity across currencies, referred to as FX market liquidity, the thesis investigates its asset pricing implications, determinants and cross-market dynamics.

The first paper is an empirical study of global liquidity risk in the FX market. Estimating liquidity with the Pastor-Stambaugh measure originally developed for the stock market, the paper documents strong liquidity commonality across currencies. Given this observation, it estimates a measure of global FX liquidity risk and shows that the risk is priced in the cross-section of currency returns. It finally evaluates the associated risk premium at around 4.7 percent per annum.

The second paper provides an empirical analysis of the determinants of the time variation in FX market liquidity documented in the first paper. Employing two measures of liquidity, transaction costs and the Pastor-Stambaugh measure from the first paper, the study finds a significant role of traditional determinants, such as global volatility, market returns and seasonality, and of funding liquidity constraints to explain both aspects of market liquidity.

Finally, the third paper is an empirical investigation of illiquidity linkages across the FX and US stock markets. Focusing on transaction costs, the paper finds strong evidence of co-movement, especially during the recent financial crisis. In this respect, illiquidity contagion across the two markets is documented. Given dealers' role as liquidity providers in both markets, their trading behaviour may have significant implications for cross-market liquidity dynamics. Indeed, focusing on the potential sources of the observed cross-market linkages, transaction costs are found to be strongly related to the liquidity supplied to the financial system.

Abbreviations

List of the abbreviations used 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

Introduction

Background to the study

The study of foreign exchange (FX) market microstructure has received an increasing attention by researchers in the last decade.

Traditionally, exchange rate determination has been related to fundamentals. Throughout the Bretton Woods era, models of exchange rate determination were related to the conditions of demand and supply in goods markets. Following the end of the Bretton Woods system of fixed exchange rates in the 1970s, models of exchange rate determination were extended to the conditions of demand and supply of currencies to purchase and sell assets. In particular, the dominant flexible-price model related exchange rates to the instantaneous adjustment of domestic prices to changes in domestic money supply. As major countries adopted freely floating exchange rate regimes, their currencies exhibited strong volatility. From this empirical observation, an alternative monetary model was developed departing from the assumption of automatic adjustments in prices underlying the flexible-price model. Relaxing the assumption of perfect substitutability between domestic and foreign assets, the portfolio balance model identified equilibrium exchange rates by the conditions on the bond and money markets. Finally, open-economy macro models emerged in the mid-1990s. Relying on dynamic general equilibrium models, these more comprehensive frameworks include frictions in both goods and assets markets to give a more realistic account of the determination of exchange rates.

While theoretically appealing, these models do not provide significant results once their empirical predictions are applied to the data. From the seminal paper of Meese and Rogoff (1983), a large body of literature has empirically investigated the theoretical implications of the traditional models and established their lack of determination power.

Following the poor empirical performance of traditional macroeconomic models, a new strand of literature emerged to explain the movements in exchange rates by departing from some important assumptions underlying macro models. The new approach to exchange rates is based on the intuition that the structure of the market in which they are determined brings relevant information on the price determination. Indeed,

the new models, referred to as microstructure models, recognize the importance of considering the presence of private information, heterogeneity of market participants and institutional characteristics of the market itself as relevant factors for the determination of exchange rates. The role of information is especially important for the price formation mechanism. While traditional models generally assumed information to be publicly available to a group of homogeneous agents, the microstructure approach differentiates among market participants with respect to the information available to them, which may not be available simultaneously to all participants. In addition, even when information is public, these models recognize that different market participants may interpret it differently. In this respect, the analysis of the interaction of agents with different characteristics is essential to the price formation mechanism in the microstructure framework.

In support of this approach, the FX market is characterized by the presence of a variety of market participants with distinct trading strategies and objectives. In particular, the FX market is composed of two main levels. At the retail level, customers place currency orders with their banks and financial intermediaries in general. Once the intermediaries receive and absorb the orders from their customers, they turn to the interdealer market to trade any positions accumulated together with their proprietary trading. Traditionally, the largest share of interdealer trading was between market makers, but more recently trading between financial institutions took over (BIS (2010)). In addition, an important trend towards the centralization of the interdealer FX market is making electronic exchanges relatively more important. Despite these on-going changes, the interdealer FX market is still decentralized and trading may take place simultaneously at different prices. Given that foreign exchange rates are determined in the FX interdealer market, it is essential to consider how information is conveyed into prices at that level. The retail market of the FX market is essential in this respect as it represents a source of private information for dealers. In fact, each dealer gathers private information from the orders she receives from her own customer base (Goodhart (1988), Cheung and Chinn (2001) and Gehrig and Menkhoff (2004)). Once she trades on the interdealer market, she will then pass the information to other dealers, or to the market via centralized electronic exchanges, through her own trading (Lyons (1997)). Finally, interdealer trading determines the price.

The departure from traditional macroeconomic models is marked by the introduction in microstructure models of two new determinants, order flow and bid-ask spreads. The inclusion of the two variables in models for exchange rate determination changes drastically the focus of the analysis from macroeconomic fundamentals to market participants and market structure. In this sense, order flow can be defined as signed transaction volume. This measure identifies the initiating party of each transaction to

associate a sign to each trade and then cumulates all signed trades of a specific currency pair in a given period of time to identify the net pressure of demand. Essentially, a transaction is included in the cumulative trading volume signed as a buy, positive, or sell, negative, depending on the side that initiated the trade. The significant role of order flow to determine exchange rates is first reported in Evans and Lyons' (2002a) seminal paper, who finds coefficients of determinations associated with order flow to be significantly larger than in empirical analysis of traditional macro models.

On the market, the counterparty of each trade is often a market maker who stands ready to absorb traders' orders. The presence of market makers in the FX market is important for its functioning and introduces the second component of the microstructure approach. Standing ready to act as counterparty for trades, market makers are suppliers of liquidity. This role is costly and risky and thus requires compensation. In fact, market makers charge a higher price to buyers, the ask, and a lower price to sellers, the bid. The bid-ask spread is the difference between the two and represents the cost of immediacy (Demsetz (1968)) and the remuneration of market makers. The bid-ask spread arises in part to cover the costs incurred by market makers for maintaining her presence on the market (Grossman and Miller (1995)). But these costs are not the only components of the spread. Allowing traders to fulfil their trades quickly, they provide a solution to the frequent time mismatching between the arrival of buyers and sellers on the market. But while providing liquidity to traders, market makers are subject to undesired changes to their inventory level. The mismatch in arrival of buyers and sellers implies that they may have to hold undesired inventory until an order of the opposite sign arrives. Given the risk of adverse exchange rate movements, holding inventory is risky as it may result in a disadvantageous unwinding of the accumulated position (Stoll (1978), Amihud and Mendelson (1980) and Ho and Stoll (1981)). To bear this risk, the market makers require a compensation which is an additional component of the bid-ask spread. Finally, the heterogeneity of market participants entails the presence of some informed and uninformed traders. When market makers engage in trades, they risk suffering losses by trading against a better informed party. To overcome this potential cost, market makers charge a price that covers the expected loss of trading with an informed trader and that is the third and last component of the spread (Copeland and Galai (1983), Kyle (1985) and Glosten and Milgrom (1985)).

Analysing the role of market makers and the bid-ask spread associated with it, it is clear that the provision of liquidity to the market comes at a cost. This cost is a friction preventing markets to be efficient and prices to be informative. A liquid market is a market where large trades are executed quickly and at low cost. Given the definition provided, market liquidity is a broad concept and comprises different aspects. According to Kyle (1985), a liquid market is deep, resilient and tight. In more

detail, market depth is the ability of the market to absorb trades with low impact on prices, whereas tightness reflects the cost for quickly turning a position around. Finally, resiliency refers to a market which quickly readjusts after an uninformative shock. The complexity underlying the definition of liquidity and the variety of aspects it entails are expectedly reflected into the number of tools available for its empirical measurement.

As liquidity providers, dealers need capital to take positions. In this respect, the concept of market liquidity has been closely related to that of funding liquidity. Funding liquidity is the ease with which traders can finance their operations. In this respect, when funding available for traders is low, their trading strategies will be affected and the market will suffer from a loss in liquidity (Brunnermeier and Pedersen (2009), Gromb and Vayanos (2010) and Acharya and Viswanathan (2011)). This may be reflected in an increase in transaction costs, that is wider bid-ask spreads, or in larger price impact of transactions, so that orders are absorbed with a substantial price change which does not readjust quickly.

Objectives and contribution of the thesis

The FX market is characterized by a significantly high level of trading volume, which is estimated at \$4 trillion daily in April 2010 (BIS (2010)). However, liquidity is a complex concept and the presence of large volume does not necessarily depict a market where trades are absorbed quickly and at low cost. Hence, whether the FX market is liquid depends on the definition and tools adopted for estimation. In addition, several currencies are traded on the FX market and the degree of market liquidity varies among them. Generally, trades in emerging market currencies are expected to have a stronger impact on the prices and incur larger transaction costs than in most traded currencies. Moreover, the liquidity of individual currencies has been documented to be time varying (Evans and Lyons (2002b) and Melvin and Taylor (2009)). As a result, there are important differences in liquidity in the FX market across currencies and across time.

This thesis studies liquidity in the FX market. After empirically documenting the presence of a time-varying common component in liquidity across currencies, I provide a thorough investigation of the determinants and implications of this phenomenon at the market level and across markets.

At the market level, I investigate the presence of a common component in liquidity across currencies. In order to consider the various aspects of liquidity, the common factor is documented with respect to two liquidity measures referring to distinct characteristics of liquidity, such as the price impact of transactions and transaction costs. In particular, the price impact of transaction is estimated employing two proxies originally developed for the stock market and based on the Pastor and Stambaugh (2003)'s measure and Kyle (1985)'s λ . First, Pastor and Stambaugh (2003)'s measure

estimates the temporary price change associated with order flow, where the subsequent reversion of an initial price reaction is interpreted as a price readjustment to an uninformative change due to illiquidity. In this respect, the empirical estimation of Kyle (1985)'s λ is an evaluation of the initial reaction of the price to order flow. Besides price impact of transactions, I employ the bid-ask spreads as an alternative estimate of liquidity related to transaction costs. Several studies have investigated the presence of a common component in liquidity in different financial markets. However, the FX market has received much less attention. The presence of a common pattern in the liquidity of a group of developed country currencies during the recent crisis period is documented in Melvin and Taylor (2009) and Mancini, Ranaldo, and Wrampelmeyer (2012). In this respect, this thesis investigates global FX liquidity for a long time period including both crisis and non-crisis periods and both developed and emerging market currencies. Its main contribution relies in providing a comprehensive study of this phenomenon filling the gap of the literature in international finance and market microstructure.

From the analysis of the common component in liquidity, it is clear that it exhibits a strong variation through time. This time variation has important implications from an asset pricing perspective. In fact, this strong variation of the level of liquidity exposes FX traders to a liquidity risk. If investors require a compensation for holding currencies which are sensitive to the risk of unexpected changes in the level of liquidity, which affect their trading costs, then there will be a liquidity risk premium in the cross-section of currency returns. Indeed, investors will require a higher premium to hold currencies which are more sensitive to liquidity risk. In this respect, through an empirical asset pricing exercise, the thesis documents higher returns associated with currencies which are more exposed to global liquidity risk and estimates a global FX liquidity risk premium. Menkhoff, Sarno, Schmeling, and Schrimpf (2012) document the presence of a risk premium associated with global FX volatility, the thesis provides evidence of another risk premium which is related to global liquidity risk.

The presence of a premium associated with global liquidity risk highlights the importance of understanding the movements in FX market liquidity and identifying its sources. Traditional theoretical models have linked the presence of market liquidity to inventory control consideration of dealers and asymmetric information (Amihud and Mendelson (1980) and Copeland and Galai (1983) among the others). More recently, a new stream of literature has developed theoretical models linking market liquidity with dealers' capital constraints (Brunnermeier and Pedersen (2009) and Acharya and Viswanathan (2011) among the others). Whilst designed primarily for the stock market, these models provide an interesting theoretical background for the choice of the possible determinants of FX market liquidity in an empirical investigation. These models are particularly relevant given the role of dealers as liquidity providers in this specific mar-

ket. Indeed, I provide evidence of the importance of determinants which are related to inventory control, such as recent market returns, volatility and seasonality, and others which arise from the specific provision of liquidity by financially-constrained traders, namely interest rates on overnight financial commercial papers. From an empirical perspective, several papers have identified an important role of volatility in determining individual currencies' bid-ask spreads (Bollerslev and Melvin (1994), Bessembinder (1994) and Ding (1999)). Focusing on the currencies of a group of developed countries, Mancini et al. (2012) document a significant role of volatility and interbank credit conditions during the recent financial crisis. However, this thesis provides a thorough study of the determinants of FX market liquidity from a global perspective and with respect to the empirical implications of the discussed theoretical models. Besides the contribution to the literature in international finance, this thesis also provides empirical support for the theoretical literature on the relation between market and funding liquidity in this global market.

The FX market is related to other financial markets in many respects. A large literature has analysed cross-market relationships with respect to market returns and volatility mainly between the stock and FX markets (Phylaktis and Ravazzolo (2005), Pavlova and Rigobon (2008) and Bartram and Bodnar (2012) among the others). From a cross-market perspective, the 2007-2009 financial crisis has highlighted the presence of strong cross-market linkages through which a drop in liquidity in one asset or market may trigger systematic liquidity drops. From the observation of these recent events, a number of theoretical models have been proposed to identify the sources of cross-market liquidity linkages. According to these models, cross-market liquidity linkages arise from financial intermediaries' leverage rebalancing strategies (Adrian and Shin (2010)), informational learning process (Cespa and Foucault (2012)) and financial constraints (Brunnermeier and Pedersen (2009), Gromb and Vayanos (2010) and Acharya and Viswanathan (2011)). In this respect and in order to complete the analysis of FX market liquidity, the thesis empirically investigates the presence of liquidity linkages across the FX and stock markets. It documents significant cross-market liquidity dynamics between the two markets. The linkages are especially tight during periods of financial distress, as shown by the focus on the recent financial crisis. Indeed, according to theory, capital constraints affect market liquidity when dealers are close to hit their funding constraints (Brunnermeier and Pedersen (2009), Gromb and Vayanos (2010) and Acharya and Viswanathan (2011)). Hence, the thesis provides empirical evidence for these models on liquidity contagion.

The contributions of the thesis are several and can be identified with respect to two major areas. The main contribution of this thesis is in the field of international finance. In this respect, the thesis contributes to the general literature on exchange

rate economics by empirically identifying a market liquidity component across currencies through a variety of proxies. It also extends the analysis to investigate the factors triggering changes in this component. Furthermore, the thesis contributes to the literature on exchange rate determinations by identifying and estimating a global liquidity risk premium across a broad section of currency returns.

In addition to international finance, the thesis provides a significant contribution to the field of market microstructure. Indeed, it extends the empirical analysis of the microstructure of financial markets studying market liquidity in an often overlooked but globally important market, the FX market. Employing a unique dataset that comprises order flow of financial institutions for a wide number of currencies and a long sample period, this thesis is able to overcome the issue of lack of data, which is often the reason for the relatively few empirical studies of the FX market. Finally, the thesis extends the analysis of liquidity in the FX market by investigating its cross-market dynamics. Indeed, it explores the linkages in transaction costs across two systemically important financial markets, the US stock and FX markets. Despite the relevance of the two markets considered, this is the first study to analyse liquidity dynamics across them.

Besides the main contribution towards academic literature, the analysis of liquidity is of interest to investors and traders in the FX market. In fact, both the presence of a liquidity risk premium and the identification of the determinants of transaction costs and price impact of transactions are relevant to traders and investors which are interested in minimizing the cost of their trades. Finally, from the regulators' perspective, it is especially important to improve the understanding of the dynamics of liquidity in the FX market given the particular role of this market for monetary authorities and for the economy of a country in general.

Structure of the thesis

This thesis presents an empirical investigation of FX market liquidity, its pricing implications, determinants and cross-market dynamics. The main body of the thesis is developed in the next three chapters, each one presenting a paper. These chapters are followed by concluding remarks that discuss the conclusions of the thesis.

The first chapter is an empirical investigation of global liquidity risk in the FX market. The analysis begins with an estimation of liquidity for a broad group of currencies. In this respect, the study employs a measure of liquidity based on the temporary price impact of transactions, which is the analogue of the Pastor and Stambaugh (2003)'s measure for the stock market. The currencies included in the sample are US dollar exchange rates of the major 10 developed and 10 emerging market countries. The transaction data is a unique data set and comprises order flow of institutional investors over 14 years, from April 1994 until July 2008. Analysing the individual currency liq-

liquidity measures, the paper shows that there is a strong common component across currencies. Having established liquidity commonality in the FX market and identified strong time variation, the paper proposes a measure of global liquidity risk, as the unexpected change in market liquidity. Finally, it provides evidence that liquidity risk is priced in the cross-section of currency returns. The methodology is based on the portfolio construction technique, which allows singling out systemic factors affecting currency returns from idiosyncratic determinants. In particular, the currencies are divided into portfolios according to their degree of sensitivity to the global liquidity risk measure proposed. Constructing a series of returns for each portfolio, the paper shows that holding the most sensitive portfolios give a higher return on average. A strategy of buy the most sensitive currencies and short the least sensitive ones returns significantly high Sharpe ratios. Finally, the paper employs a standard Fama-MacBeth procedure to estimate the liquidity risk premium in the FX market. The procedure is a two-step estimation method starting with the estimation of the sensitivities of portfolios' returns to global liquidity risk. These sensitivity measures are then regressed on the portfolios' returns at each point in time to estimate their average market price. The paper estimates the liquidity risk premium to be around 4.7 percent per annum.

In the second chapter, the second paper provides a thorough empirical analysis of the determinants of the time variation in FX market liquidity documented in the first paper. The study relies on two measures of liquidity, the bid-ask spread and the Pastor and Stambaugh (2003)'s measure presented in the first paper. Analysing the same panel of currencies of the first paper, the main study is conducted with the bid-ask spread data for a sample period of 13 years, from January 1998 until December 2011. However, for the second measure the sample period is shorter, from January 1998 until July 2008, due to data availability limitations of the transaction data. In support of the traditional theoretical models of bid-ask spread determination, this study documents a significant impact of recent market returns, global volatility and seasonality on FX market liquidity. In addition, it provides empirical support to the theoretical models linking market and funding liquidity. In this respect, changes in funding constraints have a significant impact on both aspects of FX market liquidity and the impact relates to market declines when liquidity providers face capital tightness, and to crisis times, when there are severe liquidity dry-ups. Furthermore, funding liquidity together with the other explanatory variables explains unexpected changes in FX market illiquidity, which is the measure of liquidity risk employed in the first paper.

The third chapter presents the third paper, which is an empirical investigation of illiquidity linkages across the FX and US stock markets. Focusing on transaction costs in the two markets for 18 years, from January 1994 until December 2011, the paper finds strong co-movement, especially during the recent financial crisis. In this respect,

the paper provides evidence of illiquidity contagion across the two markets. The data set analysed in this paper comprises bid-ask spreads for the five most traded currency pairs of the FX market and the corresponding measures for the stocks traded on the NYSE/AMEX markets. After identifying a common component in liquidity in both the FX and stock markets, the paper investigates the cross-market liquidity dynamics including these variables in a vector autoregression (VAR) model. The VAR estimation is then analysed with respect to the standard contemporaneous correlation matrix of the VAR innovations, Granger causality tests and impulse response functions. These analyses are supportive of the presence of illiquidity linkages across the two markets. These links are especially strong during the 2007-2009 financial crisis, providing evidence of illiquidity contagion across the markets. Given dealers' role as liquidity providers both in the stock and FX markets, their trading behaviour may have significant implications for the observed dynamics. Turning to the potential sources of the cross-market linkages documented, the paper includes several funding liquidity measures as endogenous variables in the basic VAR and finds transaction costs to be strongly related to the liquidity supplied to the financial system during times of distress. Finally, extending the analysis to common illiquidity in emerging FX markets, the paper addresses the controversial issue of the impact of liquidity provision by developed countries' monetary authorities on emerging markets currencies. In this respect, I show that shocks to developed countries' funding liquidity affect the illiquidity level of FX emerging markets when financial markets are under distress, consistently with the results of the main analysis.

Chapter 1

Global Liquidity Risk in the Foreign Exchange Market

1.1 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 intra-day 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. Analysing 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, Naik, and Radcliffe (1998); Chordia, Roll, and Subrahmanyam (2000a); Chordia, Roll, and Subrahmanyam (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 et al. (2012). 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 behaviour 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 1.2 provides an overview of the relevant literature. In Section 1.3 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 1.4. The core empirical results are reported in Section 1.5, where we document the presence of a common component in liquidity across currencies, and estimate the liquidity risk premium. Section 1.6 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

¹Adopting 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 Pedersen (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.

in Section 1.7. Finally, Section 1.8 concludes.

1.2 Literature review

1.2.1 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 analysing 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 and 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).

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

²Order 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), Bjonnes 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).

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 (1995), 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.

1.2.2 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 (1995) 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 Næs, Skjeltorp, and Ødegaard (2011)). 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 recently, Mancini et al. (2012) 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.

1.2.3 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 Subrahmanyam (1996); Brennan, Chordia, and Subrahmanyam (1998); Datar et al. (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.

³Another 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.

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

Some studies also focus on the time variation of liquidity and on its co-movements cross-sectionally. Chordia et al. (2000a) analyse 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 et al. (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

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 (2005)'s 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.

1.3 Data

1.3.1 Description of the data

The main data set analysed 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

⁵The determinants considered are inventory control variables (such as daily returns and volatility) and informed trading variables (such as dummies for macroeconomic announcement dates).

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 rand, and Turkish lira).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:

$$r_t = \ln(S_t) - \ln(S_{t-1}) \quad (1.1)$$

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:

$$er_t = \ln(S_{t+1}) - \ln(F_t) \quad (1.2)$$

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 behaviour 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 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

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

⁷This 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)).

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

1.3.2 Descriptive statistics

Table 1.1 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 second-order autocorrelation.

Table 1.2 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

⁸While 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).

⁹However, 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).

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

1.4 Methodology

1.4.1 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:

$$r_{i,t} = \alpha_i + \beta_i \Delta x_{i,t} + \varepsilon_{i,t}, \quad (1.3)$$

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 behaviour of risk-averse market makers. While Pastor and

¹⁰However, 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 Bjørnnes and Rime (2005).

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 (1.3) above to include lagged order flow:

$$r_{i,t} = \alpha_i + \beta_i \Delta x_{i,t} + \gamma_i \Delta x_{i,t-1} + \varepsilon_{i,t}. \quad (1.4)$$

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:

$$L_{i,m} = \hat{\gamma}_{i,m}, \quad (1.5)$$

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.

1.4.2 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, Subrahmanyam, and Anshuman (2000b); Pastor and Stambaugh (2003)), excluding the two most extreme observations:

$$DL_{i,m} = (L_{i,m} - L_{i,m-1}) \quad (1.6)$$

$$DL_m = \frac{1}{N} \sum_{i=1}^N DL_{i,m}. \quad (1.7)$$

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:

$$DL_m = \rho_0 + \rho_1 DL_{m-1} + \varepsilon_m \quad (1.8)$$

and set $DL_m^C = \widehat{\varepsilon}_m$. Following Chordia et al. (2000b), 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:

$$DL_{i,m} = \delta_{0i} + \delta_{1i} DL_m^C + \epsilon_{i,m}. \quad (1.9)$$

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

1.4.3 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 (1.4), 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 (1.6) to (1.8).

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:

$$r_{i,m} = \zeta_{0i} + \zeta_{1i} DL_m^C + \varepsilon_{i,m}. \quad (1.10)$$

¹¹An 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.

¹²In 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.

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.

1.4.4 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 and 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:

$$er_{j,m} = \alpha_j + \beta_j^{LIQ} f_m^{LIQ} + \beta_j^{other} f_m^{other} + \epsilon_{j,m} \quad \text{for } j = 1, \dots, 4 \quad (1.11)$$

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:

$$er_{j,m} = \beta_j^{LIQ} \lambda_m^{LIQ} + \beta_j^{other} \lambda_m^{other} + \varepsilon_{j,m} \quad \text{for } m = 1, \dots, M \quad (1.12)$$

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

$$\widehat{\lambda^{LIQ}} = \frac{1}{M} \sum_{m=1}^M \lambda_m^{LIQ} \quad (1.13)$$

$$\widehat{\lambda^{other}} = \frac{1}{M} \sum_{m=1}^M \lambda_m^{other} \quad (1.14)$$

$$\widehat{\varepsilon_j} = \frac{1}{M} \sum_{m=1}^M \varepsilon_{j,m}. \quad (1.15)$$

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

1.5 Empirical results

1.5.1 The FX liquidity measure

Table 1.3 reports the results from estimating regression (1.4), 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 (1.4) since they capture the return reversal. For the currencies of advanced economies, the regressions have particularly high explanatory power, exceeding 18 percent for CHF.

Running the same regression for each independent month in the sample period gives a time series of monthly γ s for each currency. These series represent our monthly proxies of liquidity for the currencies considered.¹⁵ We then calculate a systematic

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

¹⁴The 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.

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

(or aggregate) liquidity measure from the liquidity measures of individual currencies, as in equations (1.6)-(1.8). 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 et al. (2012) analyse 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 analysed here includes both crisis and non-crisis periods, an answer to 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 (1.6)-(1.8).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 1.1 we show the evolution over time of both the level of systematic liquidity and its innovation. Regression (1.9) 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 1.4). 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.

1.5.2 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 1.5 (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

¹⁶A 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.

spread in average returns is substantial and gives empirical support to the presence of a systematic liquidity risk premium.

In order to check whether the results of this analysis are driven by the Turkish lira's extreme behaviour during the 2001 crisis, we cap the monthly excess returns to ± 10 percent.¹⁷ Table 1.5 (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 1.2.¹⁸

Analysing 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 (1.10)) 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.

1.5.3 Liquidity risk: a priced common risk factor

Table 1.6 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.

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

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

¹⁸It 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.

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 et al. (2011), where the dollar risk factor does not explain any of the cross-sectional variation of the portfolios' excess returns. However, as Lustig et al. (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 et al. (2012) 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 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.

1.6 Further analysis

1.6.1 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

¹⁹These results are confirmed in the analysis of Menkhoff et al. (2012) for carry trade portfolios.

²⁰We 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 et al. (2012). However, we find that global FX volatility risk is not statistically significant in explaining our cross section of excess returns.

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 β s measuring systematic liquidity risk are estimated using the following regressions:

$$er_{j,m} = \alpha_j + \beta_j^1 DL_m^C + \varepsilon_{j,m} \quad (1.16)$$

$$DL_{j,m} = \alpha'_j + \beta_j^2 DL_m^C + \varepsilon'_{j,m}. \quad (1.17)$$

The first regression is the equivalent of regression (1.11), with innovations in global liquidity 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' β s measuring systematic liquidity risk are given by:

$$\hat{\beta}_j = \hat{\beta}_j^1 - \hat{\beta}_j^2. \quad (1.18)$$

At this point, we conduct the same empirical asset pricing analysis as above in equation (1.12). 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).

1.6.2 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

²¹We 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.

liquidity measure to the one in the main analysis.

Estimating regression (1.3) 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:

$$L_{i,m} = -\widehat{\beta}_{i,m}. \quad (1.19)$$

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 1.7 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.

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:

$$r_{i,t} = \alpha_i + \beta_i \Delta x_{i,t} + \gamma_i \Delta x_{i,t-1} + \delta_i r_{i,t-1} + \varepsilon_{i,t}. \quad (1.20)$$

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

$$L_{i,m} = \widehat{\gamma}_{i,m}. \quad (1.21)$$

Next, we use these new estimates of liquidity to calculate the innovation in common liquidity from equations (1.6)-(1.8) and conduct the same portfolio and empirical asset pricing analysis as in the core results. The results of this analysis are reported in Table 1.8, 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).

1.6.3 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 1.9, Panel A). Furthermore, the liquidity risk premium associated with this sample is significantly higher, exceeding 7 percent (Table 1.9, Panel B). In short, liquidity is more important in pricing the cross-section of currency returns of emerging markets and less traded developed currencies.

1.6.4 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 does not allow us to analyse 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

²²We 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.

until May 27, 2011.

The order flow data analysed 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 1.3 (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 1.10 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 1.3. 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 et al. (2012).

Analysing 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 (1.10)) 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.

1.7 Robustness checks

1.7.1 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 (1.8).

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 1.11), 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.

²³Specifically, taking the measures of changes in liquidity of individual currencies $DL_{i,m}$ from equation (1.6), 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.

1.7.2 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 Table 1.12 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 1.12 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.

1.7.3 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.

1.8 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.

Table 1.1: **Descriptive statistics of log returns**

Curr	Mean (*100)	Median (*100)	St dev (*100)	Skew	Kurt	AC(1)	pAC(2)
<i>Developed countries</i>							
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
<i>Emerging markets</i>							
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 1.2: 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)
<i>Developed countries</i>										
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*
<i>Emerging markets</i>										
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 1.3 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 1.3: Regression of returns on order flow

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

Notes: Regression (1.4):

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

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 1.4: **Regression of currencies' liquidity on common liquidity**

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

Notes: Regression (1.9):

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

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 1.5: **Descriptive statistics of the portfolios**

Panel A					
<i>Portfolio</i>	1	2	3	4	4-1
<i>mean</i>	-0.1348	0.0360	0.0338	0.0835	0.2184
<i>median</i>	-0.0221	0.0137	0.0208	0.1335	0.1022
<i>st dev</i>	0.1853	0.0693	0.0754	0.0958	0.1782
<i>sharpe ratio</i>	-0.7274	0.5195	0.4482	0.8719	1.2255
Panel B					
<i>Portfolio</i>	1	2	3	4	4-1
<i>mean</i>	0.0177	0.0278	0.0466	0.0871	0.0694
<i>median</i>	0.0078	-0.0028	0.0286	0.1214	0.0358
<i>st dev</i>	0.0809	0.0645	0.0729	0.0842	0.0746
<i>sharpe ratio</i>	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 1.6: **Results of the cross-sectional pricing analysis**

Panel A				
	<i>LIQ</i>	<i>constant</i>	χ^2	
λ	0.0465	-	0.7813	
<i>t-stat (SH)</i>	(2.7003)			
Panel B				
	<i>LIQ</i>	<i>AVE</i>	χ^2	
λ	0.0372	0.0440	0.1623	
<i>t-stat (SH)</i>	(2.7016)	(1.9846)		
Panel C				
	<i>LIQ</i>	<i>HML</i>	<i>constant</i>	χ^2
λ	0.0413	-0.0566	-	0.2325
<i>t-stat (SH)</i>	(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 χ^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 et al. (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 1.7: **Alternative liquidity measure: Kyle's lambda**

Panel A					
<i>Portfolio</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>4-1</i>
<i>mean</i>	0.0380	0.0033	0.0493	0.0801	0.0421
<i>median</i>	0.0364	0.0072	0.0424	0.1055	0.0295
<i>st dev</i>	0.0765	0.0835	0.0645	0.0720	0.0601
<i>sharpe ratio</i>	0.4964	0.0393	0.7650	1.1128	0.7002
Panel B					
	<i>LIQ</i>	<i>constant</i>	χ^2		
<i>lambda</i>	0.0458	-	0.0000		
<i>t-stat (SH)</i>	(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 χ^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 1.8: **Alternative liquidity measure: accounting for serial correlation in returns**

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

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 (1.20). 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 χ^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 1.9: **Portfolio for emerging markets and less traded developed countries**

Panel A					
<i>Portfolio</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>4-1</i>
<i>mean</i>	0.0342	0.0019	0.0664	0.1768	0.1426
<i>median</i>	0.0411	0.0150	0.0692	0.1900	0.1306
<i>st dev</i>	0.0858	0.0952	0.0809	0.0878	0.1024
<i>sharpe ratio</i>	0.3988	0.0202	0.8208	2.0135	1.3925
Panel B					
	<i>LIQ</i>	<i>constant</i>	χ^2		
<i>lambda</i>	0.0718	-	0.1310		
<i>t-stat (SH)</i>	(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 χ^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 1.10: **Crisis period: portfolio analysis**

<i>Portfolio</i>	<i>1</i>	<i>2</i>	<i>2-1</i>
<i>mean</i>	-0.0079	0.0730	0.0808
<i>median</i>	0.0566	0.1355	0.1187
<i>st dev</i>	0.1002	0.1445	0.1095
<i>sharpe ratio</i>	-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 1.11: **Analysis with volume-weighted currencies**

<i>Portfolio</i>	<i>1</i>	<i>2</i>	<i>3</i>	<i>4</i>	<i>4-1</i>
<i>mean</i>	0.0380	0.0033	0.0493	0.0801	0.0421
<i>median</i>	0.0364	0.0072	0.0424	0.1055	0.0295
<i>st dev</i>	0.0765	0.0835	0.0645	0.0720	0.0601
<i>sharpe ratio</i>	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 1.12: Analysis with 1-month and 3-month rebalancing

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

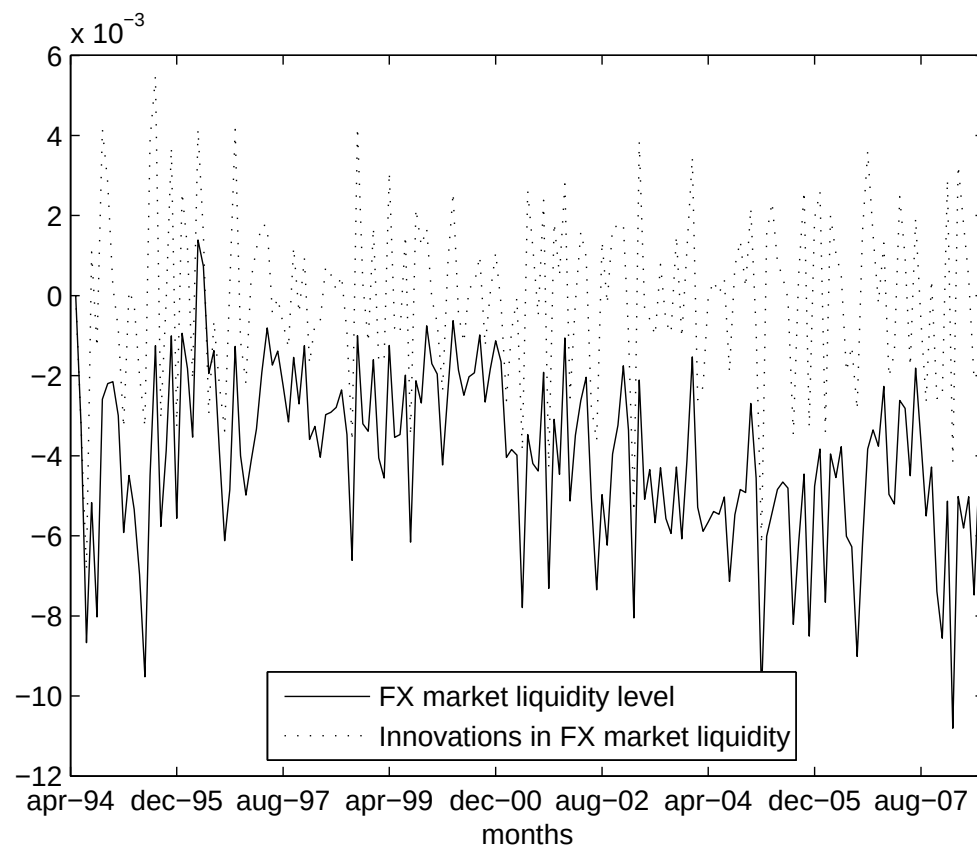


Figure 1.1: **FX market liquidity level and its innovations.**

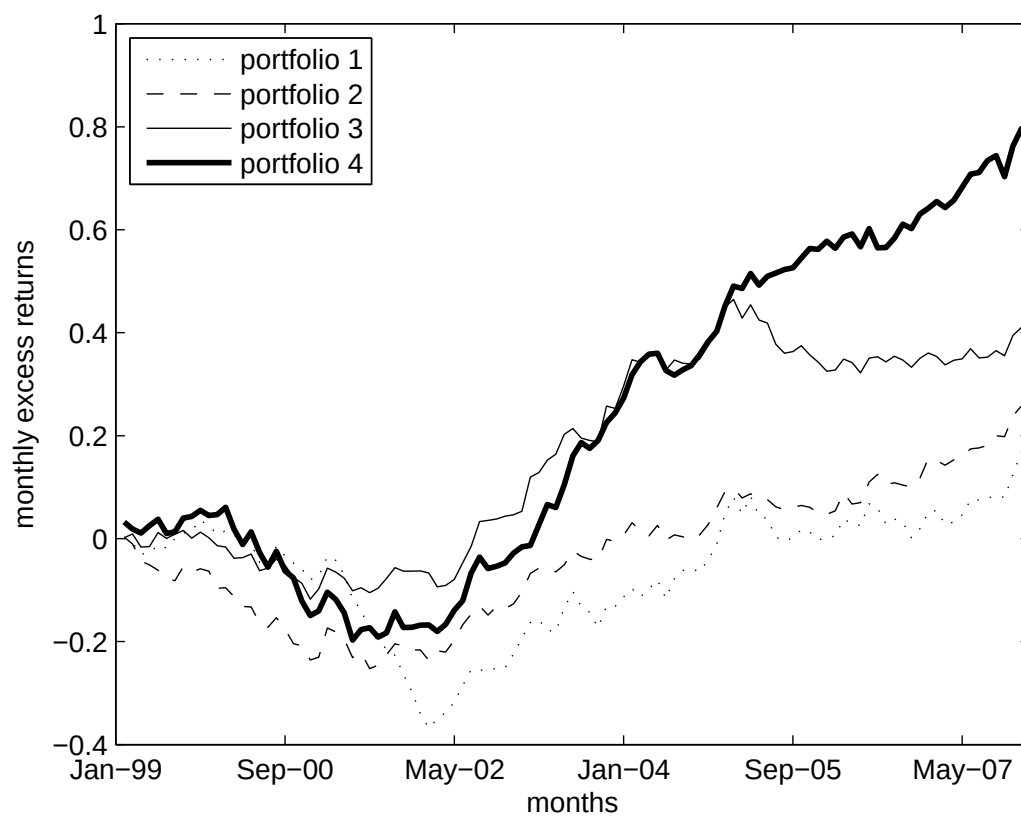


Figure 1.2: **Cumulative excess returns of portfolios.** Portfolio 1 contains the currencies with the lowest sensitivities to liquidity risk, while Portfolio 4 contains the currencies with the highest sensitivities.

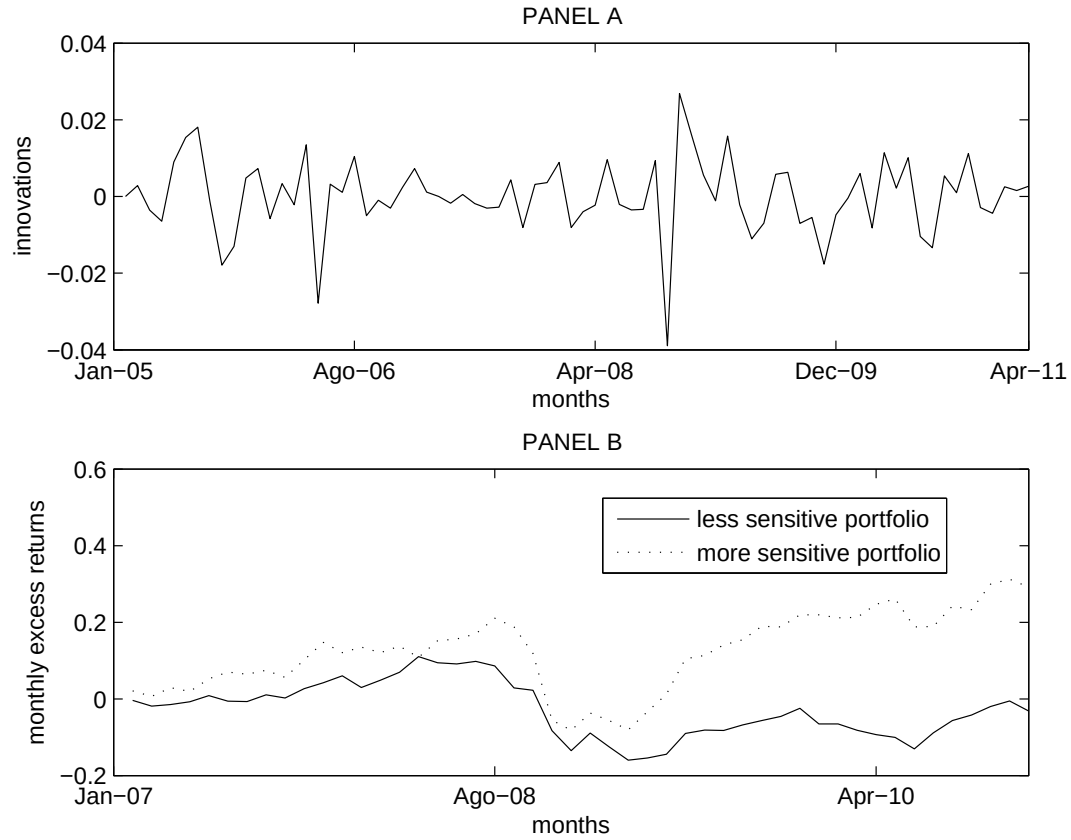


Figure 1.3: **Crisis period analysis: Innovation in common liquidity and cumulative excess returns of portfolios.** Crisis period analysis conducted with an alternative data set comprising the recent crisis period (years 2005-2011). Panel A shows the innovation in common liquidity estimated during this 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.

Chapter 2

FX market illiquidity and funding liquidity constraints

2.1 Introduction

Trading volume in the foreign exchange (FX) market is particularly high if compared to other financial markets. Whether the large trading volume corresponds to a highly liquid FX market depends on the definition of liquidity adopted and the proxy employed to measure it. With respect to trading volume and the bid-ask spread, there are significant differences across currencies both in the level of liquidity and its time-variation. Furthermore, measuring liquidity as the temporary price impact of transactions, recent studies have found that there is a common component in FX market liquidity across currencies. This common component often referred to as commonality in FX market liquidity can arise from variations in the determinants of dealer inventory levels, which is one of the two channels that microstructure has identified of how dealers operations affect market liquidity (Stoll (1978); Ho and Stoll (1981)).¹ For example, variations in market interest rates are likely to induce co-movements in inventory carrying costs, and optimal inventory levels which lead in turn to co-movements in bid-ask spreads of individual assets, a proxy for liquidity. Studies have found that shocks to this common component are priced in the cross-section of currencies excess returns (Mancini et al. (2012); Banti, Phylaktis, and Sarno (2012)). Interestingly, FX market liquidity exhibits a strong variation through time (Melvin and Taylor (2009); Mancini et al. (2012); Banti et al. (2012)).

In this paper we focus on the time-variation of the commonality in FX market liquidity (thereafter referred to as FX market liquidity) and the identification of its determinants, focusing on funding liquidity constraints. To our knowledge this is the first paper that provides a systematic analysis of the impact of funding liquidity on FX

¹The other channel is the asymmetric information channel (Copeland and Galai (1983); Kyle (1985); Glosten and Milgrom (1985); Admati and Pfleiderer (1988)).

market illiquidity. While some papers have investigated the determinants of changes in liquidity cross-sectionally in the stock market (Chordia et al. (2001); Huberman and Halka (2001)), in the bond market (Fleming (2003)), and across the stock and bond markets (Chordia, Sarkar, and Subrahmanyam (2005); Goyenko and Ukhov (2009)), the FX market has received little attention. Mancini et al. (2012) identified a negative relationship between both the VIX and the TED spread measures and FX market liquidity for the most traded currencies during the recent financial crisis. A number of papers have analysed individual currency liquidity and investigated the determinants of changes in the bid-ask spreads over time (Bollerslev and Melvin (1994); Bessembinder (1994); Ding (1999)). Among the different variables proposed, an interesting common result is the positive relationship between volatility and the bid-ask spreads of some currencies in different frequencies and time periods.

More recently, a literature on the interaction of market liquidity and funding liquidity has emerged in order to provide an explanation to the severity of the liquidity drop observed during the recent financial crisis (Brunnermeier and Pedersen (2009); Hameed, Kang, and Viswanathan (2010); Acharya and Skeie (2011); Acharya and Viswanathan (2011)). That is, traders' financial constraints influence the liquidity of financial markets (Shleifer and Vishny (1997); Gromb and Vayanos (2002)). It is important to underline the systematic nature of such an effect: funding liquidity constraints affect all the operations of traders, creating a systematic source of variation in liquidity across financial assets.

Building on the recent theoretical literature on the interaction of funding liquidity and market liquidity, we examine whether the time-variation in FX market liquidity is due to changes in the funding liquidity of the principal traders in FX, namely financial intermediaries. Indeed, the ease with which financial intermediaries are able to finance their operations has an impact on traders' operations in the cross-section of the financial assets they trade, we expect to find a positive relationship between changes in funding constraints and market illiquidity. Furthermore, we take into account two variables related to the inventory control risk, namely volatility (Copeland and Galai (1983)) and market movements (Hameed et al. (2010)), and seasonality (Bessembinder (1994)). Our approach is empirical in line with Chordia et al. (2001) investigation of the determinants of market liquidity in the stock market.

Liquidity is a broad concept and no unique definition exists. Several proxies have been developed to measure it, each referring to some specific aspects. Using a broad data set for 20 daily exchange rates of both developed and emerging markets' currencies over 13 years, we employ the daily percentage bid-ask spreads as our measure of individual currency illiquidity. Averaging across individual currencies, we construct a measure of illiquidity in the FX market. Thus, our main proxy for FX market illiquidity measures

the level of transaction costs. Our results are robust to another measure of liquidity that has recently received significant attention, namely the temporary return reversal inspired by Pastor and Stambaugh (2003), which relates to the depth of the market.

In order to proxy for funding liquidity, we employ the interest rate on financial commercial papers. We show that a lowering in the cost of funding of financial intermediaries is associated with a decrease in transaction costs that is an increase in the liquidity of the FX market. Our findings are robust to controlling for global FX volatility, market movements and seasonality. Global FX volatility is found to increase transactions costs, consistent with previous studies at the individual currency level. Thus, while global FX volatility is able to explain a share of the changes in market liquidity, it does not drive out the effect of funding liquidity on market liquidity. Even though funding liquidity and volatility are intertwined, their effect on market liquidity can be individually measured. Market returns are also found to have a strong impact on FX market illiquidity. A decline in market returns results in an increase in transaction costs the following day. While different from the concept of market index in the equity market, as dealers trade across a set of currencies, their positions and trading strategy are systematically affected by common movements in currency returns. Taking the perspective of a US agent, when FX market returns decline, the agent long in foreign currencies and short in US dollar will incur losses on his positions. In addition, exchange rate movements trigger changes in investor expectations and through their impact on wealth, prompt changes in inventories and in optimal portfolio compositions. This confirms the results found for the equity market (Chordia et al. (2001); Huberman and Halka (2001)). There are also strong day of the week effects on FX global liquidity, declining on Fridays and increasing on Mondays, confirming the increase in spreads before weekends (Bessembinder (1994)). Finally, we include lags of the FX market liquidity variables to correct for serial correlation of the residuals. Our explanatory variables capture an appreciable fraction of the daily time series variation in market wide liquidity of 35%. Furthermore, funding liquidity together with our other explanatory variables are found to explain unexpected changes in FX market illiquidity as well.

Funding liquidity constraints are more likely to be hit during market declines (Hameed et al. (2010)). During market declines, dealers find it more difficult to adjust inventory than in rising markets. We expand our analysis to examine whether market declines affect FX market liquidity and whether this relationship is indicative of funding constraints in the market. Having confirmed that this is indeed the case, we explore whether liquidity dry-ups are worse during crisis episodes (Brunnermeier and Pedersen (2009)). Our sample period allows us to focus on several crisis episodes.² We show

²Our analysis of crisis periods includes the Asian crisis, the LTCM collapse and Russia crisis in

that there is a strong relationship between funding liquidity constraints and market illiquidity during crisis episodes.

We check the robustness of our results by extending our analysis to another measure of liquidity, the temporary return reversal inspired by the Pastor and Stambaugh (2003)'s proxy developed for the stock market. While the bid-ask spread measures transaction costs, the return reversal proxy is related to market depth. Conducting our analysis at monthly frequency, we take into account two variables for funding liquidity constraints: the amount outstanding of repurchase agreements of primary dealers in the US and the interest rate on financial commercial papers. Our results confirm the importance of funding liquidity in explaining variations of FX market liquidity, even after controlling for volatility and market returns.

In the next section we review the relevant literature. The methodology for the construction of our liquidity measures and proposed determinants is presented in Section 2.3. Section 2.4 reports some preliminary analysis of the data and the results of the regression analysis. Robustness tests, including the extension of our analysis to an additional proxy for FX market liquidity, are conducted in Section 2.5. Finally, Section 2.6 concludes.

2.2 Literature review

2.2.1 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. Due to the heterogeneity of market participants, the FX market is characterized by informational asymmetries, so that dealers gather and disperse information from the orders placed by their customers (Lyons (1997)). Indeed, FX market practitioners' surveys highlight how order flow³ 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)). Such asymmetry of information influences liquidity (Copeland and Galai (1983); Kyle (1985); Glosten and Milgrom (1985); Admati and Pfleiderer (1988)). In fact, 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

2008, the events of 9/11, the Argentina crisis in 2001 and the recent collapses of Bear Sterns and Lehman Brothers during 2008.

³Order 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).

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).

Analysing the intra-day trading of DM/USD in two interbank FX markets (London and 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 non-trading intervals. Indeed, dealers' inventory control conditions affect the liquidity of the market. 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)).

Furthermore, dealers' financial constraints can be a source of market illiquidity. Shleifer and Vishny (1997) first introduce financially constrained arbitrageurs that are unable to fully exploit arbitrage opportunities due to the risk of investors' redemption. Gromb and Vayanos (2002) explicitly model the financial constraints, arguing that margin requirements affect arbitrageurs' ability to provide liquidity to the market.⁴ Referring to the risk of the worsening of counterparty risk, Brunnermeier and Pedersen (2009) extend the Grossman-Miller model to include the interaction of funding liquidity with the provision of liquidity by traders. Indeed, traders' provision of liquidity depends on their ability to finance their operations. Hence, margin constraints can have a significant role on the determination of market liquidity. However, the ability to finance the operations of traders depends on market liquidity as well. So, under certain conditions, this interaction between market liquidity and funding liquidity can lead to a margin spiral leading to liquidity dry-ups. Acharya and Viswanathan (2011) relate market liquidity and funding liquidity to agency problems that impair the ability of financial intermediaries to roll over their short-term debt. In bad economic conditions, a high level of debt to be rolled over is related to a strong risk-shifting problem, reducing funding liquidity available to intermediaries. As a consequence, the constrained intermediaries will have to sell assets in order to repay their debt, in turn affecting

⁴The asset pricing effects, in terms of return and risk, of margin-constrained traders are also modelled by Garleanu and Pedersen (2011).

market liquidity.

2.2.2 Measures of market 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 (1995) 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. Furthermore, because the spread is valid only for transactions up to a certain size, it provides no information on the prices at which larger transactions might take place, or how the market might respond to a long sequence of transactions in the same direction, which could be generated when a trader breaks a large trade into many smaller ones, that could span several days. In contrast, measures such as those proxying for price impact capture that aspect better than the bid-ask spread (Vayanos and Wang (2012)).

As a result of these possible limitations, we use in our analysis in addition to the bid-ask spread, a liquidity measure, which proxies for the price impact to obtain a more complete picture. 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. Mancini et al. (2012) 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 their analysis of FX global liquidity risk, Banti et al. (2012) employ a similar measure to estimate the monthly FX market liquidity drawing on both developed and emerging market currencies over 14 years.

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. 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. There are other measures of liquidity, such as the Amihud (2002) illiquidity ratio, which measures the elasticity of liquidity, which have not been used in FX market because of lack of data.

2.2.3 Estimation of funding liquidity

Funding liquidity is defined as the ease with which traders can obtain funding. The presence of constraints to the ability of traders to finance their operations can affect negatively market liquidity (Gromb and Vayanos (2002); Brunnermeier and Pedersen (2009); Acharya and Skeie (2011); Acharya and Viswanathan (2011)).

In the literature, financial constraints are defined as margin requirements (Gromb and Vayanos (2002); Brunnermeier and Pedersen (2009); Garleanu and Pedersen (2011)), as limits to the availability of external capital financing (Shleifer and Vishny (1997)) or as short-term debt that needs to be rolled over (Acharya and Skeie (2011); Acharya and Viswanathan (2011)).

In order to empirically analyse funding liquidity, different proxies are used to measure the conditions with which financial intermediaries can access financing.

Some studies employ measures for funding liquidity based on the interest rate on the interbank market: the TED spread (Coffey and Hrungr (2009), Cornett, McNutt, Strahan, and Tehranian (2011), Garleanu and Pedersen (2011); Mancini et al. (2012)) and the LIBOR-OIS spread (Acharya and Skeie (2011); Mancini et al. (2012)). The TED spread is the difference between the three-month London Interbank Offered Rate (LIBOR) and the three-month Treasury rate. Since the Treasury rate is considered as the risk-free rate, the TED spread measures the perceived credit risk of interbank lending. Similarly, the LIBOR-OIS spread is the spread between the LIBOR and the Overnight Interest Swap rate (where the flexible interest rate is usually considered the Federal funds rate). The difference in the interbank interest rates of unsecured term (three months) borrowing and unsecured overnight borrowing is considered as a measure of credit risk in the interbank market. In addition, Chordia et al. (2001) employ two measures for short-selling constraints and margins, the daily first difference in the Federal funds rate and the daily change in the difference between the yield on a constant maturity 10-year Treasury bond and the Federal funds rate. Coffey and Hrungr (2009) measure margin requirements through the overnight agency MBS-Treasury repurchase agreement spread, which is the difference in the repurchase agreement rate when the collateral are agency mortgage-backed securities (MBS) and when the collateral are Treasury securities.

Conversely, other studies look at funding liquidity aggregates: asset-backed com-

mercial papers⁵, financial commercial papers⁶ and repurchase agreements (REPOs)⁷ (Brunnermeier and Pedersen (2009)). In particular, Brunnermeier and Pedersen (2009) identify funding constraints for financial intermediaries, and banks, relating to collateralized borrowing, from other banks, insurance companies and the Federal Reserve Bank, for which we believe REPOs are a reasonable proxy. However, banks also finance their operations through uncollateralized short-term debt. More specifically in the FX market, Adrian, Etula, and Shin (2010) analyse the funding liquidity ability of US financial intermediaries by considering the amount outstanding of commercial papers and repurchase agreements, and find that changes in funding liquidity affect exchange rate variation of some currencies versus the US dollar. In another paper, Adrian and Shin (2010) show that financial intermediaries adjust their balance sheets according to the state of the market by adjusting leverage through repurchase agreements and reverse repurchase agreements, in a pro-cyclical manner, that is increasing leverage during booms and reducing it during busts. Furthermore, they show that the financial intermediaries' response to market conditions is similar to Brunnermeier and Pedersen (2009) "margin spiral" where increased margins and falling prices reinforce market distress. When the price of securities falls, the financial intermediaries adjust leverage by selling securities, which will be leading to further price falls. When there is the possibility of a feedback, since leverage has been found to be pro-cyclical, the adjustment of leverage and price changes will reinforce each other in an amplification of the financial cycle. In view of the above, we use in our analysis financial commercial paper and REPOs.

2.3 Methodology

2.3.1 Estimation of FX market liquidity

No unique definition of liquidity exists. According to Kyle (1985), liquidity is a "slippery and elusive concept" because of its broadness. In fact, the concept of market liquidity encompasses the properties of "tightness", "depth", and "resiliency". These attributes describe the characteristics of transactions and their price impact. In particular, a market is liquid if the cost of quickly turning around a position is small, the price impact of a transaction is small, and the speed at which prices recover from a random,

⁵Asset-backed commercial papers are collateralized commercial papers issued by Special Purpose Vehicles created by the financial intermediary that originally owned the asset collateralized. On the one hand, the original owner of the asset finances itself through the sale of these same assets to the SPV. On the other hand, the SPV finances the purchase of such assets through the issuance of ABCP.

⁶Financial commercial papers are unsecured promissory notes issued as a form of short-term financing (maturities are up to 270 days, but usually around 30 days).

⁷Through a repurchase agreement, a financial institution sells a security and buys it back at a pre-agreed price on an agreed future date. The repurchase agreement is equivalent to a secured loan with the interest rate being the difference in the sale price and the repurchase price.

uninformative shock is high. In our main analysis we are employing the percentage bid-ask spreads as a proxy for transaction costs. In an extension of the main analysis, we also consider another proxy for liquidity: the temporary price impact of transactions or market depth, a modified version of Pastor and Stambaugh (2003)'s measure.

2.3.1.1 Illiquidity as transaction costs

In order to measure transaction costs, we employ the percentage bid-ask spread to increase the comparability of spreads among currencies.

We build the percentage bid-ask spreads of the USD against other currencies following the American system:

$$PS_{i,t} = \frac{(ask_{i,t} - bid_{i,t})}{mid_{i,t}}, \quad (2.1)$$

where $ask_{i,t}$, $bid_{i,t}$ and $mid_{i,t}$ are the daily series of the ask, bid and mid prices of the USD against currency i .

The percentage bid-ask spread measures the transaction costs. Hence, the larger the spread, the transaction costs and the lower the liquidity level. It is important to note that the percentage spread measure is thus a measure of illiquidity.

Next, we calculate market illiquidity by averaging across currencies the individual percentage spread series excluding the two most extreme observations (e.g. Chordia et al. (2000a); Pastor and Stambaugh (2003)), as follows:

$$PS_t = \frac{1}{N} \sum_{i=1}^N PS_{i,t}. \quad (2.2)$$

Since we are interested in the changes of market illiquidity, we take the first difference of the logs of the market illiquidity measure just calculated:

$$\Delta PS_t = \log(PS_t) - \log(PS_{t-1}). \quad (2.3)$$

Furthermore, we examine percentage changes as we were not able to reject the hypothesis that PS is non-stationary.

Table 2.1A in Appendix 2A shows that market illiquidity explains a substantial proportion of the movements in individual currencies' illiquidity. Furthermore, in accord with Mancini et al. (2012), we find that more liquid FX rates, such as the EUR/USD and GBP/USD tend to have lower liquidity sensitivity to market wide FX liquidity. The opposite is true for less liquid FX rates, such as the Brazilian real/USD and the Hungarian forint/USD.

2.3.2 Identifying the determinants of market liquidity

Building on the recent theoretical literature on the interaction of funding and market liquidity, we examine whether changes in the availability of funding to traders determine the time-variation in FX market liquidity. In addition, we take into account variables which are related to the inventory control risk such as volatility and FX market returns, and seasonality.

2.3.2.1 Funding liquidity constraints

Financial commercial papers are unsecured promissory notes issued as a form of short-term financing.

Since we are interested in the tightening of funding liquidity, we take the first difference of the logs of financial commercial paper interest rate, as follows:

$$\Delta FCP_t = \log(FCP_t) - \log(FCP_{t-1}), \quad (2.4)$$

where FCP is the daily series of the overnight financial commercial paper interest rate. Furthermore, we take the first difference as we were not able to reject the hypothesis that that FCP is nonstationary.

We expect to find a positive relationship between changes in funding liquidity and changes in FX market illiquidity. In detail, a decrease in the financial commercial paper interest rates is associated with a decrease in the cost of funding to traders. As a result, traders are expected to increase their operations leading to an increase in FX market liquidity.

2.3.2.2 Margin requirements

In addition to the measure of funding liquidity constraints, we look at proxies for margin requirements. Hence, we include in our analysis the variation in the Federal funds effective rate to proxy for short-selling constraints and margins in the stock market liquidity (Chordia et al. (2001)).

We also build the TED spread, the difference between the 3-month LIBOR and the 3-month Treasury rate, which is another widely used measure of this kind as it has been noted above.

2.3.2.3 Global FX volatility

We also include a measure of FX market volatility as a possible determinant of FX market liquidity (Menkhoff et al. (2012)). Following the inventory control theoretical models, an increase in the volatility affects the riskiness associated with holding inventory in the currencies involved. The increase in the uncertainty will thus result in a decrease in liquidity. While this relationship is found for individual currency liquidity (Bollerslev and Melvin (1994); Bessembinder (1994); Ding (1999)), it should also be

in place once market-wide liquidity is considered. An observed increase in FX market volatility will impact the riskiness of holding any inventories in FX, thus leading to a decrease in the liquidity of the FX market as a whole.

We employ the JP Morgan VXY volatility index that captures the implied volatility from currency options of G7 countries. Since the series exhibits non stationarity, we take the first difference of the logs of the measure, as follows:

$$VOL_t = \log(VXY_t) - \log(VXY_{t-1}). \quad (2.5)$$

2.3.2.4 FX market returns

Following Chordia et al. (2001) and Hameed et al. (2010), we include recent market activity as one of our explanatory variables. Although, there is no equivalent market index in the FX market, participants are following closely what is happening in the key exchange rate markets. Recent exchange rate moves affect the value of foreign currency denominated assets and through their effect on wealth impact on exchange rate expectations in accord with portfolio balance models of exchange rate determination (Obstfeld and Rogoff (1996)), prompting changes in inventories and optimal portfolio compositions.

We calculate FX market returns as follows:

$$MKT_t = \sum_{i=1}^{20} \left(\frac{r_{i,t}}{20} \right), \quad (2.6)$$

where $r_{i,t}$ is the log return of the USD against currency i at time t .

2.3.2.5 Weekly Seasonality

According to Bessembinder (1994) there is a seasonal pattern in changes in spreads of major currency pairs. Spreads widen before weekends and non-trading intervals. This is due to several reasons: higher costs of carrying liquid currency inventories as the weekend approaches, higher opportunity costs over weekends because inventories are held for more days; and the risk of changes in inventory value. Thus we include day of the week dummies to test whether such seasonality exists for FX market liquidity.

We include in our analysis dummies for Monday, Tuesday, Wednesday and Thursday.

2.4 Empirical analysis

2.4.1 Preliminary analysis of the data

2.4.1.1 Description of the data

The data set analysed in this paper comprises daily data for 20 bid, ask and mid exchange rates of the USD versus 20 currencies for a time period of 13 years, from January 01, 1998 to December 31, 2010. 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 rand, and Turkish lira).⁸ The selection of the currencies reflected the importance of the currencies in FX trading according to BIS (2010) and the availability of data.

To build the percentage bid-ask spreads of the USD against these currencies, we obtained the daily series of the ask, bid and mid prices of the USD against the currencies from Datastream (WM/REUTERS). The quotes provided by WM/Reuters are collected at 16 GMT, which is the time of highest liquidity in the FX market. For a large sample of the currencies in our data set (AUD, CAD, CHF, CZK, DKK, EUR, GBP, HUF, JPY, MXN, NOK, NZD, PLN, SGD, SEK, TRY, ZAR) the ask and bid rates are from actual trades and they are calculated independently as the median of actual trades during a fixing period (one minute). If actual trade rates are not available, quoted rates are reported. For the other currencies (BRL, CLP, KRW), the bid and ask rates are quotes from Reuters.⁹ Furthermore, in order to estimate FX market returns as the average daily log returns of individual currency pairs, we calculate log returns as the difference of the log of the FX spot exchange rates of the US dollar versus the 20 currencies, also obtained from Datastream. They are the WM/Reuters Closing Spot Rates, provided by Reuters at around 16 GMT.

As a proxy for funding liquidity constraints, our data set comprises overnight AA financial commercial paper (FCP) interest rate. The daily data of the FCP interest rate is available from the U.S. Federal Reserve Board and it is collected by The Depository Trust & Clearing Corporation (DTCC), a national clearinghouse for the settlement of securities trades and a custodian for securities. The FCP interest rate index elaborated by the Federal Reserve Board is an aggregation of the interest rates on the trades of financial commercial papers by dealer and direct issuer to investors (supply side), which are weighted according to the face value of the relevant commercial paper. As such, the daily interest rate on financial commercial papers is representative of the interest rates on the actual trades during the day.

In addition, we employ two series to proxy for margin requirements: the Federal Funds (FF) rate and the TED spread. The daily series of the Federal Funds rate is available from the U.S. Federal Reserve Board. To construct the TED spread, we obtain

⁸The classification in developed and emerging countries above does not correspond to the IMF classification, but follows instead common practice in the FX market.

⁹It should be noted that Phylaktis and Chen (2009) find using various information measures that the matched tick by tick indicative data bear no qualitative difference from the transaction data and have higher information content.

the 3-month LIBOR from Datastream and the 3-month Treasury rate from the U.S. Federal Reserve Board.

2.4.1.2 Preliminary analysis of the variables

Table 2.1 reports the descriptive statistics of our main variables, changes in FX market illiquidity and changes in financial commercial paper interest rate. In detail, our proxy of changes in FX market illiquidity exhibits a strong variability, with a high standard deviation. The strong variation through time can be seen in Figure 2.1. Indeed, transaction costs exhibit a high variation during the first part of the sample period. In particular, there are spikes in illiquidity during 1998, when the Asian countries and Russia were hit by a severe financial crisis. Furthermore, FX market illiquidity has a negative skewness and kurtosis, which indicates fat tails of the observations. Interestingly, our measure presents a high serial correlation.

Changes in financial commercial paper interest rate exhibit a high standard deviation as well. The series shows strong variation during some crisis periods, such as 1998, 2001, and during the latest financial crisis (see Figure 2.2). The negative skewness and the large positive kurtosis indicate that the series exhibits fat tail on the negative side.

Figure 2.3 shows the daily changes in the TED spread. The variables show strong variation at the beginning and at the end of the sample period, during financial crisis episodes. In particular, the larger spikes coincide with the most recent financial crisis. Brunnermeier (2009) and Cornett et al. (2011) give a vivid account of the behaviour of TED spread during the recent financial crisis. The other margin requirement variable, changes in FF rate, follows a similar path (not shown).

Global FX volatility is plotted in Figure 2.4. It shows a strong variation through time, but significantly high spikes during the latest financial crisis.

The correlation matrix reported in Table 2.2 shows the correlation coefficients among our funding liquidity variables and global FX volatility. The correlation between the changes in financial commercial paper interest rate and the Federal funds rate is strong, in excess of 26%. Changes in the proxies for margin requirements, FF rate and TED spread, are negatively correlated, with a coefficient of -4%. In addition, global FX volatility is positively correlated with changes in financial commercial paper interest rate, with a correlation coefficient of over 3%.

2.4.2 Regression analysis

2.4.2.1 Market illiquidity and funding liquidity constraints

We conduct a regression analysis to test whether movements in the proposed variables explain a sizable share of variation in FX market illiquidity.

We start our analysis by looking at funding liquidity constraints. So, we run the

following regression of the changes in market illiquidity on the proposed determinants:

$$\begin{aligned} \Delta illiq_t = & \alpha + \beta \Delta FCP_t + \gamma_1 d_t^{MON} + \gamma_2 d_t^{TUE} + \gamma_3 d_t^{WED} + \gamma_4 d_t^{THUR} \\ & + \sum_{i=1}^4 \theta_i \Delta illiq_{t-i} + \varepsilon_t, \end{aligned} \quad (2.7)$$

where ΔFCP_t is the first difference of the log of the financial commercial paper interest rates at time t . We take into account the day of the week effect including in our regression the dummies for Monday, Tuesday, Wednesday and Thursday, d_t^{MON} , d_t^{TUE} , d_t^{WED} , and d_t^{THUR} respectively. Finally, we include in the regression four lags of the dependent variable, to account for the strong serial correlation in the residuals. We run the regression using OLS and adjusting standard errors via Newey and West (1987). As a robustness test we repeat the estimation in a subsequent section using GMM.

Table 2.3 reports the results of this regression in model (1). The regression has a high explanatory power, with an adjusted R-square of 35%. Looking at funding liquidity constraints, changes in the interest rates of financial commercial papers (ΔFCP) is significant in explaining changes in daily transaction costs. In detail, the positive coefficient tells us that an increase in the funding liquidity constraints results in an increase in transaction costs. As expected given the high serial correlation of our illiquidity measure, the lagged dependent variables are statistically significant. In order to differentiate the statistical significance of ΔFCP from that of the lagged dependent variables and day of the week effects, we run model (1) in Table 2.3 without ΔFCP . The R squared is 0.3393. We performed an F test, which confirms the statistical significance of ΔFCP . The day of the week dummies are all significant and negative, suggesting that market liquidity declines on Friday. Monday has the largest absolute coefficient suggesting that liquidity appreciably increases on Monday.¹⁰ This confirms the findings of Bessembinder (1994) and Ding (1999) of increases in FX spreads before weekends. A similar pattern was found in Chordia et al. (2001) for the equity market.

At this point, we extend our regression analysis to include other explanatory variables, FX market volatility, margin requirements and lagged FX market returns as

¹⁰On Fridays, when the four day of the week dummies are zero, the positive intercept implies an increase in transaction costs, i.e. a decline in FX market liquidity. If Monday instead of Friday is the zero base case for day of the week dummies, the intercept is statistically significant and its sign is reversed confirming our interpretations of the day of the week dummies. Results can be made available on request.

follows:

$$\begin{aligned}
\Delta illiq_t = & \alpha + \beta \Delta FCP_t + \delta VOL_t + \varphi \Delta TS_t + \zeta \Delta FF_t \\
& + \mu MKT_{t-1} + \gamma_1 d_t^{MON} + \gamma_2 d_t^{TUE} + \gamma_3 d_t^{WED} + \gamma_4 d_t^{THUR} \\
& + \sum_{i=1}^4 \theta_i \Delta illiq_{t-i} + \varepsilon_t,
\end{aligned} \tag{2.8}$$

where VOL_t is the proxy for global FX volatility, ΔTS_t is the changes in the TED spread at time t , ΔFF_t is the changes in the Federal Funds rate at time t , and MKT_{t-1} are the lagged FX market returns. As above, we add dummies for the day of the week as well as the lagged dependent variables.

Model (2) in Table 2.3 presents the results. Global FX volatility is significant in explaining the movements in FX market illiquidity, consistently with previous studies at the individual currency level (Bollerslev and Melvin (1994); Bessembinder (1994); Ding (1999)). The coefficient is positive as expected, since an increase in volatility is associated with an increase in transaction costs. Furthermore, the impact of volatility on market illiquidity was further confirmed when we investigated the sensitivity of funding liquidity on FX market illiquidity obtained by running regression (2.8) with a 2-year rolling window and conducting a correlation between the obtained series of the sensitivities and global FX volatility, proxied by the standard deviation of FX market returns. The correlation was over 20%, indicating that the higher the volatility, the stronger the impact of changes in funding liquidity constraints on transaction costs. This supports Vayanos (2004) suggestion that if transaction costs are higher during volatile times the impact of volatility would be even stronger emphasising the connection between changes in market volatility and liquidity. As expected, FX market returns on the previous day have a strong impact on FX market illiquidity. Given the negative sign of the coefficient, a decline in the market returns results in an increase in transaction costs the following day. Importantly, volatility and lagged market returns do not drive out the impact of changes in funding conditions on FX market illiquidity. Indeed, changes in the FCP interest rate stay significant. Realizing that some European banks might have been cut off from the FCP market and our measure of US liquidity might not represent the conditions facing some banks we used an alternative proxy for funding liquidity, LIBOR-OIS spread (Bloomberg available from 2001) and the Euribor-Eonia spread (Datastream available from 1999). Neither proxy was found to be statistically significant. There could be two reasons for that. First, the accuracy of LIBOR rates during the crisis became an important subject of controversy, as pointed out by McAndrews (2009). Secondly, LIBOR rates are only available at 11 am London time, thus not matching our foreign exchange quotes. This issue is bound to have been important

especially during the crisis given the extreme market volatility. Changes in margin requirements, TED spread and FF rate, are not statistically significant. In model (3) we present the results by excluding margin requirements.

2.4.2.2 Market liquidity, market declines and funding liquidity

Having confirmed the importance of funding liquidity in explaining variations in FX market illiquidity, we explore in this section whether funding liquidity constraints are more likely to be hit during market declines (Hameed et al. (2010)). Price declines induce greater changes in liquidity as market-makers find it more difficult to adjust inventory in falling markets than in rising markets. We thus examine first whether market returns induce asymmetric effects on FX market illiquidity and then investigate whether this relationship is indicative of capital constraints in the market place by interacting negative market returns with changes in funding liquidity constraints.

We start our analysis by examining whether the impact of market returns is asymmetric by interacting lagged market returns with a dummy for negative market returns and a dummy for positive market returns, as follows:

$$\begin{aligned} \Delta illiq_t = & \alpha + \beta \Delta FCP_t + \mu_1 d_{t-1}^+ MKT_{t-1} + \mu_2 d_{t-1}^- MKT_{t-1} \\ & + \delta VOL_t + \gamma_1 d_t^{MON} + \gamma_2 d_t^{TUE} + \gamma_3 d_t^{WED} + \gamma_4 d_t^{THU} \\ & + \sum_{i=1}^4 \theta_i \Delta illiq_{t-i} + \varepsilon_t, \end{aligned} \quad (2.9)$$

where d_{t-1}^+ is a dummy for increases in lagged market returns, d_{t-1}^- is a dummy for declines in lagged market returns and MKT_{t-1} is the lagged market return. Given the focus of the analysis, we first include the main variables, changes in FCP interest rates, the interactive variables for market declines and market increases and the day of the week dummies, and then we add the volatility measure as control variable.¹¹

Model (1) in Table 2.4 shows that the effect of market declines alone affects future transaction costs. The dummy for market rises is not statistically significant, confirming Chordia et al. (2001) for the US equity market. The funding liquidity constraint variable stays statistically significant. Again, while statistically significant, the inclusion of FX market volatility does not change our results (model (2)).

We proceed with our analysis to test whether the impact of market declines is indicative of capital constraints by interacting FX market returns with a dummy for

¹¹Given that the margin constraints measures were not significant in the main analysis above, we exclude them.

lagged positive changes in the funding constraint variable, as follows:

$$\begin{aligned}\Delta liq_t = & \alpha + \beta \Delta FCP_t + \mu d_{t-1}^{+FUND} d_{t-1}^{-} MKT_{t-1} + \delta VOL_t \\ & + \gamma_1 d_t^{MON} + \gamma_2 d_t^{TUE} + \gamma_3 d_t^{WED} + \gamma_4 d_t^{THUR} \\ & + \sum_{i=1}^4 \theta_i \Delta illiq_{t-i} + \varepsilon_t,\end{aligned}\tag{2.10}$$

where MKT_{t-1} is the lagged market return, d_{t-1}^{-} is a dummy for declines in market returns in the previous day, and d_{t-1}^{+FUND} is a dummy for positive changes in funding liquidity constraints in the previous day. We first run the regression with the main variables, changes in FCP interest rates and the interactive variable for market declines and worsening funding conditions, and then we add the volatility measure as control variable.

As shown in Table 2.4, the interacting dummy with the measure of funding liquidity constraints is statistically significant (model (3)). Furthermore, it stays significant once we include the volatility variable (model (4)), indicating that market declines are related to capital constraints in the market. Furthermore, our funding constraints and FX market volatility variable remain statistically significant. It should be noted that the day of the week effects do not change in this analysis.

2.4.2.3 Crisis episodes

Given that market declines are indicative of funding liquidity constraints, we explore whether liquidity dry-ups are worse during crisis episodes (Brunnermeier and Pedersen (2009)). Indeed, our data set enables us to study several important crisis episodes. These are: the Asian crisis from October 1997 until February 1998, the LTCM collapse and the Russian crisis from May until September 1998, the events of 9/11, the Argentinean default in December 2001 and the more recent events of the collapse of Bear Sterns in May 2008 and Lehman Brothers from September 2008 until December 2008.

We take the level of the TED spread as an indicator for crisis periods and interact it with our measure of changes in funding constraints, financial commercial paper interest rate¹². In detail, we run the following regression:

$$\begin{aligned}\Delta illiq_t = & \alpha + \beta(TS_t * \Delta FCP_t) + \delta VOL_t + \mu MKT_{t-1} \\ & + \gamma_1 d_t^{MON} + \gamma_2 d_t^{TUE} + \gamma_3 d_t^{WED} + \gamma_4 d_t^{THUR} \\ & + \sum_{i=1}^4 \theta_i \Delta illiq_{t-i} + \varepsilon_t,\end{aligned}\tag{2.11}$$

¹²The TED spread is a better indicator of crisis periods than a 0/1 dummy, which appears to be a crude proxy, not being able to pick accurately the severity of crises, such as the Lehman Brothers collapse (Cornett et al. (2011)).

where TS is the level of the TED spread that is interacted with changes in FCP rates, ΔFCP . We also include four lagged dependent variables and the dummies for the day of the week as in the main analysis above (2.8). However, we exclude changes in financial commercial paper interest rate from the regression to avoid multicollinearity issues.

Table 2.5 shows the results of the analysis. The TED spread interacted with changes in financial commercial paper interest rate explains significantly changes in transaction costs. Thus, during crisis periods, the changes in funding liquidity constraints have a strong positive impact on FX market illiquidity. In addition, global FX volatility and lagged market returns are also significant determinants of changes in illiquidity in the FX market.

2.5 Robustness tests

2.5.1 Market depth and funding liquidity

2.5.1.1 Market depth as an alternative measure of FX Market liquidity

Liquidity is a broad concept and compasses different aspects of the functioning of a market. As a result, several tools have been developed to measure it. In our main analysis above we analysed changes in transaction costs as a measure of changes in the illiquidity of the FX market. Here, we extend our analysis to a different proxy for FX market liquidity. Following Pastor and Stambaugh (2003), we measure liquidity as the expected temporary return reversal accompanying order flow. Pastor and Stambaugh's measure is based on the theoretical insights of Campbell et al. (1993). Extending the literature relating time-varying stock returns to non-informational trading (e.g. De Long et al. (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 behaviour of risk-averse market makers, thus identifying market depth. While Pastor and Stambaugh use signed trading volume as a proxy for order flow, we employ actual order flow.

In detail, we employ a data set of daily FX spot exchange rates of the USD over our 20 currencies and their order flow for 10 years, from January 01, 1998 to July 17,

2008.¹³ The FX transaction data is obtained from State Street Corporation (SSC).¹⁴

Following closely Banti et al. (2012), we estimate the return reversal associated with order flow regressing the contemporaneous and lagged order flow on the contemporaneous foreign exchange log returns:

$$r_{i,t} = \alpha_i + \beta_i \Delta x_{i,t} + \gamma_i \Delta x_{i,t-1} + \varepsilon_{i,t}. \quad (2.12)$$

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. Given the construction of our proxy and the availability of daily data of order flow, we conduct our analysis of market depth at monthly frequency. Thus, the monthly proxy for liquidity of a specific exchange rate is:

$$L_{i,m} = \hat{\gamma}_{i,m}. \quad (2.13)$$

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 ($\gamma_i < 0$).

Next, we construct a measure of changes in common liquidity by averaging across currencies the individual monthly liquidity measures and taking the first difference:

$$L_m = \frac{1}{N} \sum_{i=1}^N L_{i,m} \quad (2.14)$$

$$\Delta L_m = L_m - L_{m-1}. \quad (2.15)$$

Table 2.6 shows some descriptive statistics of the variable thus constructed. The variable shows a high standard deviation, indicating a strong variation. Furthermore, it exhibits strong negative serial correlation. Figure 2.5 shows the strong time variation

¹³The same order flow data set was employed in Banti et al. (2012).

¹⁴As 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 behaviour 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 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.

of the series.

2.5.1.2 Are funding liquidity conditions a determinant of market depth?

We now turn our attention to monthly funding liquidity conditions. Since we are interested in the monthly frequency, we take the last observation available in each month for overnight AA financial commercial paper interest rates. Furthermore, an interesting measure of funding liquidity condition is available at lower frequency, the amount outstanding of repurchase agreements. Repurchase agreements are contracts under which a financial institution sells a security and buys it back at a pre-agreed price on a agreed future date. According to Adrian and Shin (2010) it represents the most significant source of financing for financial intermediaries. The data of the amount outstanding in repurchase agreements is collected by the Federal Reserve Bank of New York on a weekly basis. It comprises the opened positions of primary dealers, serving as trading counterparties of the New York Fed in its implementation of monetary policy. Since we are interested in the monthly effects of funding liquidity on the movements of FX market liquidity, we construct the monthly series by averaging the weekly amount outstanding.

Since we are interested in the variation of funding liquidity, we take the first difference of the log of the funding liquidity variables, as follows:

$$\Delta FCP_m = \log(FCP_m) - \log(FCP_{m-1}), \quad (2.16)$$

$$\Delta REPO_m = \log(REPO_m) - \log(REPO_{m-1}), \quad (2.17)$$

where FCP and $REPO$ are the series of the financial commercial paper interest rates and amount outstanding of repurchase agreements respectively and the subscript m indicates the monthly frequency.

Now that we have identified the measures of funding liquidity conditions, we investigate whether changes in the availability of funding liquidity have an impact on the changes in FX market liquidity. So, we run the following regression:

$$\begin{aligned} \Delta L_m = & \alpha + \gamma \Delta REPO_m + \beta \Delta FCP_m + \delta VOL_m \\ & + \varphi \Delta TS_m + \zeta \Delta FF_m + \mu MKT_{m-1} + \theta \Delta L_{m-1} + \varepsilon_m, \end{aligned} \quad (2.18)$$

where VOL_m is the monthly standard deviation of daily currency returns, ΔTS and ΔFF are the monthly series of changes in the TED spread and the Federal funds rate respectively, and MKT_{m-1} is the lagged monthly FX market returns. We include the lagged dependent variable to account for autocorrelation in the residuals.

Table 2.7 shows the results. In model (1) we present the results without the controlling variables. As expected, the coefficient associated with changes in the amount

outstanding of REPOs is positive and statistically significant. In fact, an increase in the availability of funding to dealers increases FX market liquidity, measured as market depth. In order to differentiate the statistical significance of ΔREPO from that of the lagged dependent variable we run model (1) in Table 2.7 without ΔREPO . The R squared is 0.2561. We performed an F test, which confirms the statistical significance of ΔREPO . Conversely to the daily analysis of transaction costs, changes in FCP interest rates are not statistically significant in explaining changes in FX market depth. Including the control variables in model (2) we find FX volatility to be significant, the negative sign implying that an increase in FX market volatility is associated with a decrease in market depth. In contrast, the variation in the TED spread and FF rate and lagged market returns do not explain changes in FX market liquidity. In model (3) we present the results without these variables. Our explanatory variables explain a substantial proportion of the variation of monthly market depth, of 41%.

In conclusion, extending our analysis of the relationship between FX market liquidity and funding liquidity constraints to another measure of liquidity and a different frequency, the availability of funding liquidity to traders is still an important determinant of FX market liquidity.

2.5.2 GMM estimation

A concern about our analysis is endogeneity. Although funding liquidity constraints affect all operations of traders creating a systemic source of variation in liquidity across financial assets, the effect may work also in the other direction. Changes in market liquidity can have a significant impact on the conditions at which funding is available to traders (Brunnermeier and Pedersen (2009); Acharya and Viswanathan (2011)). In view of that we run a VAR to test for Granger causality. We found that there was no causality running from FX market illiquidity to FCP. However, there could be further endogeneity issues related to the other variables so we check the robustness of our results by estimating model (2.8) using GMM, which allows for endogeneity by employing ad hoc instrumental variables for the moment conditions to improve the estimation. Following Hansen (1982), we improve the identification of the coefficients θ by employing a set of sample moment conditions from the standard model (2.8) with the inclusion of an additional moment condition on the lagged FCP variable. In more detail, the moment conditions for model (2.8) are:

$$g_T(\theta) = \frac{1}{T} \sum_{t=1}^T \epsilon(\theta)_t Z_t, \quad (2.19)$$

where the set of instruments Z_t includes the one-day lagged financial commercial paper variable in addition to the regressors of the model and ϵ_t are the residuals. We then

proceed to minimize a quadratic form of the moments using an initial weighting identity matrix $W = I$, as follows:

$$\hat{\theta}_1 = \min_{\hat{\theta}} g_T(\hat{\theta})' W g_T(\hat{\theta}).$$

After the first iteration, we proceed to estimate the parameters $\hat{\theta}_2$ with a new weighting matrix, based on an estimation of the long-run covariance matrix of the moment conditions from the first step, $\hat{S} = \frac{1}{T} \sum_{t=1}^T g_T(\hat{\theta}) g_T(\hat{\theta})'$, corrected for heteroskedasticity with Newey-West (1987):

$$\hat{\theta}_2 = \min_{\theta} g_T(\theta)' \hat{S}^{-1} g_T(\theta).$$

Similarly, we proceed to estimate model (2.18) via GMM for robustness of the monthly analysis with the alternative measure of illiquidity based on market depth. The results are robust to this alternative estimation (Tables 2.1B and 2.2B in Appendix 2B).

2.5.3 Unexpected changes in FX market illiquidity

In the analysis of the determinants of time-variation in FX market illiquidity, we looked at changes in common illiquidity. As a robustness check, we now investigate whether unexpected changes, or shocks, to FX market illiquidity have the same determinants identified so far.

In order to identify the unexpected component of changes in FX market illiquidity, we take the residuals of an AR(5) model of the common illiquidity measure as our proxy.¹⁵ In detail, we run the following regression:

$$\Delta illiq_t = \alpha + \sum_{i=1}^5 \beta_i \Delta illiq_{t-i} + \varepsilon_t, \quad (2.20)$$

and we take ε_t to be our measure of shocks in FX market illiquidity, $\Delta^{UNEXP} illiq_t$.

Next, we regress our measure of shocks in FX market, $\Delta^{UNEXP} illiq_t$, on the determinants identified above in regression (2.8). Thus, we run the following regression:

$$\begin{aligned} \Delta^{UNEXP} illiq_t = & \alpha + \beta \Delta FCP_t + \delta VOL_t + \varphi \Delta TS_t \\ & + \zeta \Delta FF_t + \mu MKT_{t-1} + \gamma_1 d_t^{MON} + \gamma_2 d_t^{TUE} \\ & + \gamma_3 d_t^{WED} + \gamma_4 d_t^{THUR} + \varepsilon_t. \end{aligned} \quad (2.21)$$

We report the results in Table 2.8. Indeed, the analysis of shocks does confirm the determinants found to be significant in explaining changes in FX market illiquidity. In model (1), the changes in the interest rate on FCP have a strong impact on unexpected

¹⁵We take an AR(5) model because it allows us to eliminate serial correlation from the residuals so that we take as our measure for shocks the unexpected component of changes in FX market illiquidity.

changes in transaction costs. This result is robust to the inclusion in our analysis of global FX volatility and lagged market returns. Changes in the margin requirements are unrelated to shocks in FX market illiquidity, similarly to our main analysis (model (2)). As expected, the R^2 is much smaller than in our main analysis.

2.6 Conclusions

The recent financial crisis brought attention to the effects of variations in funding liquidity. In this paper, we investigate the role of funding liquidity on the commonality of FX market illiquidity, an area not yet explored in the literature. We examine the commonality of FX market illiquidity of 20 exchange rates of both developed and emerging markets currencies over 13 years. Our results confirm the prediction of Brunnermeier and Pedersen (2009) that funding liquidity is a driving state variable of commonality in liquidity.

We study two different aspects of FX market liquidity, transaction costs and market depth. We find funding liquidity constraints to be important determinants of FX market liquidity. The results are similar for both liquidity measures, even though financial commercial papers are relevant for transaction costs and repurchase agreements for market depth. Funding liquidity is also found to explain unexpected changes in FX market illiquidity.

The results are robust to controlling for volatility, FX market returns and seasonality. Global FX volatility is found to increase transactions costs, consistent with previous studies at the individual currency level (Bessembinder (1994); Ding (1999)). Market returns are also found to have a strong impact on FX market illiquidity. A decline in market returns results in an increase in transaction costs the following day. Exchange rate movements trigger changes in investor expectations, and through their impact on wealth prompt changes in inventories and optimal portfolio compositions. This confirms the results found for the equity market (Chordia et al. (2001); Huberman and Halka (2001)). There are also strong day of the week effects on FX global liquidity, declining on Fridays and increasing on Mondays, confirming the increase in spreads before weekends (Bessembinder (1994)). Our explanatory variables capture an appreciable fraction of the daily time series variation in market wide liquidity, 35% in the case of transaction costs and 41% in the monthly variable in the case of market depth. Funding liquidity and our other explanatory variables are found to explain unexpected changes in FX market illiquidity as well. Our results are robust to alternative methods of estimation, such as GMM, which allows for endogeneity, which could be a concern in our analysis.

We also find that market declines impact negatively on FX liquidity, suggesting that inventory accumulation concerns are more important in declining markets, and

that this relates to periods when the suppliers of liquidity are likely to face capital tightness. This is further confirmed when we find that liquidity dry-ups during crisis times impact on FX market illiquidity.

In conclusion, our study finds that funding liquidity constraints are important determinants of the commonality of FX market illiquidity and supports the impact of liquidity dry-ups on financial markets (Shleifer and Vishny (1997); Gromb and Vayanos (2002)).

Appendix 2A. Regression of currencies' illiquidity on market illiquidity

Table 2.1A: Regression of currencies' illiquidity on market illiquidity

	AUD	BRL	CAD	CHF	CLP	CZK	DKK	EUR	GBP	HUF
Constant	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	<i>-0.0234</i>	<i>0.0148</i>	<i>0.0399</i>	<i>-0.0015</i>	<i>-0.0687</i>	<i>-0.0012</i>	<i>0.0078</i>	<i>-0.0236</i>	<i>0.0052</i>	<i>0.1184</i>
ΔPS_t	0.0004	0.0018	0.0001	0.0003	0.0007	0.0013	0.0003	0.0002	0.0001	0.0012
	<i>8.4932</i>	<i>4.4322</i>	<i>2.8215</i>	<i>9.0788</i>	<i>5.3742</i>	<i>10.4307</i>	<i>9.9348</i>	<i>10.7568</i>	<i>3.0099</i>	<i>10.8784</i>
<i>AdjustedR</i> ²	0.041	0.050	0.005	0.055	0.045	0.079	0.053	0.064	0.004	0.065
	JPY	KRW	MXN	NOK	NZD	PLN	SEK	SGD	TRY	ZAR
Constant	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	<i>-0.0009</i>	<i>0.0162</i>	<i>-0.0570</i>	<i>0.0734</i>	<i>-0.0336</i>	<i>-0.0465</i>	<i>-0.0002</i>	<i>-0.0726</i>	<i>0.0015</i>	<i>0.0225</i>
ΔPS_t	0.0001	0.0023	0.0009	0.0006	0.0011	0.0019	0.0004	0.0002	0.0017	0.0035
	<i>3.5932</i>	<i>9.1085</i>	<i>6.6479</i>	<i>10.9386</i>	<i>10.2925</i>	<i>15.1388</i>	<i>9.1919</i>	<i>6.4213</i>	<i>2.0360</i>	<i>12.2277</i>
<i>AdjustedR</i> ²	0.006	0.084	0.073	0.079	0.090	0.128	0.055	0.020	0.002	0.157

Notes: The table reports the results of the regression of changes in each individual currency illiquidity on changes in common market illiquidity:

$$\Delta PS_{i,t} = \alpha_i + \beta_i \Delta PS_t + \varepsilon_{i,t}.$$

The coefficients are reported in bold when the variable is statistically significant at 5%. *t*-statistics are adjusted via Newey-West (1987) and reported under the coefficients. The sample period is from January 1998 to December 2010. The currencies are against the USD.

Appendix 2B. Alternative estimation via GMM

Table 2.1B: Transaction costs and funding liquidity via GMM

	1	2
ΔFCP_t	0.03940	0.03792
	2.1796	2.2654
VOL_t		0.17054
		1.9850
MKT_{t-1}		-1.10859
		-3.3902
d_t^{MON}	-0.02787	-0.02917
	-4.9478	-5.1405
d_t^{TUE}	-0.02794	-0.02897
	-5.3858	-5.4932
d_t^{WED}	-0.01980	-0.02145
	-3.8810	-4.1148
d_t^{THUR}	-0.01286	-0.01403
	-2.4493	-2.6615
$\Delta illiq_{t-1}$	-0.69922	-0.70428
	-28.4518	-28.7649
$\Delta illiq_{t-2}$	-0.49693	-0.49936
	-17.0090	-17.0973
$\Delta illiq_{t-3}$	-0.32467	-0.32659
	-11.4468	-11.5310
$\Delta illiq_{t-4}$	-0.18353	-0.18324
	-8.2978	-8.3187
Constant	0.0174	0.01841
	4.7901	4.9919
$AdjustedR^2$	0.35	0.35
LM test - pval	0.02	0.01

Notes: The table reports the results of the regression analysis of the determinants of FX market liquidity, measured as transaction costs, in regression (2.8) estimated via GMM. The coefficients are reported in bold when the variable is statistically significant at 5%. t -statistics are adjusted via Newey-West (1987) and reported under the coefficients. The sample period is from January 1998 to December 2010.

Table 2.2B: Market depth and funding liquidity via GMM

	1	2
$\Delta REPOS_m$	0.0094	0.0091
	<i>5.5136</i>	<i>5.4566</i>
ΔFCP_m	-0.0003	0.0001
	<i>-0.2004</i>	<i>0.0472</i>
VOL_m		-0.4399
		<i>-3.6337</i>
ΔL_{m-1}	-0.4989	-0.5035
	<i>-7.7416</i>	<i>-8.1203</i>
Constant	-0.0001	0.0016
	<i>-0.5562</i>	<i>3.3864</i>
$AdjustedR^2$	0.37	0.41
LM test - pval	0.08	0.12

Notes: The table reports the results of the regression analysis of the determinants of FX market liquidity, measured with the Pastor-Stambaugh measure, in regression (2.18) estimated via GMM. The coefficients are reported in bold when the variable is statistically significant at 5%. t -statistics are adjusted via Newey-West (1987) and reported under the coefficients. The sample period is from January 1998 to July 2008.

Table 2.1: Descriptive statistics of changes in FX market illiquidity and changes in financial commercial paper interest rate

	Δilliq	ΔFCP
mean	-0.00003	-0.00369
median	0.00071	0
st dev	0.11454	0.09241
min	-0.55196	-2.07944
max	0.58896	1.50408
skew	-0.01154	-4.00308
kurt	2.32023	147.02724
AC(1)	-0.46000	-0.06987

Notes: Descriptive statistics are reported for the measure of changes in market illiquidity and changes in financial commercial paper interest rate. The latter is the overnight AA financial commercial paper interest rate. The measure for the variation is obtained as the difference of the daily log of the series. AC(1) refers to the first order autocorrelation of the series.

Table 2.2: **Correlation matrix**

	ΔFCP	ΔFF	ΔTS
ΔFF	0.2686		
ΔTS	-0.0379	-0.0383	
ΔVOL	0.0322	0.0794	0.1781

Notes: The correlation matrix reports the correlation coefficients between the variables. FCP indicates the daily series of overnight AA financial commercial paper interest rate. TS indicates the TED spread. FF is the Federal funds rate. VOL is the FX market volatility, estimated as the JP Morgan implied volatility index, VXY. A Δ indicates the daily changes in the variable.

Table 2.3: Determinants of FX market illiquidity

	1	2	3
ΔFCP_t	0.03892 2.0436	0.03512 2.0007	0.03752 2.1144
VOL_t		0.18953 2.3540	0.1761 2.2110
MKT_{t-1}		-1.08659 -3.1042	-1.0724 -3.0555
ΔTS_t		-0.02296 -0.9288	
ΔFF_t		-0.00040 -0.0205	
d_t^{MON}	-0.02847 -5.1479	-0.03192 -5.6702	-0.02952 -5.3350
d_t^{TUE}	-0.02814 -5.2224	-0.02869 -5.2851	-0.02903 -5.3823
d_t^{WED}	-0.02018 -3.9048	-0.02113 -4.0304	-0.02167 -4.1781
d_t^{THUR}	-0.01321 -2.5573	-0.01389 -2.6143	-0.01426 -2.7584
$\Delta illiq_{t-1}$	-0.70127 -31.6545	-0.70711 -31.5916	-0.70536 -31.9579
$\Delta illiq_{t-2}$	-0.49889 -17.0825	-0.50156 -16.9590	-0.50048 -17.2240
$\Delta illiq_{t-3}$	-0.32712 -11.1426	-0.32910 -11.2492	-0.32764 -11.2588
$\Delta illiq_{t-4}$	-0.18440 -8.0731	-0.18308 -7.9921	-0.18363 -8.0808
Constant	0.01752 4.4966	0.01822 4.6068	0.01848 4.7333
Adjusted R^2	0.35	0.35	0.35
LM test - pval	0.02	0.01	0.01

Notes: The table reports the results of the different specifications of regression (2.8):

$$\begin{aligned}
\Delta illiq_t = & \alpha + \beta \Delta FCP_t + \delta VOL_t + \varphi \Delta TS_t + \zeta \Delta FF_t \\
& + \mu MKT_{t-1} + \gamma_1 d_t^{MON} + \gamma_2 d_t^{TUE} + \gamma_3 d_t^{WED} + \gamma_4 d_t^{THUR} \\
& + \sum_{i=1}^4 \theta_i \Delta illiq_{t-i} + \varepsilon_t.
\end{aligned}$$

The coefficients are reported in bold when the variable is statistically significant at 5%. t -statistics are adjusted via Newey-West (1987) and reported under the coefficients. The sample period is from January 1998 to December 2010.

Table 2.4: **FX market illiquidity and market returns**

	1	2	3	4
ΔFCP_t	0.03953	0.03811	0.03737	0.03606
	2.1490	2.1674	2.0136	2.0273
$d_{t-1}^+ MKT_{t-1}$	0.07004			
	0.1210			
$d_{t-1}^- MKT_{t-1}$	-2.22438	-2.18597		
	-3.7228	-3.8672		
$d_{t-1}^{+FUND} d_{t-1}^- MKT_{t-1}$			-2.1366	-2.0672
			-3.0261	-2.9672
VOL_t		0.1706		0.1667
		2.1518		2.0980
d_t^{MON}	-0.0286	-0.0293	-0.0279	-0.0285
	-5.1818	-5.3045	-5.0367	-5.1466
d_t^{TUE}	-0.02837	-0.02895	-0.02891	-0.02945
	-5.2623	-5.3660	-5.3558	-5.4484
d_t^{WED}	-0.02010	-0.02123	-0.01932	-0.02043
	-3.8895	-4.0927	-3.7391	-3.9388
d_t^{THUR}	-0.01349	-0.01422	-0.01269	-0.01342
	-2.6204	-2.7593	-2.4611	-2.5970
$\Delta illiq_{t-1}$	-0.70500	-0.70522	-0.70393	-0.70400
	-31.9596	-32.0436	-31.8204	-31.8553
$\Delta illiq_{t-2}$	-0.50067	-0.50026	-0.50071	-0.50021
	-17.2558	-17.2820	-17.2444	-17.2792
$\Delta illiq_{t-3}$	-0.32822	-0.32762	-0.32964	-0.32894
	-11.2819	-11.2981	-11.2877	-11.2989
$\Delta illiq_{t-4}$	-0.18415	-0.18406	-0.18610	-0.18600
	-8.0805	-8.1104	-8.1539	-8.1726
Constant	0.01367	0.01451	0.01575	0.01643
	3.1902	3.6126	3.9956	4.1573
Adjusted R^2	0.35	0.35	0.35	0.35
LM test - pval	0.01	0.01	0.02	0.01

Notes: The table reports the results of the analysis of the interaction of market illiquidity and market returns. Models (1) reports the results of regression (2.9) without volatility. Model (2) reports the results of regression (2.9) with volatility as control variable, but excluding the interaction variable of market returns increases. Models (3) and (4) report the results of regression (2.10) without and with volatility as control variable. The coefficients are reported and in bold when the variable is statistically significant at 5%. t -statistics are adjusted via Newey-West (1987) and reported under the coefficients. The sample period is from January 1998 to December 2010.

Table 2.5: Market illiquidity and crisis episodes

$TS_t \Delta FCP_t$	0.02084
	2.3908
VOL_t	0.1687
	2.1683
MKT_{t-1}	-1.0564
	-2.9509
d_t^{MON}	-0.02972
	-5.3412
d_t^{TUE}	-0.02911
	-5.3587
d_t^{WED}	-0.02158
	-4.1404
d_t^{THUR}	-0.01402
	-2.6957
$\Delta illiq_{t-1}$	-0.70693
	-31.5688
$\Delta illiq_{t-2}$	-0.50251
	-17.3148
$\Delta illiq_{t-3}$	-0.32850
	-11.2533
$\Delta illiq_{t-4}$	-0.18301
	-8.1009
Constant	0.01848
	4.6914
Adjusted R^2	0.35
LM test - pval	0.01

Notes: The table reports the results of regression (2.11):

$$\begin{aligned}
 \Delta illiq_t = & \alpha + \beta(TS_t * \Delta FCP_t) + \delta VOL_t + \mu MKT_{t-1} \\
 & + \gamma_1 d_t^{MON} + \gamma_2 d_t^{TUE} + \gamma_3 d_t^{WED} + \gamma_4 d_t^{THUR} \\
 & + \sum_{i=1}^4 \theta_i \Delta illiq_{t-i} + \varepsilon_t.
 \end{aligned}$$

The coefficients are reported and in bold when the variable is statistically significant at 5%. t -statistics are adjusted via Newey-West (1987) and reported under the coefficients. The sample period is from January 1998 to December 2010.

Table 2.6: **Descriptive statistics of changes in market depth**

mean	median	st dev	min	max	skew	kurt	AC(1)
-0.00001	0.00006	0.0024	-0.0057	0.0059	0.0153	-0.0085	-0.5119

Notes: Descriptive statistics are reported for the monthly measure of changes in market liquidity. FX market liquidity is calculated as the return reversal associated with transaction volume. AC(1) refers to the first order autocorrelation of the series.

Table 2.7: Market depth and funding liquidity

	1	2	3
$\Delta REPO_m$	0.0089 <i>4.7687</i>	0.0086 <i>4.4494</i>	0.0085 <i>4.5598</i>
ΔFCP_m	-0.0003 <i>-0.2453</i>	0.0001 <i>0.0414</i>	0.0000 <i>-0.0063</i>
VOL_m		-0.3978 <i>-3.1818</i>	-0.4405 <i>-3.4300</i>
ΔTS_m		-0.0003 <i>-0.3899</i>	
ΔFF_m		-0.0002 <i>-0.1570</i>	
MKT_{m-1}		0.3387 <i>1.8786</i>	
ΔL_{m-1}	-0.4987 <i>-7.5560</i>	-0.5030 <i>-7.6906</i>	-0.5053 <i>-7.9817</i>
Constant	-0.0001 <i>-0.3616</i>	0.0014 <i>2.9117</i>	0.0016 <i>3.2653</i>
<i>AdjustedR</i> ²	0.37	0.41	0.41
LM test - pval	0.08	0.17	0.12

Notes: The table reports the results of the regression analysis of the determinants of FX market liquidity, measured with the Pastor-Stambaugh measure, in regression (2.18):

$$\Delta L_m = \alpha + \gamma \Delta REPO_m + \beta \Delta FCP_m + \delta VOL_m + \varphi \Delta TS_m + \zeta \Delta FF_m + \mu MKT_{m-1} + \theta \Delta L_{m-1} + \varepsilon_m.$$

The coefficients are reported and in bold when the variable is statistically significant at 5%. *t*-statistics are adjusted via Newey-West (1987) and reported under the coefficients. The sample period is from January 1998 to July 2008.

Table 2.8: Analysis of the determinants of shocks to FX market illiquidity

	1	2
ΔFCP_t	0.03404 1.9831	0.03327 1.9331
VOL_t	0.17051 2.1719	0.18376 2.3070
MKT_{t-1}	-1.02569 -2.9329	-1.03947 -2.9756
ΔTS_t		-0.0182 -0.7636
ΔFF_t		-0.0056 -0.2920
d_t^{MON}	-0.03064 -5.5666	-0.03266 -5.8199
d_t^{TUE}	-0.02793 -5.2705	-0.02764 -5.1637
d_t^{WED}	-0.01998 -3.8515	-0.01930 -3.6778
d_t^{THUR}	-0.01306 -2.5332	-0.01235 -2.3348
Constant	0.01787 4.6333	0.01742 4.4549
Adjusted R^2	0.02	0.02
LM test - pval	0.01	0.00

Notes: The table reports the results of the regression analysis of the determinants of unexpected changes, or shocks, to FX market illiquidity, regression (2.21):

$$\begin{aligned} \Delta^{UNEXP} illiq_t = & \alpha + \beta \Delta FCP_t + \delta VOL_t + \varphi \Delta TS_t + \zeta \Delta FF_t \\ & + \mu MKT_{t-1} + \gamma_1 d_t^{MON} + \gamma_2 d_t^{TUE} + \gamma_3 d_t^{WED} + \gamma_4 d_t^{THUR} \\ & + \varepsilon_t. \end{aligned}$$

Shocks are estimated as the residuals of a AR model of order 5 to eliminate serial correlation. The coefficients are reported and in bold when the variable is statistically significant at 5%. t -statistics are adjusted via Newey-West (1987) and reported under the coefficients. The sample period is from January 1998 to December 2010.

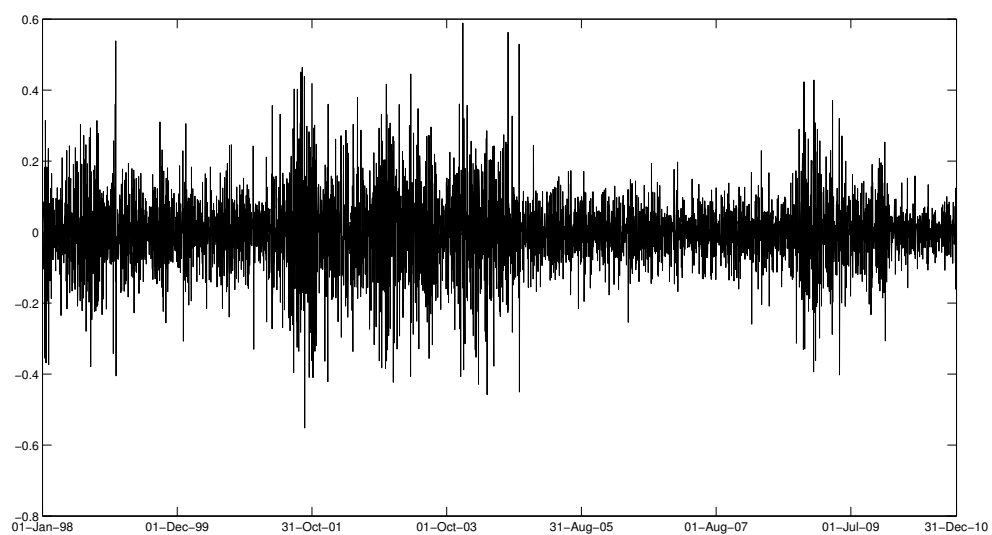


Figure 2.1: Changes in FX market illiquidity

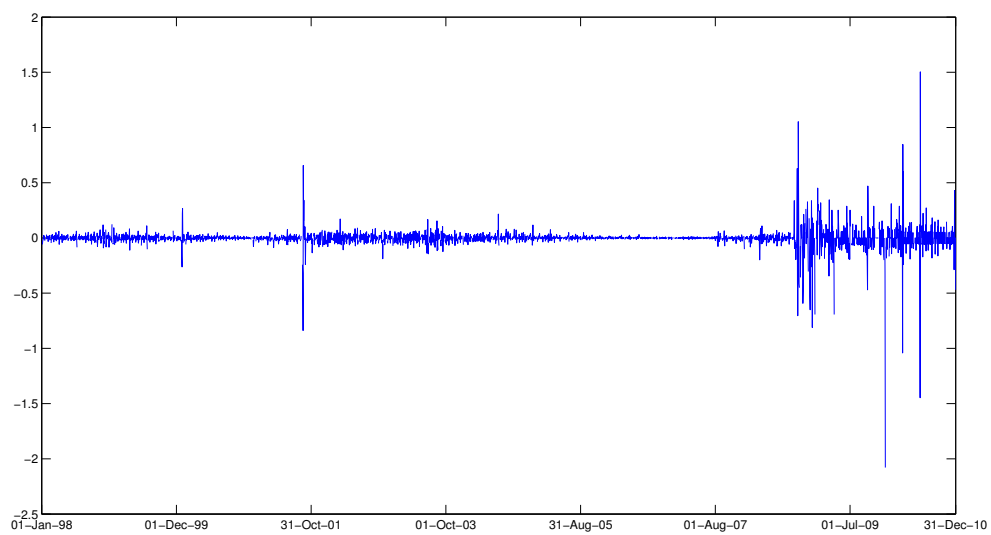


Figure 2.2: **Changes in financial commercial paper interest rate**

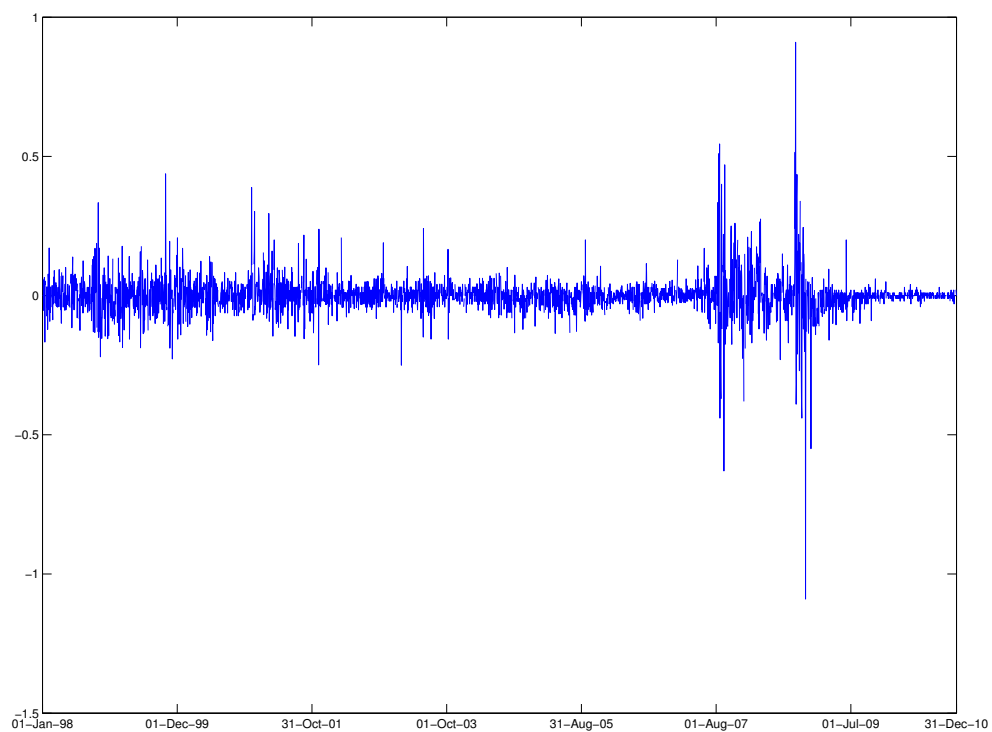


Figure 2.3: Changes in TED spread

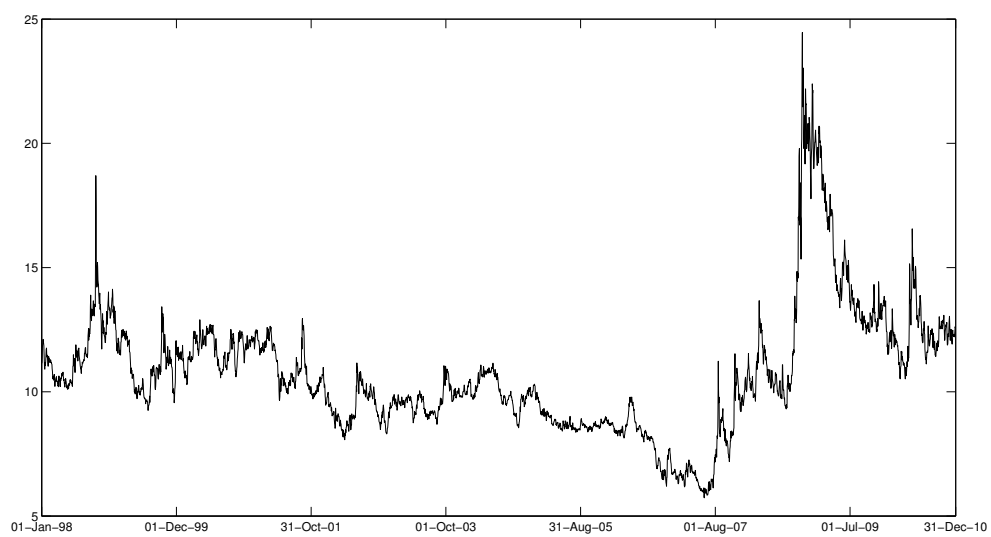


Figure 2.4: Global FX volatility

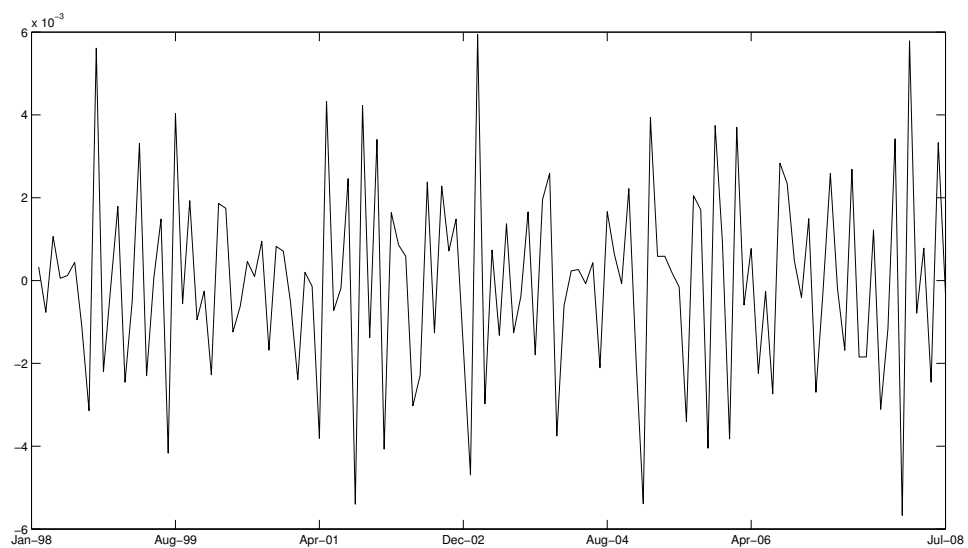


Figure 2.5: **Changes in monthly FX market depth**

Chapter 3

Illiquidity in the stock and FX markets: an investigation of the cross-market dynamics

3.1 Introduction

Market liquidity is defined as the ease of placing large trades quickly and at low cost. There are different sources of frictions preventing a market from being liquid. The presence of transaction costs relates to the cost for obtaining immediacy (Demsetz (1968)). The concept of market liquidity, its measurement tools, determinants and asset pricing implications have been investigated with respect to different asset classes. Most recently, the 2007-2009 financial crisis has highlighted the importance of understanding the systemic dynamics of liquidity to avoid the costly consequences associated with its sudden collapse across financial markets. This paper investigates whether illiquidity in the stock and foreign exchange (FX) markets shares similar patterns analysing in detail cross-market illiquidity linkages. In this respect, the focus on the crisis allows to identify the presence of illiquidity contagion across the financial markets during times of distress. After establishing the presence of illiquidity linkages across the two markets, the paper explicitly analyses the role of funding liquidity as a potential source of such relation.

Following the recent financial crisis, a number of theoretical studies have emerged to identify the potential sources of the observed systematic liquidity component. Adrian and Shin (2010) focus on dealers systematic liquidation of assets following shifts in their leverage structures triggered by price movements that affect their balance sheets.¹ From an informational transmission perspective, cross-asset learning may induce commonality in illiquidity across different assets (Cespa and Foucault (2012)). Finally, the ease with which dealers finance their operations exerts a significant impact on the liquidity

¹Well before the crisis, Kyle and Xiong (2001) refer to dealers systematic asset sales following changes in their risk aversion after suffering trading losses.

supplied to the markets in which they operate (Brunnermeier and Pedersen (2009); Gromb and Vayanos (2010); Acharya and Viswanathan (2011)). In this respect, banks finance their trading activity via wholesale deposits and other short-term financing, such as commercial papers and repurchase agreements (Cornett et al. (2011)). Under certain conditions, shocks to funding liquidity may impair banks' ability to trade and thus to provide liquidity across different assets. The cross-sectional implications are clear: shocks to speculators' financing affect all securities for which speculators provide liquidity. The consequences may be dramatic and turn a drop in market liquidity into an illiquidity spiral. In this sense, Brunnermeier and Pedersen (2009) refer to destabilizing margins. When financiers cannot distinguish fundamental from liquidity shocks, they tighten margin requirements, exacerbating market illiquidity. Similar destabilizing effects are documented by Acharya and Viswanathan (2011) with reference to the presence of moral hazard, in the form of risk-shifting incentives, when financial intermediaries need to roll over short-term debt that may result in credit rationing. In the event of market liquidity shortage, the subsequent desired de-leveraging may not be absorbed, leading to illiquidity spirals.

The presence of a time-varying common component in stock market liquidity has been determined by a number of studies, some of which also investigate its determinants (among others Chordia et al. (2001); Hameed et al. (2010)). Similarly, a common component in the liquidity of FX market has been documented by Mancini et al. (2012) and Banti et al. (2012). Banti and Phylaktis (2012) extend the analysis to the determinants of its time variation. Overall, these studies suggest that changes in market returns, volatility and funding liquidity constraints induce systematic changes in liquidity in equity and FX markets. Interestingly, liquidity in both markets responds to changes in the same set of variables. Movements in market returns and volatility affect the liquidity level in the two markets. Tightening funding liquidity constraints, such as increases in interbank credit risk or drops in the availability of financing (reflected in rising yields on financial commercial papers or repurchase agreements), limits traders' ability to take positions and thus provide liquidity.

This paper analyses illiquidity linkages across the stock and FX markets. To investigate the dynamic relationship between illiquidity levels in stock and FX markets, I take the common component of transaction costs in both markets for 18 years. After documenting strong illiquidity spillovers across the two markets, I focus on the sources of these linkages. In both markets, liquidity is supplied by market makers and dealers that stand ready to act as trading counterparty. Hence, I explicitly consider funding liquidity. From the discussion of the theoretical models above, cross-market illiquidity dynamics may stem from traders' capital constraints. When analysing the role of funding liquidity in this context, an important distinction arises from theory. Financing

conditions do not interact with market illiquidity when traders are far from their capital constraints (Brunnermeier and Pedersen (2009)). Conversely, when funding liquidity becomes tight, traders are less willing to take on positions and provide less liquidity to the markets. For this reason, I investigate cross-market dynamics during the whole sample period and then focus on the 2007-2009 financial crisis. As expected from theory, market illiquidity and funding liquidity are deeply intertwined. This is especially true during the financial crisis, when shocks to funding liquidity have a significant impact on stock and FX market illiquidity. In this respect, I provide evidence that stock market illiquidity acts as a transmission channel for shocks from funding liquidity to FX market illiquidity. Moreover, I document a significant impact of shocks to stock market illiquidity on funding liquidity. In fact, in times of distress a shock to stock market illiquidity may trigger a tightening in margin requirements (Brunnermeier and Pedersen (2009)) and reduce the ease of rolling over short-term debt (Acharya and Viswanathan (2011)).

Cross-market liquidity dynamics have been analysed with respect to stock and bond markets (Chordia et al. (2005); Goyenko and Ukhov (2009)), but to my knowledge this is the first paper to focus on illiquidity linkages across these two systemically important financial markets. A large body of literature studies the linkages in terms of market returns and volatility across the stock and FX markets. For instance, international portfolio balancing models link trading in different asset classes to traders' investment decisions across the border to explain the commonality observed in stock prices and exchange rates (Hau and Rey (2005) and Pavlova and Rigobon (2008)). Several papers document these linkages empirically (Bartov, Bodnar, and Kaul (1996); Kanas (2000); Phylaktis and Ravazzolo (2005) and Bartram and Bodnar (2012)).

Finally, emerging market leaders claim to have suffered the backlash of the large supply of liquidity provided by monetary authorities to tackle the recent financial crisis in developed markets. The consequences of this "liquidity tsunami", in the words of the Brazilian President Dilma Rousseff, are large inflows of capital and a subsequent strong appreciation of currencies in emerging markets. Through the framework developed in this paper, I can assess whether financing conditions of traders in developed countries, such as the US, UK and European Union, affect transaction costs in emerging market currencies. After building a measure of FX illiquidity in emerging markets, I document a positive reaction of illiquidity to tightening funding constraints during the crisis. In other words, an increase in the supply of liquidity in developed markets increases the liquidity of emerging market currencies, reducing their transaction costs.

The paper is organized as follows. In the next section, I provide an analysis of the institutional frameworks of the stock and FX markets considered. I proceed to review the literature on systemic liquidity and identify clear testable hypotheses in

Section 3.3. In Section 3.4, I present the data set, some descriptive statistics and a preliminary analysis. Cross-market illiquidity linkages between stock and FX markets are investigated in Section 3.5. Section 3.6 explicitly extends the analysis to include funding liquidity. Section 3.7 analyses the role of funding liquidity on the illiquidity of emerging market currencies. Finally, Section 3.8 concludes.

3.2 Institutional features of NYSE/AMEX and the FX market

In terms of trading volume, the FX market is the most liquid financial market, with an average daily turnover in April 2010 of \$3.98 trillion (BIS (2010)). In contrast, the New York Stock Exchange (NYSE) daily average turnover in the same period was around \$50 billion (NYSE website).

The differences between the two markets are not restricted to the turnover. The NYSE/ AMEX² are centralized markets with floor-based trading and physical rooms where specialists meet with each other. In contrast, the direct FX market is decentralized so that traders are physically separated and interact by telephone or computer. The brokered FX market may be classified as quasi-centralized, because each broker accumulates and matches orders from different dealers without entering transaction themselves (Sarno and Taylor (2002); Sager and Taylor (2006); Evans (2011)). In 2010, over 40% of FX trading was executed through electronic methods (BIS (2010)). Electronic exchanges, with automatic matching of orders through an electronic broker (such as the Electronic Banking System (EBS) or Reuters Matching 2000/2), account for the larger share of such trading (BIS (2010)). The on-going development and improvement of such platforms may lead to the “virtual centralization” of the FX market (Sarno and Taylor (2002)). However as for now, the FX market appears to be fragmented and trades can take place at the same time at different prices. As a consequence, it is generally characterized by a lack of transparency. In fact, while NYSE/AMEX specialists are required to disclose information on trades after the execution, there is no such requirement in the FX market (Sarno and Taylor (2002); Harris (2002)).

On the NYSE/AMEX a single specialist acting as market maker manages all trading in a particular security. Traditionally, trading in the FX market took place mainly among market makers³ (Sarno and Taylor (2002)). More recently, the share of trades between market makers and other financial institutions (BIS non-reporting banks, hedge funds, pension funds, mutual funds, insurance companies and central banks) increased

²The American Stock Exchange (AMEX) merged with the New York Stock Exchange (NYSE Euronext) on October 1, 2008. On December 1, 2008, the AMEX Equities trading floor was moved to the NYSE Trading floor. In May 10, 2012 NYSE AMEX has changed its name to NYSE MKT LLC. I will refer to the two markets as NYSE/AMEX.

³While the market maker is the principal in the trades, the broker acts as an agent on behalf of customers.

substantially and in 2010 surpassed the share of trading among market makers (BIS (2010)). Moreover, the FX market is characterized by an on-going trend towards concentration (BIS (2010)). In 2010, 75% of turnover in London and the US was managed by 7 and 9 banks respectively (BIS (2010)).

3.3 Cross-market illiquidity linkages: from theory to empirical investigation

From the analysis of the institutional features above, it becomes clear that dealers are important liquidity providers in both the stock and FX markets. As a result, dealers' trading behaviour has important implications for their price and liquidity dynamics. In order to define empirically testable hypotheses on the illiquidity linkages across the two markets, I proceed to review the theoretical models on illiquidity commonality across different financial assets and markets.

From the observation of systemic liquidity drops during the recent crisis, a number of theoretical models have been proposed to describe the mechanisms behind such events. Adrian and Shin (2010) refer to systematic liquidity effects induced by changes in the leverage structure of dealers. In fact, price movements may lead dealers to deleverage, especially if they actively manage their leverage structure. The aggregate dynamics of these balance sheet adjustments may result in systematic changes of market liquidity. Well before the financial crisis hit the system, Kyle and Xiong (2001) linked systematic liquidation of unrelated financial assets to the wealth effects of shifts in dealers' risk aversion. Cespa and Foucault (2012) relate illiquidity contagion across financial markets to cross-asset learning. In this framework, dealers gather price information on the specific asset in which they trade from the observation of another asset's price. When a drop in liquidity in the asset observed leads to low price informativeness, a rise in dealers' risk aversion may induce dealers to widen their bid-ask spreads. Another class of theoretical models focuses on the relationship between the ease with which dealers finance their operations and the liquidity they supply to the markets in which they operate (Brunnermeier and Pedersen (2009); Gromb and Vayanos (2010); Acharya and Viswanathan (2011)).

The models described above provide theoretical support for the presence of illiquidity linkages across financial markets. Price movements may trigger systematic illiquidity co-movement in the stock and FX markets as agents adjust to shift in their leverage structure or risk aversion. Furthermore, if dealers in the two markets gather information on prices from the observation of the other market, illiquidity commonality may arise from cross-market informational transmission mechanisms. In this respect, market price volatility may affect negatively the observed informational content. Hence, I expect to find evidence of illiquidity linkages across the markets and dynamic interactions with

market returns and volatility in and across stock and FX markets. In order to capture and investigate these dynamics, I include stock and FX market illiquidity into a vector autoregression (VAR) model together with both stock and FX market returns and volatility.

Furthermore, theory suggests an interesting role for funding liquidity conditions. According to Brunnermeier and Pedersen (2009), when funding liquidity is tight, traders take less positions resulting in a reduced supply of liquidity in the markets in which they operate. As a consequence, shocks to speculators' financing conditions affect all securities for which they provide liquidity. In more detail, asset j liquidity λ depends on asset specific margin requirements and general funding liquidity conditions that reflect capital scarcity:

$$|\lambda_t^j| = m_t^j(\Phi_t - 1), \quad (3.1)$$

where m is the margin requirement on asset j and Φ is funding liquidity. Large Φ corresponds to lower available funding than needed by the speculator. Φ is common to all securities held by the speculator, unlike margin requirements that are asset-specific. Aside from collateralized borrowing, the speculator holds capital W given by:

$$W_t = W_{t-1} + (p_t - p_{t-1})x_{t-1} + \eta_t, \quad (3.2)$$

where p is the vector of asset prices, x represents the portfolio held by the speculator and η is an exogenous shock to the speculator's wealth. In this framework, funding liquidity is a function of a speculators' capital and the specific margin requirement on the collateralized borrowing, $\Phi = f(W, m)$. An exogenous shock to speculator's capital may result in an increase in market illiquidity given the tightening of funding liquidity conditions. However, funding liquidity does not affect market illiquidity when traders are far from reaching their capital constraints. But when traders' funding liquidity becomes scarce, traders are less willing to take positions providing less liquidity.

Similar implications are found in Gromb and Vayanos (2010)'s model, where commonality in liquidity across financial markets comes from capital constrained arbitrageurs. In their framework, funding constraints impair the ability of operators to trade and exploit arbitrage opportunity.

In the light of the analysis above, I expect to find a significant impact of shocks to funding liquidity on market liquidity, especially during financial distress. To account for the different sources of financing, I employ different proxies related to unsecured interbank financing conditions both overnight and at longer horizons and constraints on funding aggregates (Cornett et al. (2011)).

The consequences of shocks to financing conditions may be dramatic and turn a

drop in market liquidity into a liquidity spiral. In this sense, Brunnermeier and Pedersen (2009) refer to destabilizing margins. When financiers are not able to distinguish fundamental from liquidity shocks, they tighten their margin requirements, exacerbating market illiquidity. Similar destabilizing effects are documented by Acharya and Viswanathan (2011). They relate the linkages between funding and market liquidity to the presence of risk-shifting moral hazard when financial intermediaries need to roll over short-term debt. Indeed, when incentives to risk-shifting are high, credit is rationed towards the most leveraged agents. Since they are unable to roll-over their debt, most leveraged institutions will proceed to liquidate their positions. However, under certain market conditions, the shortage of liquidity to absorb these deleveraging trades leads to liquidity spirals.

In order to analyse the described dynamics of market and funding liquidity, I include the stock and FX market illiquidity measures in a VAR, alongside funding liquidity variables as endogenous variables. The focus on the recent financial crisis allows investigating the presence of illiquidity spirals when banks face tight funding liquidity constraints.

3.4 Data

3.4.1 Measuring illiquidity: transaction costs

Liquidity is a broad concept comprising different aspects. It generally relates to the ease of placing large trades quickly and at low cost. Although several measures have been developed to study liquidity in the stock market, limitations on data availability have restricted the number of proxies employed in the analysis of FX market. In this study, I estimate illiquidity in the two markets by their average transaction costs. As a result, I restrict the definition of illiquidity to the cost for obtaining immediacy (Demsetz (1968)).

Transaction costs are measured as percentage bid-ask spreads, that is the difference of ask and bid prices scaled by their mid price, as follows:

$$ps_{i,t} = \frac{(ask_{i,t} - bid_{i,t})}{mid_{i,t}}, \quad (3.3)$$

where $ask_{i,t}$, $bid_{i,t}$ and $mid_{i,t}$ are daily series of ask, bid and mid prices of asset i .

I estimate stock market common illiquidity by taking the cross-sectional average of the daily percentage spreads between closing bid and ask quotes of NYSE/AMEX ordinary common shares (Stoll (2000) and Chordia et al. (2000a) among others), as shown below:

$$ILLIQ_t^{eq} = \sum_{i=1}^N \frac{ps_{i,t}^{eq}}{N}, \quad (3.4)$$

where $ps_{i,t}^{eq}$ are daily series of individual share percentage bid-ask spreads and N is the number of shares in the sample at time t .

Consistently, the common illiquidity proxy for the FX market is built as the cross-sectional average of the daily percentage bid-ask spreads of the USD against the 5 most traded currencies (Australian dollar, Euro, Great Britain pound, Japanese yen and Swiss franc)⁴ (Bessembinder (1994), Menkhoff et al. (2012)):

$$ILLIQ_t^{fx} = \sum_{i=1}^5 \frac{ps_{i,t}^{fx}}{5}, \quad (3.5)$$

where $ps_{i,t}^{fx}$ are daily series of individual currency percentage bid-ask spreads.

3.4.2 Market volatility and returns

Realized volatility is obtained from the cross-sectional equally weighted average of squared asset returns, while market returns are the equally weighted average of individual asset returns, as follows:

$$VOL_t^{eq} = \sum_{i=1}^N \frac{sr_{i,t}^2}{N}, \quad (3.6)$$

$$VOL_t^{fx} = \sum_{i=1}^5 \frac{er_{i,t}^2}{5}, \quad (3.7)$$

$$RET_t^{eq} = \sum_{i=1}^N \frac{sr_{i,t}}{N}, \quad (3.8)$$

$$RET_t^{fx} = \sum_{i=1}^5 \frac{er_{i,t}}{5}, \quad (3.9)$$

where sr are individual stock returns, N is the number of stocks in the sample at time t and er are foreign exchange rate returns.

3.4.3 Data description

The data set comprises daily percentage bid-ask spreads, market returns and realized volatility for both the stock and FX markets from January 1994 until December 2011.

The stock market data set includes the closing price, bid and ask quotes of NYSE/AMEX

⁴The choice of these pairs of currencies is based on BIS (2010).

ordinary common shares (CRSP share code 10 or 11). The closing ask and bid prices are from the last representative quotes before the markets close for each trading day, where closing time is 16.00 EST. The data is from CRSP through Wharton Research Data Services (WRDS). The raw data is adjusted for errors and outliers. In detail, when the value of the spread is zero or the percentage spread is higher than half the mid price in any given year, the quotes are excluded from the data set in that year. Also, when the stock price in any year is higher than \$999, the stock is excluded from the analysis to avoid extremely large share prices driving the measure.

The FX market data set includes ask, bid and mid prices of the USD against the Australian dollar, the Euro⁵, the Great Britain pound, Japanese yen and the Swiss Franc. The data is collected at 21.50 GMT or 16.50 EST by Thomson Reuters and it is available from Datastream.⁶

3.4.4 Preliminary analysis

Table 3.1 presents some descriptive statistics for illiquidity, volatility and returns in the two markets. Comparing the illiquidity measures, the FX market is considerably more liquid than the stock market. It is important to note that the measure of FX market illiquidity includes the most traded currencies, and thus it is representative of the most liquid segment of the FX global market. The variation of the measures appears to be similar in terms of standard deviation relative to the mean. Not surprisingly, both series exhibit a strong autocorrelation. Indeed, illiquidity is persistent and an illiquid day is likely to be followed by another illiquid day. Looking at volatility, the FX market is generally more volatile than the stock market. Furthermore, both volatility measures show significant autocorrelations. Similarly, FX market returns present a larger variation than the stock market measure and generally low serial correlation.

The illiquidity measures are plotted in Figure 3.1. Both measures exhibit a decline over time, consistent with the steady decrease in transaction costs. While the declining trend is more pronounced for the stock market, it is also evident in the FX market. In addition, both measures increase sharply during crisis episodes. Stock market illiquidity presents large spikes during the recent financial crisis. FX market illiquidity shows large increases at the beginning of the sample period, corresponding to the 1995 Mexican crisis and 1998 Asian crisis. An increase in transaction costs can be observed also during the latest financial crisis, even though it appears to be milder than the dramatic liquidity drop in the stock market.

Contemporaneous correlations are examined in Table 3.2. Panel A shows the correlation matrix for the whole sample period. Stock and FX market illiquidity are highly

⁵Datastream provides an historical time series from the conversion rates of each national currency set against the Euro on 31 December 1998.

⁶No filtering is applied to FX data because there is no evidence of outliers in the observations.

correlated, with a coefficient around 72%. There is evidence of strong correlation in volatility as well. Stock market volatility is highly correlated with the illiquidity of both stock and FX markets. As opposed to volatility, market returns are not correlated with illiquidity in either market. Generally, absolute correlation coefficients increase substantially in Panel B, where the sample period is restricted to the recent financial crisis. In both markets, the correlation between volatility and illiquidity increased significantly as did the one between market returns and illiquidity.

Strong contemporaneous linkages provide an interesting starting point for a dynamic analysis of illiquidity across the markets.

3.5 The dynamics of illiquidity in the stock and FX markets

From the contemporaneous correlation analysis it is clear that stock and FX markets share common patterns in terms of illiquidity. To investigate the dynamics of these linkages, I include the variables in a VAR. To define the VAR, the series are first tested for stationarity. Table 3.3 reports the results of ADF tests and shows that the null of unit root can be rejected for all series at the conventional significance level. The number of lags to be included in the VAR is estimated via the Schwarz criterion for parsimony.⁷ Chordia et al. (2001), Hameed et al. (2010) and Banti and Phylaktis (2012) suggest the presence of strong seasonal patterns in both market measures. So, I include seasonal dummies in the VAR.⁸

I estimate the following VAR with five lags:

$$\begin{aligned} X_t^{EQ} &= \sum_{i=1}^5 X_{t-i}^{EQ} + \sum_{i=1}^5 X_{t-i}^{FX} + SEAS_t + \varepsilon_t \\ X_t^{FX} &= \sum_{i=1}^5 X_{t-i}^{EQ} + \sum_{i=1}^5 X_{t-i}^{FX} + SEAS_t + v_t, \end{aligned} \quad (3.10)$$

where X_t^{EQ} and X_t^{FX} are vectors containing the endogenous variables for illiquidity ($ILLIQ_t^{eq}$ and $ILLIQ_t^{fx}$), returns (RET_t^{eq} and RET_t^{fx}) and volatility (VOL_t^{eq} and VOL_t^{fx}) for stock and FX markets respectively, and $SEAS_t$ is a matrix containing seasonality dummies.

⁷Testing the VAR residuals for serial correlation, I can reject the null of no serial correlation in the residuals for five lags. Instead of feeding in lags and making the estimates less precise, I employ an HAC correction of the standard error. Matlab codes are from Kevin Sheppard's Toolbox.

⁸Seasonal dummy variables are: day of the week, month in a year, tick change in the NYSE/AMEX from 1/8 to 1/16 on 24 June 1997, tick change in the NYSE/AMEX from 1/16 to the decimal system on 29 January 2001, days before and after holidays in the U.S. stock exchange, and a time trend. According to Hamilton (1994), I deal with seasonality directly in the VAR.

3.5.1 Contemporaneous correlation of VAR innovations

Starting the analysis of the VAR estimation, I focus on the contemporaneous correlation of VAR innovations mainly to clarify the nature of the correlation between shocks to illiquidity across the markets. Indeed, if shocks to illiquidity are systemic, they have an unexpected impact on the illiquidity, market returns or volatility of the other market. Alternatively, they may be related to specific market events.

Table 3.4 Panel A reports the correlation coefficients and shows that shocks to the illiquidity level in one market have a weak impact on unexpected changes in the other market illiquidity. Given the low correlation coefficient at around 2%, shocks to market illiquidity are generally market specific events. Turning to the relation with volatility, the correlation between shocks to illiquidity and volatility is strong in the stock market, but significantly lower in the FX market. Similarly, shocks to market return and illiquidity in the stock markets are strongly negatively correlated, but positive and low for the FX market.

During the 2007-2009 crisis (Panel B), the correlation between innovations is generally stronger. In particular, illiquidity shocks in the two markets are correlated at over 12%. Given the sharp rise in the correlation coefficient, market specific illiquidity shocks turn systemic during times of distress. Thus, the analysis provides evidence of illiquidity contagion across the two markets.

3.5.2 Cross-market causality

Table 3.5 reports the results of Granger causality tests for the whole sample period (Panel A) and for the latest financial crisis (Panel B). The results clearly document significant cross-market causation between stock and FX market illiquidity. In the stock market, volatility and returns Granger cause market illiquidity and they are caused by it. In the system considered, FX market illiquidity is Granger caused by both FX and stock market returns, but not by volatility. Furthermore, the two markets are strongly intertwined via market returns. In fact, stock market returns Granger cause both returns and volatility in the FX market.

The Granger causality relationships described during the whole sample period weaken substantially during the financial crisis period, when cross-market causality is evident solely in illiquidity.

3.5.3 Do illiquidity shocks in one market affect illiquidity in the other market?

From the previous causality analysis, it is clear that illiquidity in one market has strong power in predicting illiquidity in the other market. In this section I focus on the illiquidity dynamics triggered by shocks to the endogenous variables.

Turning to the impulse response analysis, I employ the Generalized impulse response functions (Koop, Pesaran, and Potter (1996) and Pesaran and Shin (1998)) to investigate the effects of a one time unit standard deviation positive shock in the endogenous variables. The Generalized impulse response functions (GIRFs) are invariant to the ordering of the variables in the VAR so that there is no need of assumptions on the sequence of shocks. In more detail, the response functions of X_t after a shock in variable j at the $t + n$ horizon given the history Ω up to $t - 1$ are given by:

$$GIRFs(n, \delta_j, \Omega_{t-1}) = E(X_{t+n} | \epsilon_{jt} = \delta_j, \Omega_{t-1}) - E(X_{t+n} | \Omega_{t-1}). \quad (3.11)$$

Based on the assumption of normality, Pesaran and Shin (1998) derive the following response functions of X to a one standard error σ shock to variable j at time t for an horizon $t + n$:

$$\psi_j(n) = \sigma_{jj}^{-1/2} A_n \Sigma e_j, \quad (3.12)$$

where $\Sigma = E(\epsilon_t \epsilon_t')$ and e_j is a selection vector of zeros with one as the j th element. Figure 3.2 shows the GIRFs of illiquidity to a shock in the other market illiquidity level. A shock to stock market illiquidity has a delayed but persistent positive impact on FX market illiquidity. Conversely, a shock to FX market illiquidity has a more short-lived positive impact on stock market illiquidity.

The dynamics of volatility are shown in Figure 3.3. When a volatility shock hits the stock market it has a strong positive impact on stock market illiquidity. Also, a shock to stock market illiquidity increases volatility. The same does not happen in the FX market. However, a shock to stock market illiquidity has a delayed positive impact on FX market volatility. Finally, volatility in one market is affected by shocks to volatility in the other.

Figure 3.4 investigates the role of market returns. Positive shocks to stock market returns have a negative impact on both stock and FX market illiquidity. There is no evidence of cross-market dynamics between market returns.

In order to investigate how these dynamics change during crisis episodes, I focus on the 2007-2009 subsample. As expected given the higher correlation between VAR innovations, the impact of illiquidity shocks in one market on the illiquidity of the other is large (Figure 3.5). Although larger than the whole sample period, the effect lasts less. Furthermore, shocks to volatility have now a positive impact on illiquidity in both markets (Figure 3.6). Conversely, the impact of shocks to returns in both markets does not change during the crisis.

In conclusion, there is evidence of strong illiquidity cross-market dynamics. While shocks to market illiquidity are generally market specific events, they are instead sys-

temic during the recent financial crisis. The substantially larger correlation coefficient between illiquidity shocks during the crisis provides evidence of contagion, a sharp increase in the commonality of liquidity shocks during times of distress. In addition, there is evidence of illiquidity causality across the two markets. Furthermore, when stock market illiquidity rises unexpectedly, there is a persistent increase in FX market illiquidity. Even if more short-lived, a shock to FX market illiquidity has a positive impact on stock market illiquidity. The focus on the recent financial crisis shows that these cross-market linkages strengthen during times of distress. In addition, the cross-market dynamics of shocks to illiquidity and volatility changes significantly during the crisis. Consistently with a sensible drop in cross-market price informativeness during periods of uncertainty, illiquidity in one market rises sharply in response to an unexpected rise in volatility in the other market.

3.6 The role of funding liquidity

3.6.1 Identifying funding liquidity

According to the theoretical models presented above (Brunnermeier and Pedersen (2009); Gromb and Vayanos (2010); Acharya and Viswanathan (2011)), when funding liquidity is tight, traders take less positions resulting in a reduced supply of liquidity to the markets. During the 2007-2009 financial crisis intermediaries were facing tight financing constraints. Hence, I empirically investigate the role of this factor on cross-market liquidity linkages focusing on the crisis when dealers are financially constrained.

Given the various aspects of funding liquidity, I include a group of measures reflecting its different aspects. First of all, I consider overnight unsecured financing conditions faced by major institutions in main financial markets. In detail, I include Federal Funds rate (FF) for the US, EONIA for the European Union and SONIA for the UK.⁹ Secondly, I estimate credit riskiness in interbank markets at longer horizon through the European and North American TED spreads. The spreads are built as the difference between the 3-month LIBOR and the yield on a generic 3-month government bond. Finally, I estimate constraints on funding aggregates through daily interest rates on overnight AA Financial Commercial Papers (FCP), which are a primary source of financing for financial intermediaries.¹⁰

To investigate the effects of funding liquidity constraints on the system, I include the proxies for funding liquidity into the basic VAR. Due to potential nonstationarity, I take the first difference of the FF, EONIA, SONIA and FCP. The VAR is estimated

⁹The inclusion of SONIA is important because banks located in the United Kingdom accounted for 37% of all foreign exchange market turnover in 2010, followed by the United States for 18%.

¹⁰Data for other measures of funding aggregates, such as repurchase agreements, is only available at lower frequencies.

with seasonal dummies as above. The analysis in this section begins from January 1999 because of the starting date of the European measures.

Hence, I estimate the following VAR with six lags:

$$\begin{aligned}
ILLIQ_t^{EQ} &= \sum_{i=1}^6 ILLIQ_{t-i}^{EQ} + \sum_{i=1}^6 ILLIQ_{t-i}^{FX} + \sum_{i=1}^6 F_{t-i} + SEAS_t + \varepsilon_t \\
ILLIQ_t^{FX} &= \sum_{i=1}^6 ILLIQ_{t-i}^{EQ} + \sum_{i=1}^6 ILLIQ_{t-i}^{FX} + \sum_{i=1}^6 F_{t-i} + SEAS_t + v_t \\
F_t &= \sum_{i=1}^6 ILLIQ_{t-i}^{EQ} + \sum_{i=1}^6 ILLIQ_{t-i}^{FX} + \sum_{i=1}^6 F_{t-i} + SEAS_t + \epsilon_t,
\end{aligned} \tag{3.13}$$

where $ILLIQ_t^{EQ}$ and $ILLIQ_t^{FX}$ are vectors containing the illiquidity endogenous variable for stock and FX markets respectively, F_t is the vector containing the funding liquidity variables (FF_t , $EONIA_t$, $SONIA_t$, FCP_t , $EURTED_t$, $USTED_t$) and $SEAS_t$ is the matrix containing seasonal dummies.

3.6.2 Contemporaneous correlation of VAR innovations

I begin the analysis by estimating the contemporaneous correlation between VAR innovations. In general, shocks to funding liquidity exhibit significant correlation coefficients with shocks to illiquidity in both markets (Table 3.6 Panel A). Interestingly, the correlation of shocks to illiquidity and funding conditions is stronger at longer horizons.

Table 3.6 Panel B presents the correlation analysis for the recent financial crisis subsample. Correlation coefficients are generally larger, the only exception being the coefficients between shocks to FX market illiquidity and both TED spread measures.

Generally, shocks to funding liquidity constraints and market illiquidity are systemic and trigger unexpected changes in other variables. Consistently with theory, market illiquidity and financing conditions present stronger correlation when funding constraints are tight, which is the case during the financial crisis (Brunnermeier and Pedersen (2009); Gromb and Vayanos (2010); Acharya and Viswanathan (2011)).

3.6.3 Informational effects of funding liquidity

Table 3.7 presents the results of Granger causality tests. Panel A shows that during the whole sample period there is evidence of some causality relationships between illiquidity of both markets and funding liquidity constraints variables. The US TED spread is the most informative measure with respect to the illiquidity level in both markets. There is also some causality from market illiquidity to funding liquidity. In particular, stock illiquidity Granger causes FF, SONIA, FCP and FCP, while FX market illiquidity

causes FF and European TED spread. In addition, there is still evidence of strong causality from stock to FX market illiquidity. However, FX market illiquidity is no more informative in predicting stock market illiquidity level.

Causality relations are significantly different during the 2007-2009 crisis period (Table 3.7 Panel B). Stock market illiquidity strongly predicts most of the funding liquidity variables. However, the causality from funding liquidity variables to market illiquidity is weaker, staying significant at the 10% level only for the US TED spread to the FX market illiquidity. In addition, FX market illiquidity loses informative power over funding liquidity. There is now evidence of a bidirectional causality relation between illiquidity in stock and FX markets.

3.6.4 Do shocks to funding liquidity affect illiquidity in the stock and FX markets?

Figure 3.7 shows the GIRFs to investigate the effects of a one time unit positive standard deviation shock on a variable on the other endogenous variables. The impact of shocks to funding constraints is small or insignificant on both stock and FX market illiquidity, except for shocks to European and US TED spreads. Indeed, an unexpected increase in 3-month funding liquidity constraints causes illiquidity in both stock and FX markets to increase. In general, shocks to market illiquidity do not have a significant impact on funding liquidity. Again, the impact is significant only with respect to funding conditions at longer horizons.

Given the different causality relationships identified in previous sections, I expect the variables to react differently to shocks during distress times. Figure 3.8 shows the GIRFs during the recent financial crisis. Shocks to funding liquidity have a significantly stronger impact on both market illiquidity measures with the only exception of EONIA. In addition, shocks to stock market illiquidity have a significant impact on the European and US TED spreads. Conversely, shocks hitting FX market illiquidity have only a relatively weaker impact on European TED spread. Importantly, there is still evidence of cross-market dynamics between market illiquidity levels.

The different results obtained for whole and crisis sample periods are consistent with theory. In fact, while liquidity is largely available to traders, market liquidity and funding liquidity are relatively independent. However, when funding liquidity dries up, a shock to financing constraints affect market illiquidity. In addition, the impact of market illiquidity on funding liquidity constraints is consistent with illiquidity spiral dynamics for which the decline in market liquidity induced by tightening funding constraints causes funding liquidity to reduce even more (Brunnermeier and Pedersen (2009); Acharya and Viswanathan (2011)).

3.6.5 Focus on the impact of funding liquidity shocks on market illiquidity

Interestingly, shocks to illiquidity in both markets have a significant impact on illiquidity of the other market and this impact is robust to the inclusion in the analysis of funding liquidity measures. In the literature, funding liquidity has been identified as an important determinant of market illiquidity. In addition, when markets are in distress, shocks to market illiquidity may have a strong impact on funding liquidity and, under certain circumstances, induce a liquidity spiral (Brunnermeier and Pedersen (2009); Acharya and Viswanathan (2011)). In the empirical analysis restricted to the crisis period, GIRFs show that shocks to funding liquidity have a significant impact on illiquidity of both stock and FX markets, even if in a number of cases with a lag of some days (Figure 3.8). In addition, shocks to stock market illiquidity have a strong impact on a group of funding liquidity variables. Hence, I can summarize that unexpected changes in stock market illiquidity affect certain funding liquidity conditions and shocks to funding liquidity have a strong effect on both stock and FX market illiquidity when financial markets are in distress.

Given the reactions documented, I am now turning the attention to the possible indirect effects taking place when a shock hits funding liquidity constraints. Especially during crisis episodes, this shock affects the illiquidity level of stock and FX markets. However, this might not be the end of the story. Given the strong causality liquidity link from stock to FX market, the stock market may act as an indirect channel through which shocks to funding liquidity constraints affect FX market illiquidity. In order to clarify this and investigate the existence of an indirect channel through which funding shocks are transmitted across markets, I impose restrictions on the coefficients of funding liquidity variables on FX market illiquidity in the VAR. These restrictions allow me to estimate the impact of shocks to funding liquidity on FX market illiquidity once the direct channel is excluded. So, when a shock hits funding liquidity constraints, its direct impact on FX market illiquidity is cancelled and any reaction observed will be attributed to the other variable acting as a transmission channel.

Figure 3.9 shows the GIRFs. From the graphical analysis it is clear that a strong reaction of FX market illiquidity to funding liquidity is still observed once this restriction is imposed. I interpret this reaction as a signal that illiquidity in the stock market is acting as a channel for the transmission of funding liquidity shocks to FX market illiquidity.

3.7 Do funding liquidity conditions in developed countries affect FX emerging markets?

The framework analysed so far can be employed to address an interesting and controversial issue related to the recent financial crisis. Emerging market leaders claim to have suffered externalities due to the large supply of liquidity provided to developed markets by their authorities to avoid market collapses. Dilma Rousseff, the Brazilian President, referred to “a liquidity tsunami” causing large inflows of capital and subsequent appreciation of currencies in emerging markets as investors seek higher returns. The framework developed in the paper allows assessing the impact of loose financing conditions in developed countries on the liquidity of emerging market currencies. In order to do so, I build a measure of common FX illiquidity across emerging market currencies.

Following the latest BIS Triennial report (BIS (2010)), I include in the analysis the most traded sample of emerging market currencies: Brazilian real, Indian rupee, Korean won, Mexican peso, Polish zloty, Russian ruble, Singapore dollar, South African rand and Turkish lira. All exchange rates are against the US dollar. To insulate systemic reaction of market illiquidity to funding liquidity from noisy idiosyncratic determinants of individual currencies liquidity, I take the common component across them. The measure of common illiquidity in FX emerging markets is calculated as the equally weighted average of transaction costs of individual currencies, as in equations (3.3) and (3.5) above, excluding the highest and lowest spread at each point in time to avoid extreme observations in an individual currency to drive the measure.¹¹ Figure 3.10 shows its pattern over time. Clearly, common illiquidity in FX emerging markets present high variation throughout the sample period with strong increases in crisis episodes such as the 1998-1999, the 2001 and the more recent financial crisis (2007-2009).

In order to investigate the relation between funding liquidity conditions in developed countries and illiquidity in emerging FX market, I include the new measure of common illiquidity in FX emerging markets in the basic VAR. The VAR is estimated with 5 lags and includes seasonality dummies as in previous sections.

Hence, I estimate the following VAR:

¹¹The individual series of percentage bid-ask spreads have generally large correlation coefficients with the common illiquidity measure. On average the coefficient is around 27%, ranging from over 8% for the Turkish lira up to over 55% for the Korean won.

$$\begin{aligned}
ILLIQ_t^{EQ} &= \sum_{i=1}^5 ILLIQ_{t-i}^{EQ} + \sum_{i=1}^5 ILLIQ_{t-i}^{FX} + \sum_{i=1}^5 F_{t-i} + SEAS_t + \varepsilon_t \\
ILLIQ_t^{FX} &= \sum_{i=1}^5 ILLIQ_{t-i}^{EQ} + \sum_{i=1}^5 ILLIQ_{t-i}^{FX} + \sum_{i=1}^5 F_{t-i} + SEAS_t + v_t \\
F_t &= \sum_{i=1}^5 ILLIQ_{t-i}^{EQ} + \sum_{i=1}^5 ILLIQ_{t-i}^{FX} + \sum_{i=1}^5 F_{t-i} + SEAS_t + \epsilon_t,
\end{aligned} \tag{3.14}$$

where $ILLIQ_t^{EQ}$ is the illiquidity endogenous variable for stock market and $ILLIQ_t^{FX}$ is a vector containing the illiquidity measures for developed currencies employed in the main analysis and the one for emerging markets introduced in this exercise, F_t is the vector containing the funding liquidity variables (FF_t , $EONIA_t$, $SONIA_t$, FCP_t , $EURTED_t$, $USTED_t$) and $SEAS_t$ is a matrix containing seasonality dummies.

Figure 3.11 Panel A shows the GIRFs of emerging FX illiquidity to shocks in developed countries' funding constraints. From the graphical analysis it is clear that shocks to funding liquidity constraints do not generally have a significant impact on illiquidity of FX emerging markets. However, during the events of the recent financial crisis, several funding liquidity variables do affect common illiquidity of emerging market currencies (Figure 3.11, Panel B). Hence, loose monetary policies in developed countries reduced the illiquidity of emerging FX market, thereby reducing their transaction costs.

3.8 Conclusions

This paper documents significant illiquidity spillovers across stock and FX markets and, based on the theoretical models on illiquidity commonality across financial markets, empirically investigates the potential sources of these interactions.

With respect to cross-market illiquidity dynamics, I find that illiquidity levels in the two markets are informative in predicting each other. Furthermore, an unexpected rise in illiquidity in the stock market causes a persistent increase in FX market illiquidity. Moreover, shocks to FX market illiquidity have a positive but more short-lived impact on stock market illiquidity. Interestingly, these linkages are found to be stronger during times of distress. In fact, shocks to market illiquidity are generally market specific events, but during the 2007-2009 financial crisis these shocks turned to be systemic and affect the other market. In this respect, the rise in the correlation coefficient between illiquidity shocks in the two markets provided evidence of contagion, that is a sharp increase in the commonality of illiquidity shocks during times of distress.

According to the theoretical models presented (Brunnermeier and Pedersen (2009);

Gromb and Vayanos (2010); Acharya and Viswanathan (2011)), when funding liquidity is tight, traders take less positions resulting in a reduced supply of liquidity to the markets. In this respect, the paper finds that market liquidity is strongly related to funding liquidity in both markets during the 2007-2009 financial crisis. In fact, shocks to financing conditions affect the illiquidity of both stock and FX markets, especially during the recent financial crisis. However, the inclusion of funding liquidity in the analysis does not eliminate the illiquidity linkages across the two markets. In contrast, stock market illiquidity acts as a transmission channel for shocks from funding liquidity to FX market illiquidity during crisis episodes. Although funding constraints have strong effects on both market illiquidity levels, there is space for other potential channels of illiquidity contagion leaving interesting questions for further empirical investigation. Furthermore, according to theory (Brunnermeier and Pedersen (2009) and Acharya and Viswanathan (2011)), I provide evidence of liquidity spiral dynamics, documenting a significant impact on longer horizon funding liquidity of shocks to stock market illiquidity during periods of distress.

Finally, extending the analysis to common illiquidity in emerging FX markets, I address the controversial issue of the impact of liquidity provision by developed countries' monetary authorities on emerging markets currencies. In this respect, I show that shocks to developed countries funding liquidity affect the illiquidity level of FX emerging markets when financial markets are under distress, consistently with the results of the main analysis.

Table 3.1: **Descriptive statistics of illiquidity, volatility and market return in the stock and FX markets**

	ILLIQ EQ	ILLIQ FX	VOL EQ	VOL FX	RET EQ	RET FX
Mean	0.0271	0.0005	0.0022	0.000050	-0.0003	0.000064
Median	0.0260	0.0005	0.0019	0.000025	0.0006	0.000002
Maximum	0.0753	0.0024	0.0195	0.0020	0.0813	0.0311
Minimum	0.0063	0.0002	0.0000	0.0000	-0.0921	-0.0293
Standard Deviation	0.0147	0.0002	0.0015	0.0001	0.0105	0.0051
Skewness	0.3922	1.6244	2.6268	9.4622	-0.8460	0.1002
Kurtosis	-1.1099	14.2894	12.9058	132.7436	9.6100	2.2959
AC(1)	0.99	0.68	0.72	0.24	0.09	-0.04

Notes: Descriptive statistics are reported for the measures of stock and FX market illiquidity, volatility and returns.

Table 3.2: **Contemporaneous correlation matrix**

<i>PANEL A whole sample 94-11</i>					
	ILLIQ FX	VOL EQ	VOL FX	RET EQ	RET FX
ILLIQ EQ	71.70%	39.18%	0.77%	-3.08%	-0.90%
ILLIQ FX	1	26.35%	-0.16%	0.16%	-0.08%
VOL EQ		1	34.56%	-9.65%	-1.54%
VOL FX			1	-9.67%	0.14%
RET EQ				1	12.35%
<i>PANEL B crisis period 07-09</i>					
	ILLIQ FX	VOL EQ	VOL FX	RET EQ	RET FX
ILLIQ EQ	63.15%	78.73%	43.44%	-9.41%	-3.84%
ILLIQ FX	1	49.45%	32.60%	-2.50%	-3.82%
VOL EQ		1	55.61%	-9.44%	-7.67%
VOL FX			1	-9.09%	-6.15%
RET EQ				1	29.48%

Notes: The correlation coefficients of the measures of illiquidity, volatility and returns for the two markets are reported for the whole sample period (1994-2011) in Panel A and for the recent financial crisis (2007-2009) in Panel B.

Table 3.3: **Unit root tests**

	ILLIQ EQ	ILLIQ FX	VOL EQ	VOL FX	RET EQ	RET FX
Test stat - Const	-1.86	-2.99*	-6.52*	-9.15*	-33.98*	-69.91*
Test stat - Const Trend	-3.70*	-6.12*	-6.65*	-9.35*	-33.98*	-69.91*

Notes: The table reports the test statistics of the ADF test for unit root. In the first row the test allows for a constant, while in the second row it allows for both a constant and a trend. * indicates significance at 5%.

Table 3.4: **Contemporaneous correlation of VAR innovations**

<i>PANEL A whole sample 94-11</i>					
	ILLIQ FX	VOL EQ	VOL FX	RET EQ	RET FX
ILLIQ EQ	1.89%	22.02%	7.73%	-28.25%	0.99%
ILLIQ FX		-0.92%	3.69%	-1.03%	2.06%
VOL EQ			20.56%	-13.57%	-1.31%
VOL FX				-8.67%	2.00%
RET EQ					12.19%
<i>PANEL B crisis period 07-09</i>					
	ILLIQ FX	VOL EQ	VOL FX	RET EQ	RET FX
ILLIQ EQ	12.26%	32.86%	14.98%	-27.23%	-5.18%
ILLIQ FX		6.50%	11.48%	-5.93%	-1.97%
VOL EQ			33.55%	-14.98%	-11.11%
VOL FX				-8.45%	-2.58%
RET EQ					30.32%

Notes: Contemporaneous correlation coefficients of the innovations of a VAR(5) for the whole sample period (1994-2011) are reported in Panel A and of a VAR(2) for the recent financial crisis (2007-2009) in Panel B. Lags to be included in the VAR are estimated via the Schwarz information selection criterion. Seasonality dummies are included in the VAR.

Table 3.5: **Granger causality test**

<i>PANEL A whole sample 94-11</i>						
	ILLIQ EQ	ILLIQ FX	VOL EQ	VOL FX	RET EQ	RET FX
ILLIQ EQ		11.39**	10.83**	3.26	36.42***	3.86
ILLIQ FX	19.31***		1.89	4.66	10.74*	15.05***
VOL EQ	93.20***	3.37		2.09	34.62***	4.77
VOL FX	8.28	2.98	8.57		12.23**	10.09*
RET EQ	9.77*	6.41	3.30	1.57		2.94
RET FX	7.22	1.90	5.84	16.30***	10.90**	
<i>PANEL B crisis period 07-09</i>						
	ILLIQ EQ	ILLIQ FX	VOL EQ	VOL FX	RET EQ	RET FX
ILLIQ EQ		7.27**	9.43***	0.55	8.20**	3.04
ILLIQ FX	28.54***		0.32	0.86	0.88	0.38
VOL EQ	12.73***	2.72		0.04	3.87	0.03
VOL FX	6.36**	1.39	2.82		3.95	0.02
RET EQ	2.33	0.48	1.55	0.13		0.19
RET FX	0.45	0.32	0.99	5.10*	4.44	

Notes: The table reports χ^2 statistics for the null of the column variables Granger causing the row variables. Panel A shows the results of the test for the whole sample period (1994-2011), while Panel B focuses on the recent financial crisis (2007-2009). The VAR models are estimated with 5 and 2 lags respectively, following the Schwarz criterion. Seasonality dummies are included in the analysis. * indicates significance at 10%, ** at 5% and *** at 1%.

Table 3.6: **Contemporaneous correlation of VAR innovations including funding liquidity**

<i>PANEL A whole sample 99-11</i>							
	ILLIQ FX	FF	EONIA	SONIA	FCP	EUR TED	US TED
ILLIQ EQ	4.20%	-1.06%	-2.37%	3.37%	0.97%	9.53%	12.42%
ILLIQ FX		2.10%	0.65%	0.37%	1.67%	5.56%	-0.12%
FF			4.50%	-1.29%	58.10%	3.90%	-0.36%
EONIA				-1.42%	3.89%	0.14%	0.14%
SONIA					3.30%	3.21%	-0.48%
FCP						7.44%	-2.71%
EUR TED							7.98%
<i>PANEL B crisis period 07-09</i>							
	ILLIQ FX	FF	EONIA	SONIA	FCP	EUR TED	US TED
ILLIQ EQ	13.78%	6.34%	-5.18%	17.46%	2.61%	14.96%	13.58%
ILLIQ FX		2.22%	-8.13%	3.05%	7.91%	1.55%	-1.10%
FF			16.27%	1.89%	53.87%	11.80%	3.13%
EONIA				1.40%	11.52%	1.83%	-1.93%
SONIA					17.56%	22.70%	7.44%
FCP						13.04%	-0.83%
EUR TED							2.24%

Notes: Contemporaneous correlation coefficients of the innovations of a VAR(6) for the whole sample period (1999-2011) are reported in Panel A and of a VAR(2) for the recent financial crisis (2007-2009) in Panel B. Lags to be included in the VAR are estimated via the Schwarz information selection criterion. Seasonality dummies are included in the analysis.

Table 3.7: **Granger causality test including funding liquidity**

<i>PANEL A whole sample 99-11</i>								
	ILLIQ EQ	ILLIQ FX	FF	EONIA	SONIA	FCP	EUR TED	US TED
ILLIQ EQ		7.90	5.16	12.36**	4.34	3.73	9.29	12.23*
ILLIQ FX	38.22***		5.20	8.03	2.05	5.42	11.20*	25.90***
FF	14.22**	14.47**		24.66***	4.62	27.10***	9.00	8.41
EONIA	2.69	4.25	5.52		5.32	8.37	3.79	2.96
SONIA	13.13**	6.78	4.54	5.22		10.39	10.69*	9.96
FCP	14.46**	6.40	27.09***	14.86**	4.48		5.22	7.58
EUR TED	8.23	12.00**	5.81	6.24	4.23	9.55		24.35***
US TED	6.16	5.24	10.35	7.46	6.23	13.5**	17.12***	
<i>PANEL B crisis period 07-09</i>								
	ILLIQ EQ	ILLIQ FX	FF	EONIA	SONIA	FCP	EUR TED	US TED
ILLIQ EQ		6.83**	3.32	2.85	0.83	3.47	0.92	0.21
ILLIQ FX	35.38***		2.45	0.46	0.33	0.28	3.85	4.74*
FF	8.69***	2.23		0.20	4.47	3.60	0.63	0.32
EONIA	0.45	0.49	0.12		1.94	0.67	3.48	1.41
SONIA	2.70	2.93	7.44**	3.83		1.14	0.13	1.32
FCP	19.80***	0.61	13.32***	0.48	4.90*		2.40	6.70**
EUR TED	12.14***	0.27	0.98	0.25	6.17**	4.62*		9.70***
US TED	8.66***	0.42	2.80	0.38	1.17	8.98***	2.60	

Notes: The table reports χ^2 statistics for the null of column variables Granger causing row variables. Panel A shows the results of the test for the endogenous variables in the VAR analysis beginning in 1999, due to the starting date of European measures (1999-2011), while Panel B focuses on the recent financial crisis (2007-2009). The VAR models are estimated with 6 and 2 lags respectively, following the Schwarz criterion. Seasonality dummies are included in the analysis. * indicates significance at 10%, ** at 5% and *** at 1%.

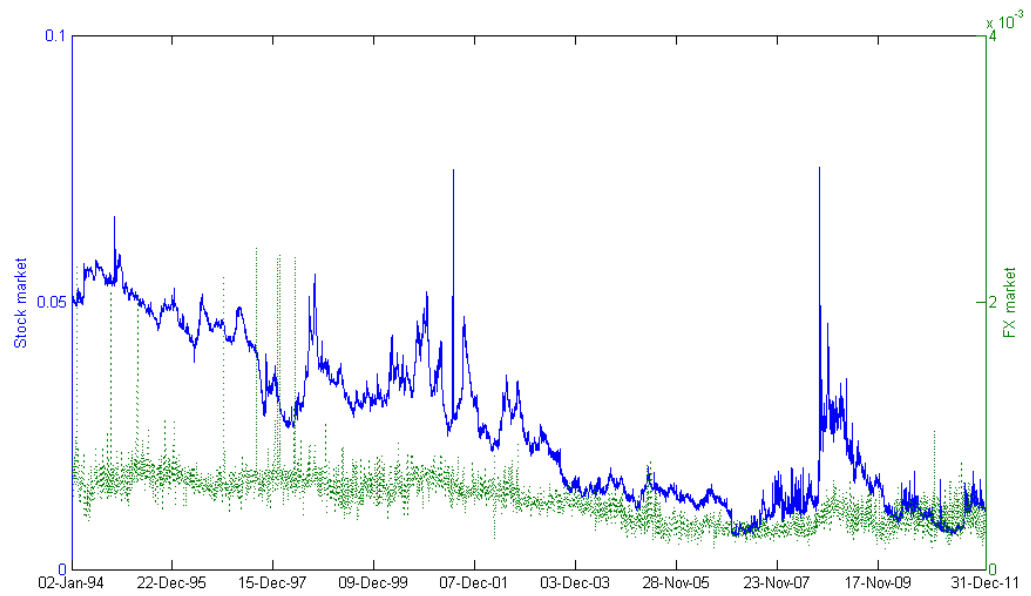


Figure 3.1: **Illiquidity level of the stock and FX markets.** The solid line represents the stock market and it is plotted against the primary axis. The dotted line is the FX market and it is plotted on the secondary axis.

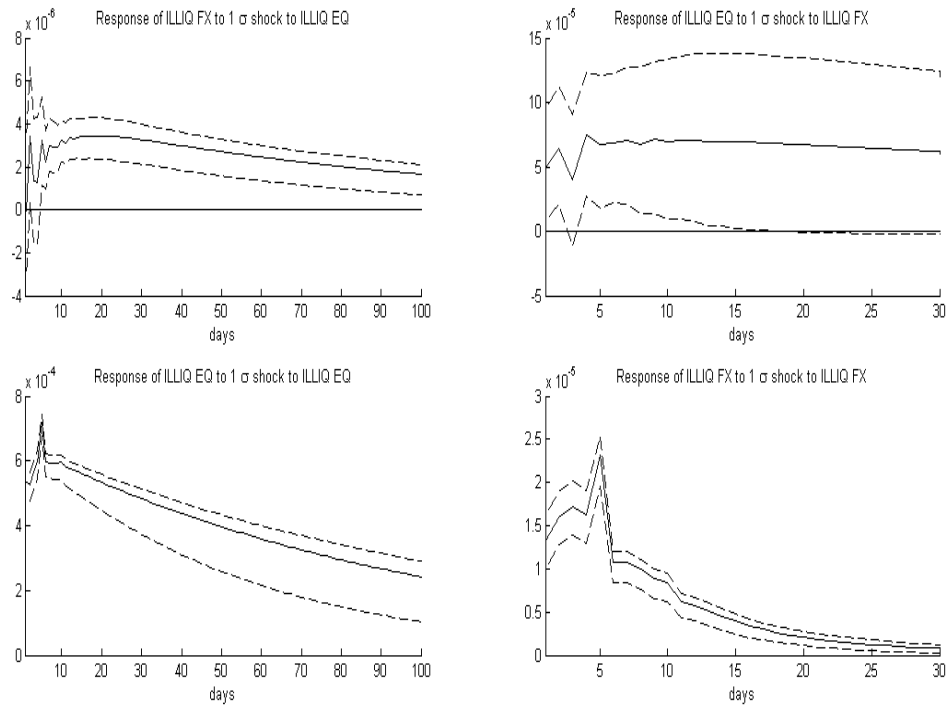
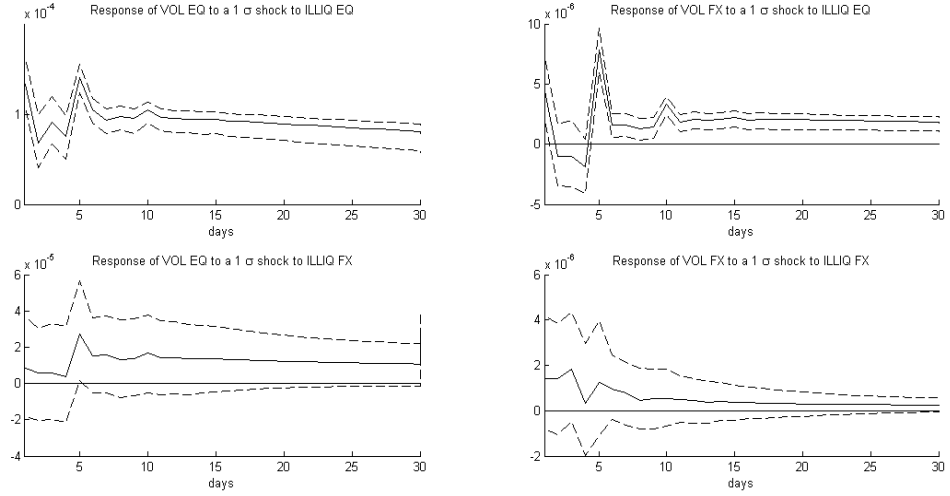
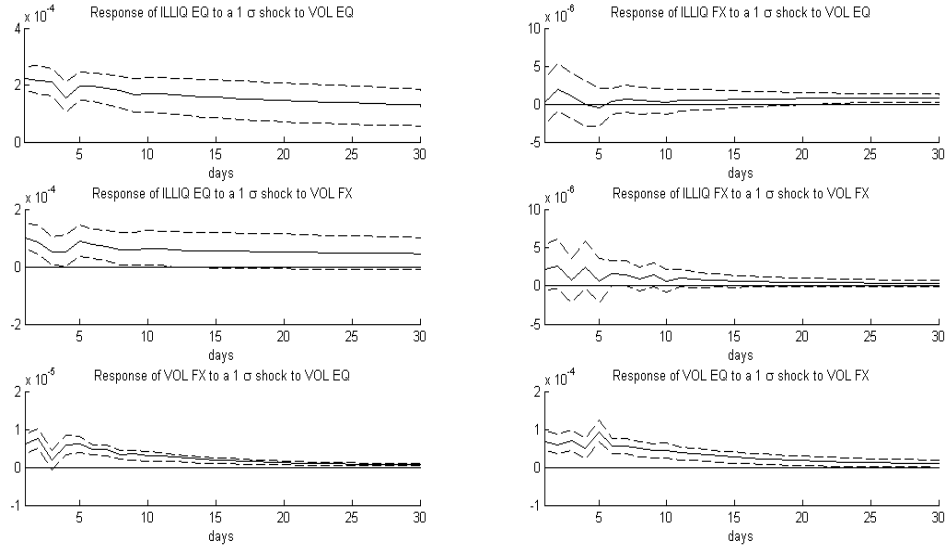


Figure 3.2: **GIRFs of illiquidity.** The solid line represents the Generalized responses of illiquidity levels in the two markets to a one time shock of one standard deviation in the illiquidity of the other market. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications.

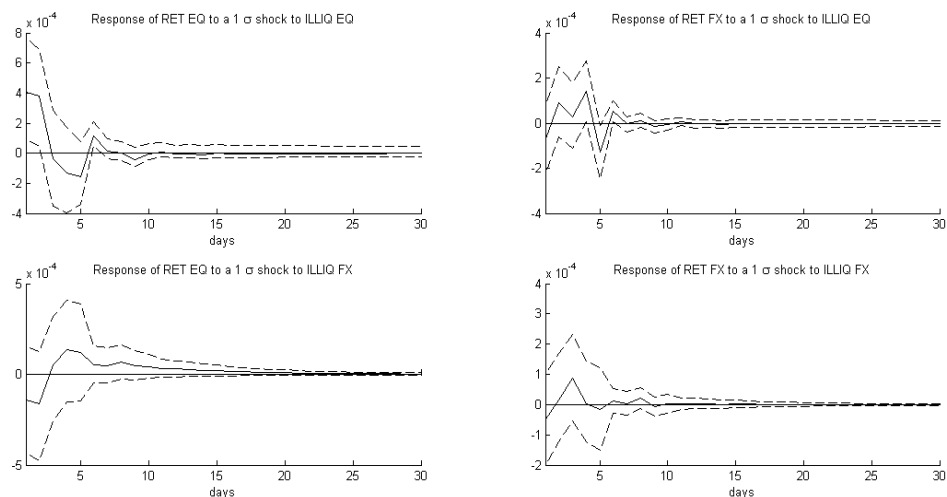


(a) GIRFs to shocks in market illiquidity

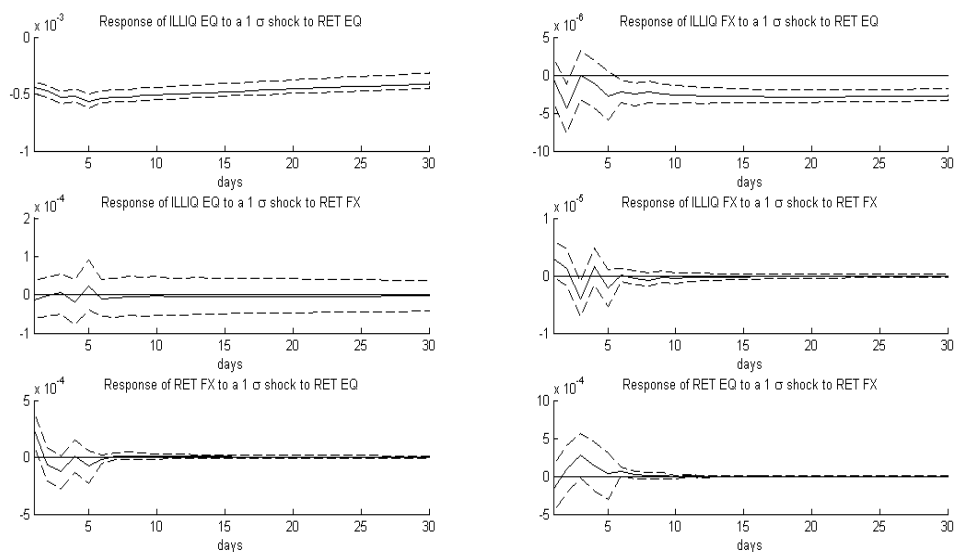


(b) GIRFs to shocks in volatility

Figure 3.3: **GIRFs of illiquidity and volatility.** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications.



(a) GIRFs to shocks in market illiquidity



(b) GIRFs to shocks in returns

Figure 3.4: **GIRFs of illiquidity and market returns.** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications.

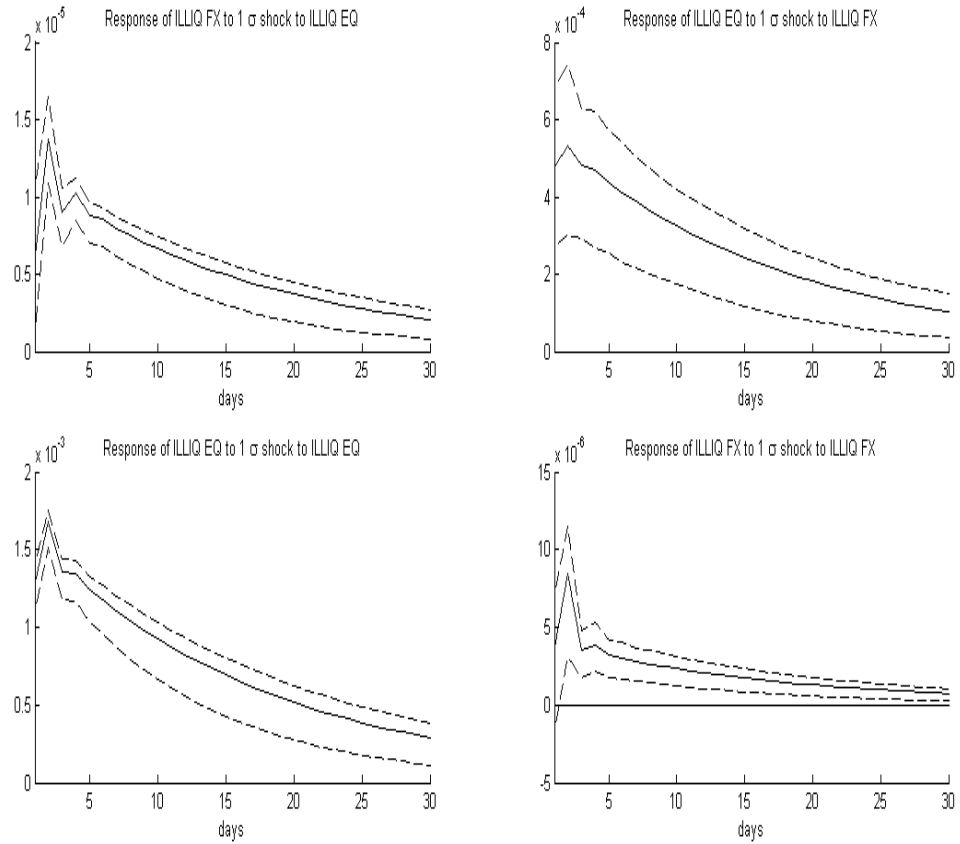


Figure 3.5: **GIRFs of illiquidity during the financial crisis of 2007-2009.** The solid line represents the Generalized responses of illiquidity levels in the two markets to a one time shock of one standard deviation in the illiquidity of the other market. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications.

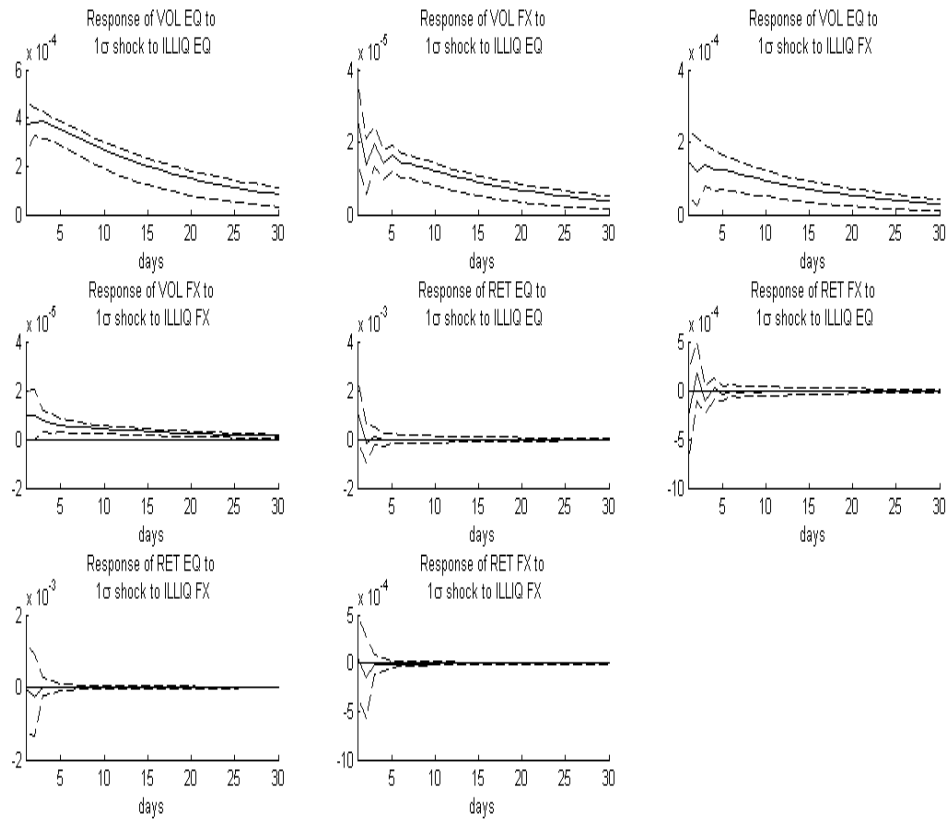


Figure 3.6: **GIRFs of illiquidity, volatility and market returns during the financial crisis of 2007-2009 - GIRFs to shocks in market illiquidity.** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications.

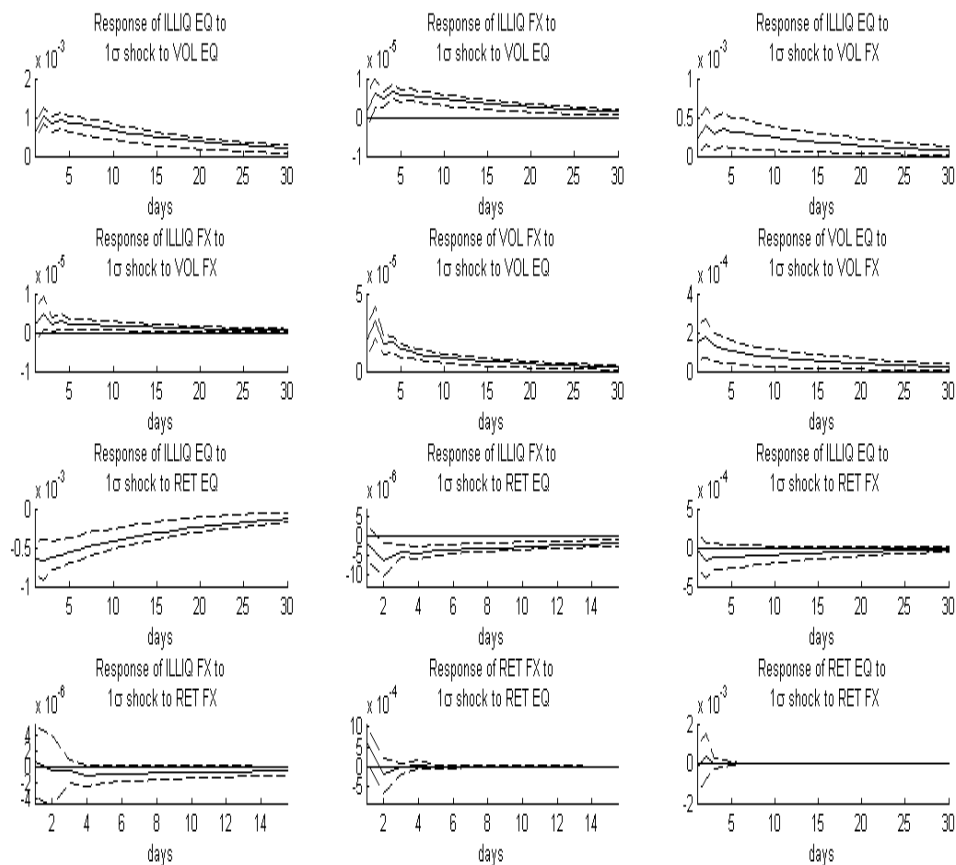


Figure 3.6 (continued): **GIRFs of illiquidity, volatility and market returns during the financial crisis of 2007-2009 - GIRFs to shocks in volatility and market returns** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications.

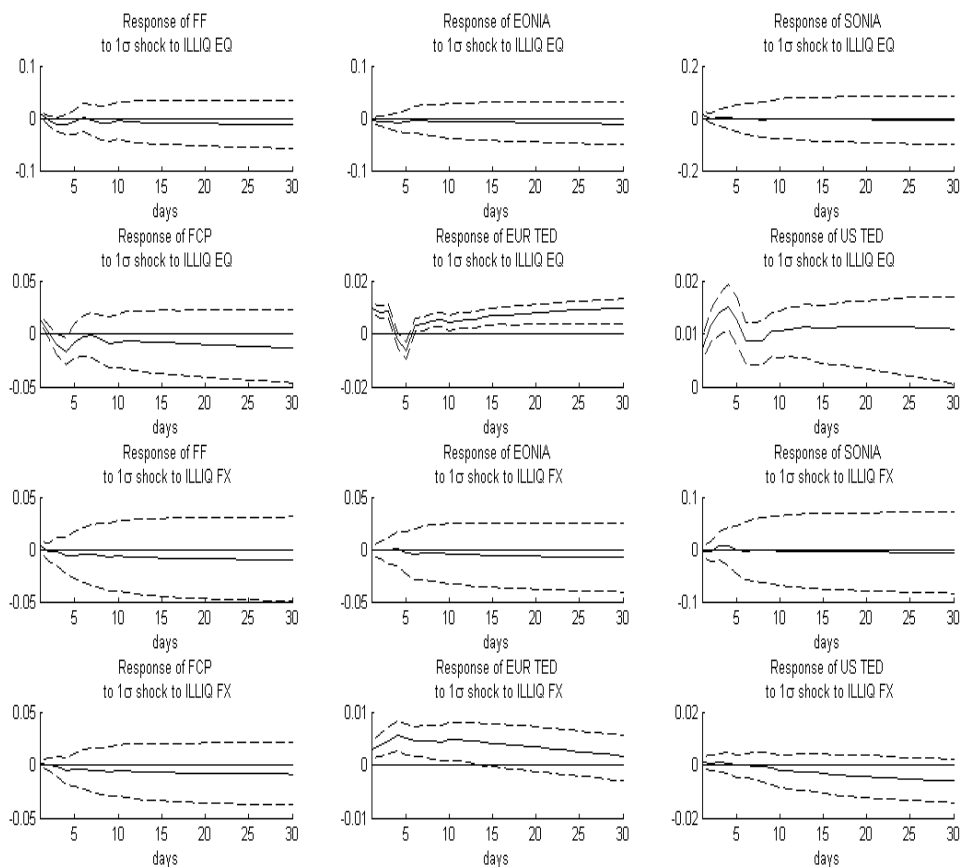


Figure 3.7: **GIRFs of illiquidity and funding liquidity - Funding constraints**
GIRFs to shocks in market illiquidity. The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications. For the variables in first difference (FF, FCP, EONIA and SONIA), the GIRFs are accumulated.

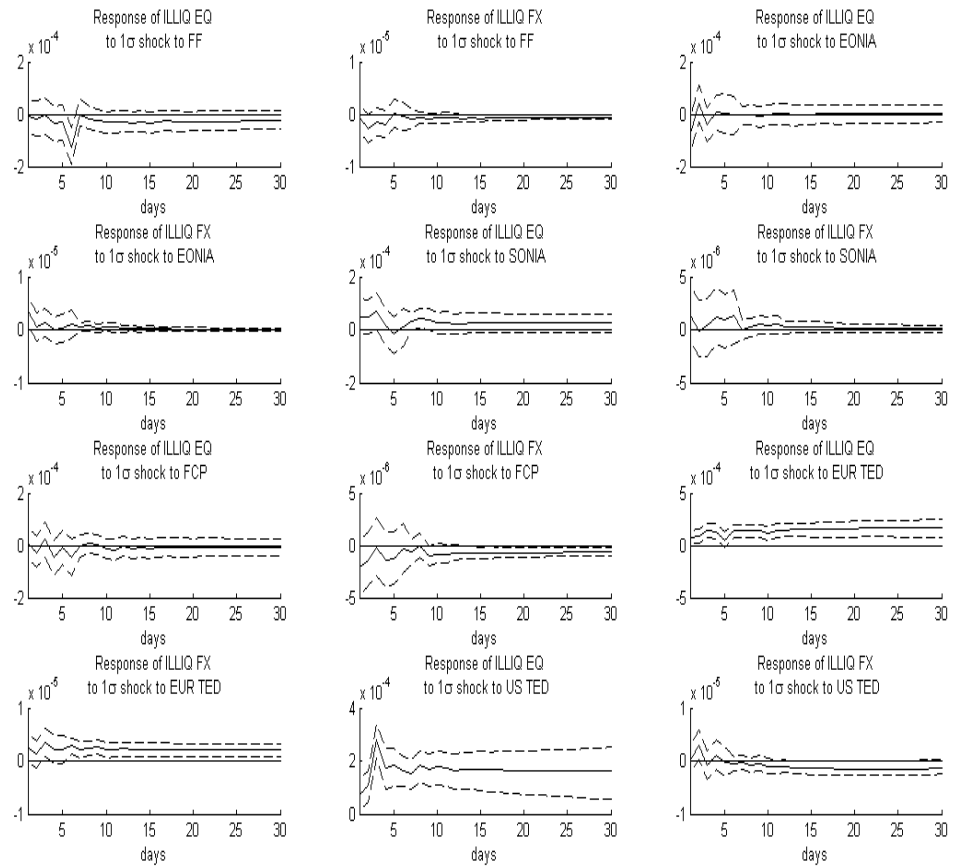


Figure 3.7 (continued): **GIRFs of illiquidity and funding liquidity - Market illiquidity GIRFs to shocks in funding constraints** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications. For the variables in first difference (FF, FCP, EONIA and SONIA), the GIRFs are accumulated.

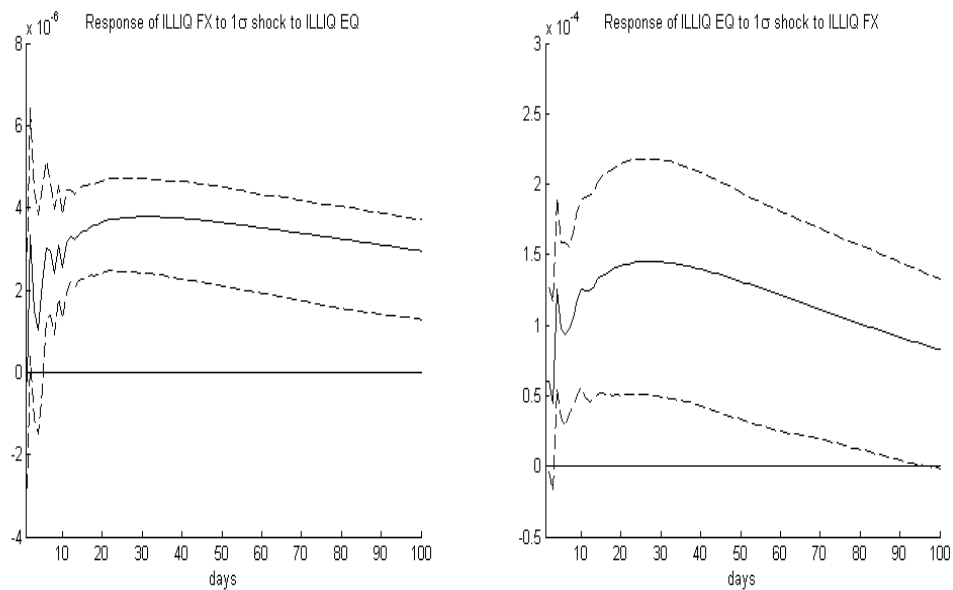


Figure 3.7 (continued): **GIRFs of illiquidity and funding liquidity - Market illiquidity GIRFs.** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications. For the variables in first difference (FF, FCP, EONIA and SONIA), the GIRFs are accumulated.

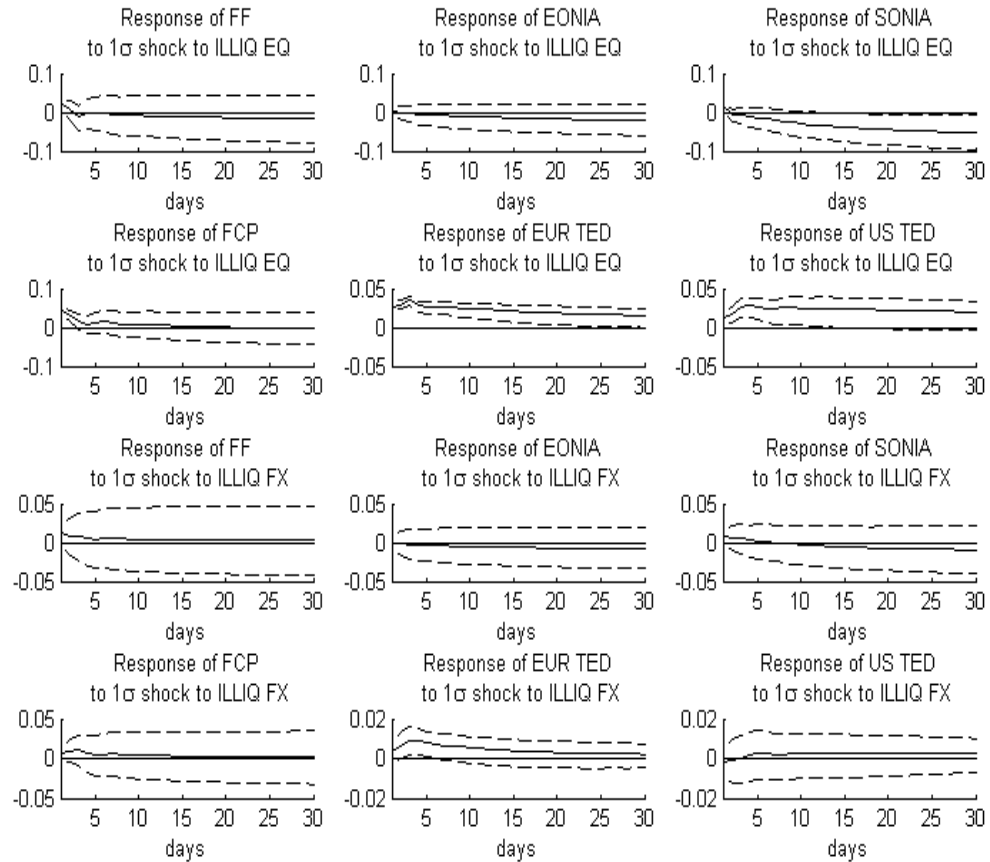


Figure 3.8: **GIRFs of illiquidity and funding liquidity during the financial crisis of 2007-2009 - Funding constraints GIRFs to shocks in market illiquidity.** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications. For the variables in first difference (FF, FCP, EONIA and SONIA), the GIRFs are accumulated.

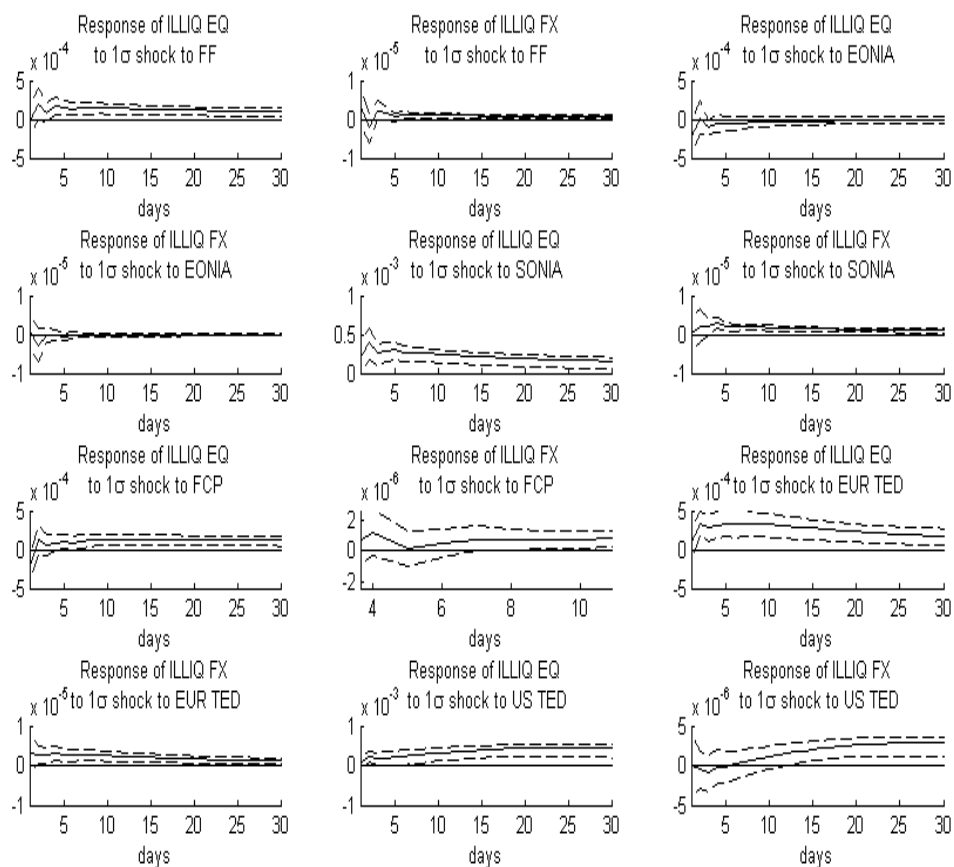


Figure 3.8 (continued): **GIRFs of illiquidity and funding liquidity during the financial crisis of 2007-2009 - Market illiquidity GIRFs to shocks in funding constraints.** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications. For the variables in first difference (FF, FCP, EONIA and SONIA), the GIRFs are accumulated.

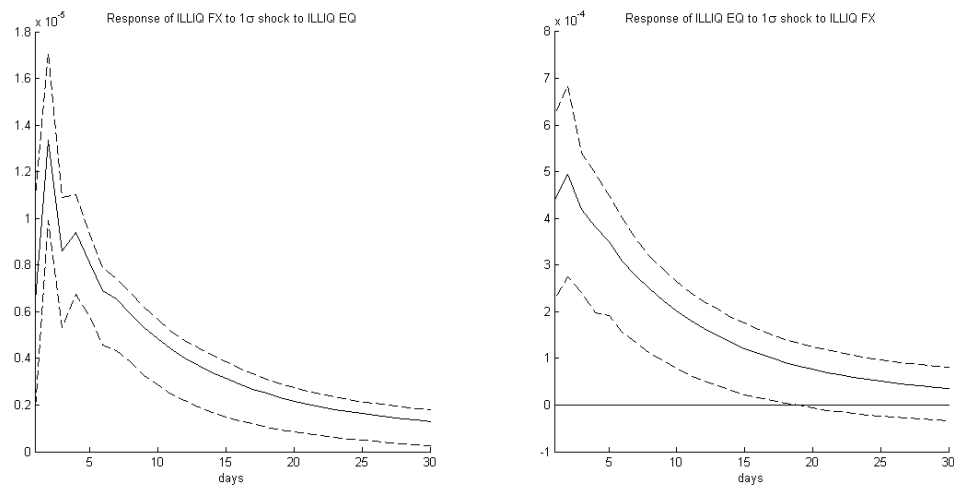


Figure 3.8 (continued): **GIRFs of illiquidity and funding liquidity during the financial crisis of 2007-2009 - Market illiquidity GIRFs.** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications. For the variables in first difference (FF, FCP, EONIA and SONIA), the GIRFs are accumulated.

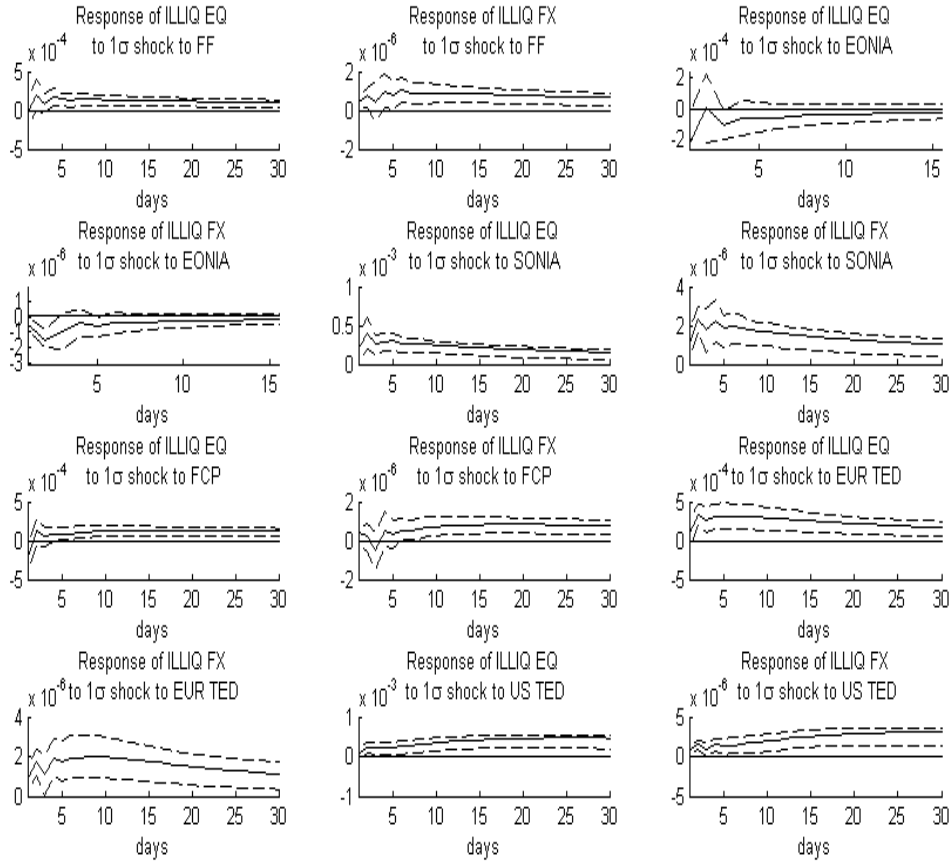


Figure 3.9: **GIRFs of illiquidity and funding liquidity during the financial crisis of 2007-2009 with restrictions on the impact of funding liquidity constraints on the FX market.** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications. For the variables in first difference (FF, FCP, EONIA and SONIA), the GIRFs are accumulated.

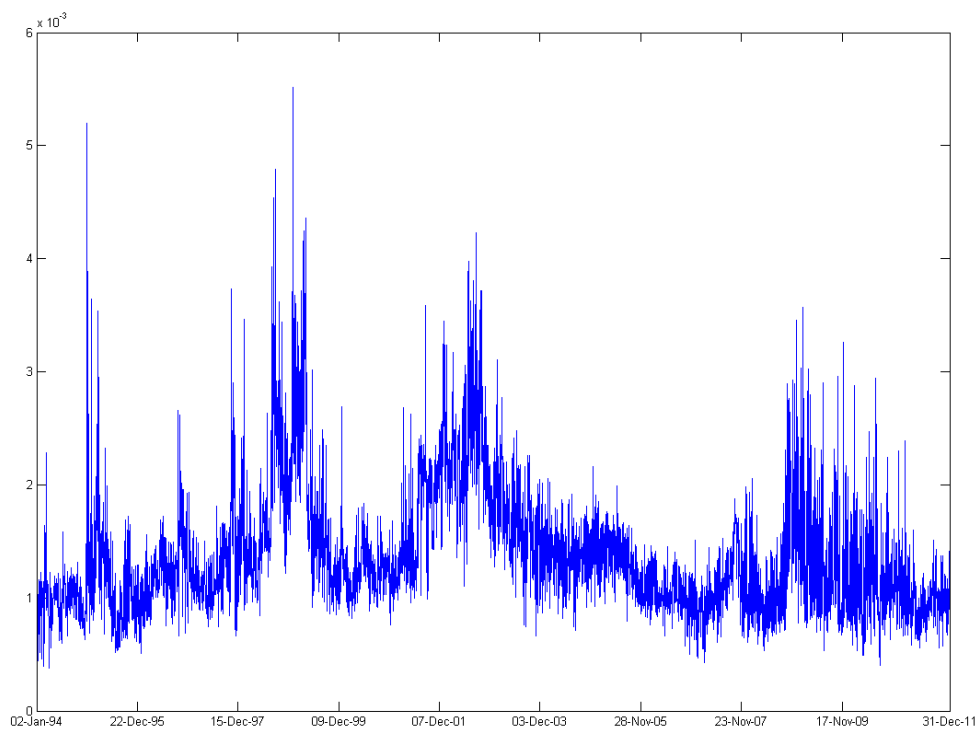
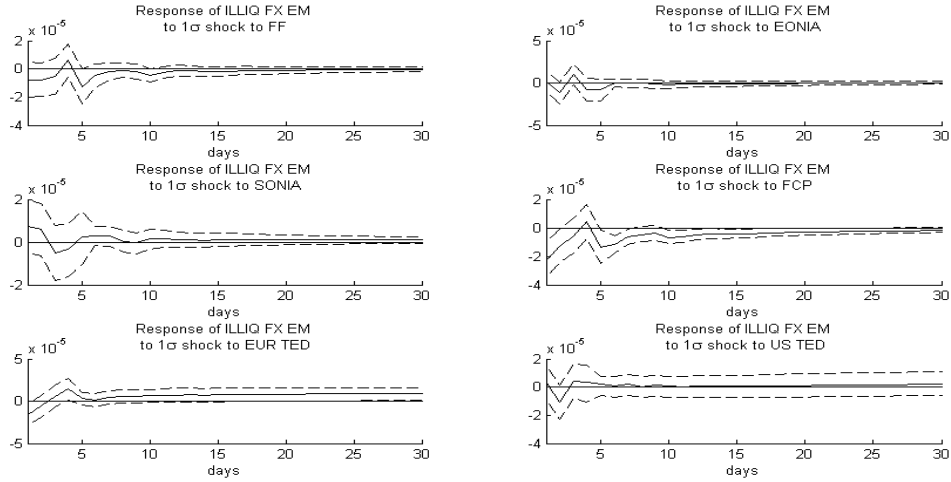
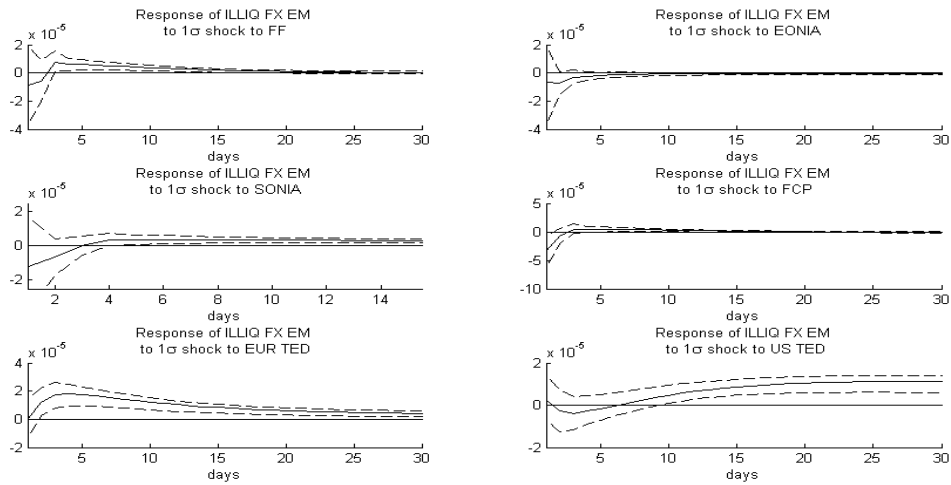


Figure 3.10: **FX common illiquidity level in emerging markets.**



(a) Whole sample period 1994 - 2011



(b) Crisis episode 2007 - 2009

Figure 3.11: **GIRFs of FX emerging market illiquidity to shocks in funding liquidity constraints.** The solid line represents the Generalized responses of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications. For the variables in first difference (FF, FCP, EONIA and SONIA), the GIRFs are accumulated.

Concluding Remarks

The FX market is characterized by a large daily turnover and as such it is generally considered liquid in comparison to other financial markets. However, a large transaction volume does not necessarily imply a market where transactions are executed quickly and at low cost. Indeed, the definition of liquidity is a complex one and comprises different aspects. In this respect, the aspect considered and measurement tools employed may lead to a different conclusion with respect to its liquidity level. In addition, as for other financial markets, there is a significant difference in the level of liquidity across currencies and through time. Despite these considerations and the recent development of a microstructure approach to exchange rate economics, this important aspect of the functioning of the FX market has received relatively little attention. The thesis fills in this gap and provides a comprehensive empirical investigation of the FX market liquidity, from its identification to its asset pricing implications, determinants and cross-market dynamics.

The first paper studies liquidity in the FX market from an asset pricing perspective. Defining illiquidity as the temporary price impact of transactions, the paper first investigates the presence of a time-varying common component in liquidity across a broad group of currencies. Through a portfolio construction technique, the paper then analyses global liquidity risk in the FX market.

Starting from the documentation of liquidity commonality in the FX market, the main finding of the paper is the presence of a global liquidity risk premium in the FX market. Market liquidity exhibits a strong variation through time implying the presence of global liquidity risk in the FX market. Currencies which are more sensitive to global liquidity risk have a higher return on average than less sensitive currencies. In this respect, the paper finds global liquidity risk premium to be around 4.7 percent per annum.

The second paper analyzes the determinants of the time variation in FX market liquidity which has been documented in the first paper. The investigation of the determinants is based on the empirical implications of the traditional theoretical models of bid-ask spread determination. In addition, more recent models have emerged to describe the relationship between market liquidity and funding liquidity.

Given the testable implications of these models, the paper documents a significant impact of recent market returns, global volatility and seasonality on FX market liquidity. Furthermore, it establishes a strong relation between FX market liquidity and funding liquidity. Indeed, especially during period of distress when margins are tight and funding scarce, changes in funding liquidity constraints trigger changes in FX market liquidity.

The third paper extends the analysis to the cross-market dynamics of FX market liquidity. Building on the results documented so far, the study investigates illiquidity linkages across the FX and US stock markets, with a specific focus on the events of the recent financial crisis. The paper also determines the potential sources of the illiquidity linkages with respect to the implications of the theoretical models developed recently to explain illiquidity contagion during the financial crisis.

The main finding of the study is the identification of strong illiquidity linkages across the stock and FX markets, especially during the recent financial crisis. In this respect, there is evidence of illiquidity contagion across the two markets during times of financial distress. The paper then proceeds to determine the potential sources of the illiquidity dynamics across the markets with a specific reference to the role played by dealers as liquidity providers in both markets. In this respect, the paper finds illiquidity in both markets to be strongly related to the liquidity supplied to the financial system during times of distress. Finally, including the common illiquidity in emerging FX markets in the analysis, the paper shows that shocks to developed countries' funding liquidity affect the illiquidity level of FX emerging markets when financial markets are under distress. Thus, it provides support for the claims of emerging markets leaders of a significant impact of developed countries monetary policy on their currency markets.

The thesis provides a contribution to the relatively recent literature on the microstructure approach to exchange rate determination in the field of international finance. It improves the understanding of liquidity, which is an important characteristic of the market where exchange rates are determined. The analysis also fills in a gap in the microstructure literature with respect to the empirical investigation of different aspects of the broad concept of liquidity in this globally important market. Furthermore, this study provides a contribution to the much broader study of another systemically important market, the US stock market.

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