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

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Abstract

In this paper, I investigate the illiquidity channel linking the stock and FX markets. The evidence of co-movement and cross-market spillovers is supportive of important dynamics in illiquidity, especially during the recent crisis. To clarify the nature of these dynamics, I consider the role of two important players on both markets, institutional investors and dealers. Overall, correlated institutional trading contributes to liquidity across markets. Furthermore, as funding availability reduces in times of crisis, dealers' funding constraints affect the observed dynamics. Finally, both correlated institutional trading and dealers' funding constraints are potential triggers of systemic illiquidity spirals.

JEL Classification: G15, G20.

I.   Introduction

The subprime mortgage market turbulence in the summer of 2007 was characterized by sharp drops in asset prices, increasing volatility and episodes of liquidity dry-ups. While most literature focuses on the dramatic reactions of the stock and bond markets, the crisis has been systematic from its very beginning and has severely affected the foreign exchange (FX) market. Indeed, Melvin and Taylor (2009) document extensively the large losses of currency trading strategies, especially the carry trade, from August 2007. Moreover, the dynamics of currency bid-ask spreads during the crisis were largely affected by factors originating outside the market (Melvin and Taylor, 2009). Building on the observation of common illiquidity patterns during the crisis and well-established linkages in stock and FX returns and volatility, I investigate the illiquidity dynamics across these two important financial markets.

The cross-market linkages originate from a variety of factors. For instance, international portfolio rebalancing models link trading in different asset classes and investment decisions across the border to explain the commonality observed in stock prices and exchange rates (Hau and Rey, 2005; Pavlova and Rigobon, 2008; Hau, Massa, and Peress, 2010). Several papers document these linkages empirically (Bartov, Bodnar, and Kaul, 1996; Phylaktis and Ravazzolo, 2005; Bartram and Bodnar, 2012). With respect to the liquidity linkages, Mancini, Ranaldo, and Wrampelmeyer (2013) and Karnaukh, Ranaldo, and Söderlind (2014) provide evidence of positive correlation between FX and stocks liquidity. This paper is, to the best of my knowledge, the first investigation of the dynamics of the illiquidity mechanisms linking the stock and FX markets, with a particular attention to illiquidity spirals. The focus is on the Nasdaq and the major FX electronic trading platforms (Reuters and EBS). Albeit with important differences, these segments are representative of significant portions of trading in stocks and currencies and share important similarities in their structure (see Section II).

The identification of this illiquidity channel is relevant in different respects. As a measure of frictions, illiquidity affects market efficiency. Hence, the identification of interdependencies in the illiquidity of financial markets contributes to the understanding of the processes towards market efficiency (Chordia, Roll, and Subrahmanyam, 2008). Furthermore, the presence of illiquidity spillovers across markets has implications for asset management. Asness, Moskowitz, and Pedersen

(2013) find significant correlation between the returns of trading strategies in stocks and currencies, determined by their exposure to liquidity risk. In addition, liquidity risk is priced in the cross-section of both asset returns (Pastor and Stambaugh, 2003; Banti, Phylaktis, and Sarno, 2012), thus understanding the sources of these linkages is relevant for asset pricing. The systemic dimension of liquidity has also important policy implications, given the severe costs and negative externalities associated with its sudden dry-ups, which have been particularly severe during the recent financial crisis.

Starting by identifying illiquidity co-movement between the stock and FX markets, I analyze their dynamic relationship by taking the common component of transaction costs in each market for 14 years and conducting a vector autoregression analysis.[1] Overall, I document significant cross-market illiquidity spillovers that are stronger during periods of market distress. Moreover, I provide insights on the sources of the observed spillovers. First, I document that the illiquidity linkages with the FX market are different for stocks depending on their market capitalization. The linkages are present irrespective of market conditions for stocks of larger firms that are mostly held by institutional investors, while stocks of smaller firms that are more exposed to financing constraints are strongly related to FX only during the recent financial crisis.

Second, I explicitly investigate the relationship between the behavior of dealers and institutional investors and cross-market illiquidity under specific market conditions in a dynamic framework. In the literature, their activity has been related to liquidity. Previous studies find that dealers' funding constraints are positively linked to illiquidity in stocks (Chordia, Roll, and Subrahmanyam, 2001; Hameed, Kang, and Viswanathan, 2010) and currencies (Banti and Phylaktis, 2015). This effect is especially pronounced when funding liquidity is tight and dealers are less willing to take positions and provide liquidity, according to the model by Brunnermeier and Pedersen (2009). Moreover, correlated trading gives rise to common buying or selling pressure from institutional investors resulting in stronger liquidity commonality across stocks (Kamara, Lou, and Sadka, 2008; Karolyi, Lee, and van Dijk, 2012; Koch, Ruenzi, and Starks, 2012). In the FX market, transactions by financial institutions have price informativeness as shown by the exchange rate predictive power of

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[1] Several studies have documented the presence of a time-varying common component across stocks (Chordia, Roll, and Subrahmanyam, 2000; Huberman and Halka, 2001; Coughenour and Saad, 2004) and currencies (Banti et al., 2012; Mancini et al., 2013).

their order flow (Carpenter and Wang, 2007; Menkhoff, Sarno, Schmeling, and Schrimpf, 2013). In addition to the market-specific role documented in the literature, I show that the behavior of these key market players has implications for cross-market illiquidity dynamics, and in particular for the insurgence of illiquidity spirals. Confirming the preliminary findings across market caps, correlated institutional trading contributes to liquidity across markets in all market conditions, whereas only during the financial crisis when funding is scarce, shocks to funding constraints trigger strong liquidity drops. Importantly, I show that the dynamics in correlated trading and funding constraints may precipitate systemic liquidity dry-ups, providing empirical evidence for the theoretical models by Brunnermeier and Pedersen (2009) and Acharya and Viswanathan (2011). In fact, both correlated trading and funding availability decline after illiquidity shocks. Thus, an illiquidity shock in one market may trigger illiquidity spirals in times of distress across markets, as institutional investors cut down their trading activity and dealers reduce their liquidity provision, further aggravating the illiquidity dynamics.

II. Institutional framework

The FX market is characterized by a variety of trading venues. Due to data availability, I focus on trading activity in the major currency pairs that takes place on the largest FX electronic platforms (Reuters and EBS). These account for $738bn of the $5.3tn average daily turnover in the global FX market (BIS, 2013). These trading platforms operate with automatic matching of orders. With respect to the Nasdaq, it is a centralized electronic market with automatic execution of trades. Although historically quote-driven, it has features of an order-driven market with the presence of market makers for the sample period of this study.

Despite the changes in the composition of traders through time, dealers play an important role in both markets. On the Nasdaq, dealers, or market makers, are required to post quotes on both sides (bid and ask). Since they are not required to post inside the spread, the aggressiveness of their quotes, and their liquidity provision, varies across time and stocks (Chung and Zhao, 2004). As a multi-dealer market, each stock has 17 registered dealers on average (NASDAQ website). Dealers are not the sole liquidity providers and they are subject to competition from their customers' limit orders (that they are required to post and execute before their proprietary ones) and from electronic

communication networks (ECNs). ECNs are open limit order books that can connect directly to the Nasdaq network and account for a large share of trading (40% of trading in 2002 according to Hendershott (2003)). Turning to FX, the electronic trading platforms have been traditionally interdealer markets. Following the introduction of prime brokerage arrangements in 2004/5, they experienced an increasing presence of non-dealer financial institutions (BIS, 2013). In fact, trading between dealers and financial institutions was 17% higher than interdealer trading in April 2013 (Rime and Schrimpf, 2013). These institutions include institutional investors (such as mutual funds and pension funds) and hedge funds, each accounting for 11% of trading in April 2013 (BIS, 2013).[2] Moreover, in both markets changes in market structure and technology have encouraged the development of high-frequency trading and led to a decline in transaction costs through time.

Differences in regulation also deserve mentioning. While the FX market is unregulated, the Nasdaq falls under the Financial Industry Regulatory Authority (FINRA) framework. Indeed, conducts and practices which are illegal in the Nasdaq may be discouraged by conventions and best practices, but are nevertheless legal in the FX market (King, Osler, and Rime, 2012). It is important to note that the unregulated nature of the FX market is currently being challenged by the regulatory responses to the recent scandals in currency trading.[3]

III. Data

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

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[2]Even if unable to trade directly on these platforms, financial institutions did trade with dealers in the costumer-dealer segment of the FX market for the first part of the sample period of this work, and in part throughout the sample. Thus, their presence and trading activity affect the dynamics of interdealer trading. See Lyons (1997) for a model of FX trading across segments.

[3]The FEMR of the Bank of England has issued a consultation document on this issue that was presented by Deputy Governor Sharik during a speech at the LSE on Oct 27th, 2014.

their average transaction costs.[4] 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 the mid. This improves comparability across stocks and currencies.[5] I estimate stock market common illiquidity by taking the cross-sectional average of daily percentage bid-ask spreads of Nasdaq shares (Stoll, 2000; Chordia et al., 2000). Consistently, I build the common illiquidity proxy for the FX market as the cross-sectional average of the daily percentage bid-ask spreads of the USD against the 5 most traded currencies: Australian dollar, Euro, British pound, Japanese yen and Swiss franc.

Data description

The stock market dataset includes bid and ask quotes of Nasdaq ordinary common shares (CRSP share code 10 or 11). The ask and bid are closing inside quotes (highest bid and lowest ask) for each trading day, where closing time is 16.00 EST. The data is from CRSP through Wharton Research Data Services.[6] 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, I exclude the quotes from the dataset in that year. Also, when the stock price in any year is higher than $999, I exclude the stock from the analysis to avoid extremely large share prices driving the measure. This is in line with the adjustments carried out by Chordia et al. (2000) and Hameed et al. (2010).

The FX market dataset includes ask and bid prices of the USD against the Australian dollar, Euro, British pound, Japanese yen and Swiss franc. The data is from actual trades in a one-minute window around 21.50 GMT or 16.50 EST, collected by Thomson Reuters and available through Datastream. For the Australian dollar and British pound, data is sourced from the Reuters Matching platform. For the other currencies, data is collected primarily from EBS.

The sample period is from January 1999 to December 2012.

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[4]In particular, I do not rely on the widely used Amihud measure due to lack of trading volume data on FX.

[5]In a robustness exercise in Section VII., I employ unscaled bid-ask spreads for an alternative illiquidity measure.

[6]For a similar period, Chung and Zhang (2014) show that Nasdaq spreads calculated with CRSP daily data are highly correlated, at over 90%, with high-frequency TAQ spreads.

Preliminary analysis

Table 1a presents some descriptive statistics for the illiquidity measures. The FX market is considerably more liquid than the stock market, with an average percentage spread of 0.04% as opposed to a 1.21% for stocks. It is important to note that the FX measure is based on the most traded currencies, and thus representative of the most liquid segment of the FX global market.[7] 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.

To investigate their time-series properties, the illiquidity measures are plotted in Figure I. Both measures exhibit a decline over time, consistent with a steady decrease in transaction costs. However, the illiquidity level increases sharply in both markets during crisis episodes, even if stock illiquidity presents larger spikes during the recent financial crisis (2007-09). Moreover, there is a a sharp increase in the volatility of FX illiquidity at the end of the sample period, corresponding to the European sub-sovereign crisis. The graphical evidence of co-movement is corroborated by the 75% correlation coefficient between the two illiquidity measures (Table 1a). The documented commonality between the series is an interesting starting point for a dynamic analysis of illiquidity across the markets.

IV.   The cross-market dynamics of illiquidity

From the contemporaneous correlation 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 model. The series are first tested for stationarity. Table 1b reports the results of the ADF tests and shows that the null of unit root can be rejected for all series at the conventional significance level. For this reason, I include the series in level and deal with the trend and seasonality directly in the VAR (Hamilton, 1994). The number of lags to be included in the VAR is determined according

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[7]In Section V., I consider the different segments of the stock market and investigates the dynamics across small and large caps and the FX market. I largely confirm the findings for the average across stocks, but with important differences.

to the Schwarz criterion for parsimony.[8] I estimate the following VAR with eight lags:

$$X_t = \sum_{i=1}^{8} X_{t-i} + SEAS_t + \varepsilon_t \qquad (1)$$

where $X_t = [ILLIQ_t^{eq}, ILLIQ_t^{fx}]$ is a matrix containing the illiquidity measures for stock and FX, and $SEAS_t$ is a matrix containing seasonal dummies to account for the presence of seasonal patterns in both market measures (Chordia et al., 2001; Hameed et al., 2010; Banti and Phylaktis, 2015).[9]

In order to investigate whether illiquidity linkages are affected by market conditions, I conduct a separate analysis for the period prior to the crisis (1999-2006) and during the recent financial crisis (2007-09).[10] It is during the crisis that Melvin and Taylor (2009) identify sharp rises in currency illiquidity. Also, theoretical models predict stronger illiquidity linkages during periods of distress. It is especially in crises that asset price drops coupled with low available funding lead to fire sales and market illiquidity (Adrian and Shin, 2010; Shleifer and Vishny, 2011). Also, as funding constraints are tighter during market downturns, traders reduce their activity and supply less liquidity (Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2010; Acharya and Viswanathan, 2011). Correlated trading across the two markets also strengthens the linkages (Karolyi et al., 2012). Furthermore, due to cross-market information learning, when investors' risk aversion is high, an illiquidity shock and the subsequent lower price informativeness in one market may lead to higher bid-ask spreads in another market (Cespa and Foucault, 2014). As a robustness exercise, I conduct the same analysis including market volatility and returns as control variables and the results are qualitatively similar.[11]

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

[9]Seasonal dummy variables are: day of the week, month in a year and a time trend.

[10]VAR(5) are estimated for the subsamples in accordance to the Schwarz criterion.

[11]Results are not tabulated for brevity, but are available from the author upon request.

Commonality and causality

Table 2a reports the VAR estimation. From the results, both market illiquidity levels are significant determinants of the future illiquidity level of the other market. To interpret the results, I conduct some standard tests.

The correlation matrix of the VAR innovations in Table 2b shows that illiquidity shocks are largely market-specific events. Indeed, the correlation coefficient of the shocks is 4%. If shocks were systemic, an illiquidity shock in one market would be accompanied by a contemporaneous shock on the illiquidity of the other market. According to the Granger causality tests in Table 2b, there is significant cross-market causation between stock and FX market illiquidity.

The sub-sample analysis confirms that prior to the crisis illiquidity shocks are market specific events (Table 3b). There is an increase in the correlation coefficient during the crisis, when illiquidity shocks present some degree of commonality. Also, there are important differences in causality across market periods (Table 3c). Prior to the crisis, there is only weak evidence of causality. During the crisis, the relation turns strong and bidirectional.

What is the impact of illiquidity shocks across markets?

Now, I turn to the dynamics of the system and employ the Generalized impulse response functions (GIRFs) to investigate the effects of a one time unit standard deviation positive shock in the endogenous variables (Koop, Pesaran, and Potter, 1996; Pesaran and Shin, 1998).[12]

Figure II reports the responses to illiquidity shocks and shows that an illiquidity shock in one market has a positive and long lived impact on the illiquidity of the other market (panel a). The reactions are not immediate, but rather delayed. The sub-sample analysis helps clarify these dynamics. As expected from theory, while weaker in normal market conditions, the impact of illiquidity shocks is immediate and strong during the crisis episode (panel b).

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[12]The 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. Indeed, the response functions account for the correlation across innovations using the historically observed distribution of errors. For robustness, I estimate orthogonalized responses with Choleski and different ordering of the variables and the (untabulated) results are qualitatively unchanged.

V. Cross-market dynamics of illiquidity across different market capitalization

While the FX measure captures the most liquid segment of the global FX market, where most trading in currencies is concentrated, the stock measure comprises a wide variety of shares of smaller and larger firms. In this section, I investigate how the observed illiquidity linkages behave for the different segments of the stock market according to market capitalization.

In order to build the measures, I sort stocks according to their market capitalization at the beginning of each year and divide them into 5 groups, the first group with smaller cap stocks and the fifth with larger cap stocks. I then calculate individual illiquidity measures for each market capitalization quintile as the cross-sectional average of the bid-ask spreads in the group. Table 4 reports some descriptive statistics for the illiquidity measures thus calculated. As expected, illiquidity level and variability decrease monotonically as market capitalization rises on average.[13] All quintiles exhibit strong correlation with FX illiquidity, at around 70%. Moreover, average returns are positive for the smallest caps and negative for the largest caps, consistent with the presence of a liquidity premium in stock returns (Amihud and Mendelson, 1986). The different illiquidity level and a certain degree of co-movement across quintiles are evident from Figure III.

To investigate the cross-market dynamics, I follow the procedure of the previous section and include the smallest and largest stock illiquidity measures in a VAR with FX illiquidity.[14] To shed light on the dynamics of the system, I conduct some standard tests on the VAR estimations.

Overall, shocks appear independent for both small and large caps and FX illiquidity, with correlation coefficients of 4% and 3% respectively (Table 5a). The commonality turns significant during the crisis, at 12% and 6% for small and large caps and FX illiquidity (Table 5a). This is in line with the findings for the overall stock measure and it signals that the largest commonality is between FX and small caps, which are less liquid on average.

According to the Granger causality tests for the overall stock measure, there is no causality between illiquidity levels in normal market conditions. However, Table 5b shows that there is some

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[13]A t-test confirms that the difference between the first and last quintiles is statistically different from zero.

[14]As in the previous analysis, the lags are determined according to the Schwarz criterion and seasonal dummies are included. I estimate VAR(10) for the whole period and VAR(5) for subsample analyses, except for VAR(4) for 1st quintile for the crisis.

evidence of causality in illiquidity from large caps to FX. Hence, the most liquid and highly traded stocks are informative to predict FX illiquidity irrespective of the market condition. In crisis, the informative linkages strengthen and the illiquidity of both small and large caps help predict FX illiquidity. In this case, the causality is bidirectional and runs also from the FX to the stock market, confirming the findings for the overall stock measure.

Turning to the analysis of responses to shocks in Figure IV, there is a general positive response of illiquidity across markets to shocks, especially during the crisis.

Institutional investors are generally invested in stocks with large market cap (Gompers and Metrick, 2001; Kamara et al., 2008). The fact that there is causality from large caps to FX irrespective of market conditions indicates that investors behavior may be relevant for cross-market illiquidity dynamics across periods. Conversely, when financial markets are in distress, causality linkages are found also between small caps and FX, and shocks commonality and impact is stronger for small caps. Importantly, trading in small caps is more sensitive to changes in the supply of liquidity, which reduced dramatically during the crisis. Thus, funding constraints appear to be most relevant for the observed dynamics in times of distress.

In conclusion, the results provided so far suggest that while in normal conditions investors trading activity may be relevant for the illiquidity dynamics, funding constraints may turn a significant factor in crisis. These forces are explicitly considered in the next section.

VI.   Potential sources of the documented illiquidity dynamics

The role of funding constraints

According to theory, when funding is tight, dealers take less positions resulting in a reduced supply of liquidity to the markets (Brunnermeier and Pedersen, 2009; Gromb and Vayanos, 2010; Acharya and Viswanathan, 2011). As opposed to stock dealers, currency dealers tend to carry no inventory overnight and during the day they pass undesired inventory positions among each others (and most recently also among other non-dealer financial institutions), the so-called hot potato phenomenon (Lyons, 1997). However, they are affected by inventory considerations when taking up positions during the day, as they are subject to the risk of not being able to offload them quickly and at the low cost, especially during crisis episodes (Melvin and Taylor, 2009).

Given their role of liquidity suppliers in both markets, I expect to find a significant positive relationship between market illiquidity and funding constraints. Moreover, the relationship is expected to be stronger during the recent financial crisis, when dealers are more likely to face tight financing constraints. With respect to the different segments of the stock market, small caps are subject to relatively tighter funding constraints, due to their lower liquidity and higher volatility on average. Hence, I expect stronger linkages with small caps. Nonetheless, large caps are held by investors that may rely on their liquidity in times of distress and are thus more likely to be liquidated in fire sales.

I estimate credit riskiness in the interbank market of two financial centers, London and New York, through the UK pound and US dollar TED spreads and LIBOR-OIS spreads. While New York is especially relevant for funding availability to dealers on the Nasdaq, London is the main platform for trading in FX. Thus, I consider funding conditions in these two financial centers representative of the financing constraints faced by dealers in both the stock and FX markets considered. The TED spread is the 3-month LIBOR over the yield on a generic 3-month government bond. The LIBOR-OIS spread is the 3-month LIBOR over the overnight index swap (OIS) rate, a measure of market expectations of future official interest rates.[15] For brevity, results are reported for the TED spreads only, but are available in the internet Appendix for the LIBOR-OIS (Table 1A and Figures 1A-5A).

To investigate the impact of funding constraints on illiquidity, I include these proxies in a VAR with illiquidity. Also, I consider the illiquidity of small and large caps alongside the market proxy.[16]

The tests on the VAR estimations provide evidence of significant shock commonality between US funding and stock illiquidity (Table 6a). Moreover, there is evidence of Granger causality from funding constraints to illiquidity (Table 6b). Also, stock illiquidity is informative for future funding conditions in both markets.

Since the linkages are expected to depend on market conditions, I now turn to the sub-sample periods to investigate the system dynamics. When shocks hit funding constraints, illiquidity in both markets reacts only weakly in normal market conditions (Figure Va). However, the reactions

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[15]Data is collected from Datastream, except for the US LIBOR-OIS from Bloomberg.

[16]As in the previous analysis, the lags are determined according to the Schwarz criterion and seasonal dummies are included in all models. I estimate VAR(5), except for a VAR(9) for the 5th quintile.

are positive and significant when the system is in distress (Figure Va). The impact is one order of magnitude larger for small caps (Figure Vb), but is also present for large caps (Figure Vc).

Looking at illiquidity shocks in Figure VI, there are again only weak responses prior to the crisis, except for a strong impact of stock illiquidity on US funding. All responses turn significant in crisis. These dynamics are consistent with illiquidity spirals, for which the increase in stock illiquidity induced by tightening funding constraints causes funding to reduce even more (Brunnermeier and Pedersen, 2009; Acharya and Viswanathan, 2011). Finally, FX illiquidity shocks have a strong impact on UK funding, as evidence for the role of London as leading global platform in currency trading.

In conclusion, funding constraints are important determinants of future liquidity in both markets. With respect to the stock market, there is evidence of stronger linkages with small caps. Nonetheless, investors are more likely to sell off the most liquid stocks they hold, generally larger caps, in times of distress to limit losses from fire sales. This is consistent with the linkages documented between funding conditions and large caps during the crisis. Moreover, illiquidity in both markets affect funding constraints during the crisis as evidence of illiquidity spirals.

The role of correlated trading

Consistent with previous work on stock and bond markets by Chordia, Sarkar, and Subrahmanyam (2005), I consider mutual funds that are active on both markets and focus on US mutual funds with investment objectives in domestic and foreign equity markets (Bouwman, Sojli, and Tham, 2013; Chiu and Kini, 2013).[17] Data for both fund types is from the Investment Company Institute and comprises monthly dollar inflows and outflows for each type of funds.[18]

As open-ended funds, mutual funds may increase their portfolio holdings following an inflow. After an outflow, they may liquidate their positions to pay for share redemptions. Studying flow-induced mutual fund trading, Lou (2012) finds that they meet redemption requests exclusively

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[17]Albeit a partial proxy for institutional trading, data availability on fund flows allows to focus on flow-driven trading (Lou, 2012). Also, defined fund types allow to build separate proxies for trading in US equity and FX (as a by-product of investments in foreign equity). Fund flows are also used to proxy for institutional price pressure in Coval and Stafford (2007).

[18]I take the raw flows as opposed to the standardized series (divided by TNA) because the interest is not on the mutual fund industry per se, but rather on the effects of fund trading on illiquidity.

by liquidating existing positions and they increase their positions after an inflow by around 62%. In both cases, funds respond by trading more. Given that the data on flows cover a substantial segment of mutual fund industry, I add inflows and outflows in a measure of correlated trading activity (Coval and Stafford, 2007; Lou, 2012). In detail, I consider the overall flows of mutual funds invested domestically as a proxy for correlated trading by funds in the US stock market. Turning to the foreign equity type, flows in and out trigger trading in both the foreign equity market and the related foreign currency (Hau and Rey, 2005). Hence, I consider the flows to and from mutual funds invested abroad as a proxy for correlated trading by funds in FX. If investors demand liquidity from the market, an increase in their trading should be accompanied by higher illiquidity. However, if they provide liquidity, the relationship between trading activity and illiquidity should be negative. Since I do not differentiate between buying and selling pressure and use the overall aggregated flows as a proxy for correlated trading, I exclude any information channel and shifts in investor sentiment from the picture to fully capture the illiquidity channel.

Over the sample period, US fund flows have been higher on average than foreign ones, 135bn\$ and 48bn\$ respectively, and there is evidence of commonality between the flows, with a correlation over 80%. Moreover, flows are negatively correlated with illiquidity in both markets, with coefficients between -30% and -50%. The negative signs are consistent with funds providing liquidity rather than consuming it, so that higher flows are associated with lower illiquidity. To investigate the dynamics of the linkages between institutional trading and illiquidity, I include the flows into a VAR with illiquidity.[19] The analysis is conducted at monthly frequency and the relatively low number of monthly observations does not allow for a sub-sample analysis.

Tests of the VAR estimation show that shocks to correlated trading exhibit strong commonality, at around 80% (Table 7a). There is also evidence of commonality in shocks to correlated trading and illiquidity. The relationship is negative in all cases, except for large caps and stock trading. Interestingly, illiquidity shocks are also correlated at monthly frequency. According to the Granger tests, there is some evidence of causality from small caps illiquidity to stock correlated trading (Table 7b).

While the causality linkages are rather weak, the analysis of the system dynamics provides

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[19]The VAR model includes 1 lag according to the Schwarz criterion. Seasonal dummies include months of the year and a time trend. Monthly illiquidity variables are obtained as the last observation in the month.

an interesting picture. In fact, a positive shock to correlated trading causes stock illiquidity to drop (Figure VIIa). That is, unexpected increases in institutional investors' trading activity reduce transaction costs in stocks. The impact is across markets for large caps, where shocks to correlated trading trigger a drop in the illiquidity of both markets in the following month (Figure VIIb). Moreover, after stock illiquidity unexpectedly rises correlated trading declines (Figure VIIc).

Overall, institutional investors do not seem to consume liquidity, but rather to contribute to it. In addition, correlated trading declines when illiquidity rises unexpectedly. Finally, this analysis confirms that the cross-market illiquidity dynamics observed at daily frequency are also present at monthly frequency.

Summary of the analysis of determinants

The results of this section show that dealers and institutional investors play an important role on the documented illiquidity linkages across markets.

In addition to increasing liquidity commonality across stocks (Chordia et al., 2000; Kamara et al., 2008; Hameed et al., 2010; Koch et al., 2012), correlated trading is associated with lower transaction costs, as it contributes rather than consumes liquidity in both markets irrespective of market conditions. Moreover, during the crisis, funding shocks cause higher illiquidity in both markets.

Furthermore, there is evidence of illiquidity spiral dynamics as shocks to illiquidity worsen funding constraints during the crisis, in line with the theoretical models by Brunnermeier and Pedersen (2009) and Acharya and Viswanathan (2011). Also, institutional investors react to illiquidity shocks in the stock market by reducing their trading activity (Adrian and Shin, 2010; Shleifer and Vishny, 2011). As such, they may exacerbate these dynamics and give rise to illiquidity spirals.

VII. Robustness test: linkages in spreads across markets

In the main analysis, the market illiquidity measures are built from the percentage bid-ask spreads to improve comparability across stocks and currencies. In this section, I test the robustness of the main results by conducting the analysis with unscaled bid-ask spreads. The market illiquidity measures are then obtained as the cross-sectional averages of spreads across stocks and currencies.

The two illiquidity measures are strongly correlated, with a correlation coefficient in excess of 40%. Both measures exhibit a decline through time and increases in level and volatility during crisis episodes (Figure VIII).

To investigate the robustness of the main results presented above the two illiquidity measures are included in a VAR. Table 8 reports the correlation analysis of VAR innovations and Granger causality tests. The results are generally comparable to the main analysis, with a correlation coefficient between illiquidity shocks of 2% in normal periods that turns to 9% in crisis. The Granger causality tests show that the forecasting power of FX illiquidity is stronger and bidirectional during the crisis, as in the main analysis. Figure IXa presents the responses to illiquidity shocks and confirms the findings of the main section. Indeed, shocks to stock market illiquidity have a positive impact on the level of FX market illiquidity and viceversa. Consistently with the main results, the reactions strengthen during the crisis (Figure IXb).

In conclusion, the results of the analysis with alternative illiquidity measures provides additional support for the evidence presented in the paper as to the presence of strong illiquidity linkages across the two markets.

VIII. Conclusion

In this paper I document that illiquidity is an important channel linking the stock and FX markets. In fact, while cross-market linkages were established between stock prices and exchange rates, their returns and volatility, this is the first study to investigate the dynamics of the illiquidity linkages between the stock and FX markets. I document significant co-movement and cross-market spillovers. Also, I show that illiquidity in the two markets is driven partly by common underlying factors, especially during the financial crisis. While market-specific events during normal market conditions, illiquidity shocks are more systemic in crisis. Moreover, illiquidity shocks affect both markets: an unexpected increase in transaction costs in one market causes an increase in the transaction costs of the other market as well, particularly during the crisis. I also document significant illiquidity predictive power. The dynamics documented at daily frequency are confirmed at monthly level. These findings clarify the observation of liquidity dry-ups across currencies at the onset of the recent financial crisis, which were largely unrelated to FX market events (Melvin

and Taylor, 2009).

Turning the attention to potential common factors that drive these dynamics, I show that dealers' funding constraints and institutional investors' correlated trading are important sources of the observed cross-market illiquidity linkages. Overall, I show that correlated institutional trading contributes to liquidity in both markets irrespective of market conditions. During the crisis when funding availability reduces, I document strong liquidity declines triggered by funding constraints shocks. Thus I provide empirical evidence for the theoretical models predicting a role for funding constraints on market illiquidity and I show that they contribute to systemic dynamics (Brunnermeier and Pedersen, 2009; Acharya and Viswanathan, 2011). Furthermore, I provide support for the models by Brunnermeier and Pedersen (2009) and Acharya and Viswanathan (2011) by empirically documenting illiquidity spirals. In fact, I show that both correlated institutional trading and dealer's funding constraints are potential drivers of illiquidity spirals. There is a significant reduction of correlated trading activity and funding availability following illiquidity shocks. Thus, an illiquidity shocks may trigger illiquidity spirals in times of distress, as institutional investors reduce their trading activity and dealers provide less liquidity. Under certain conditions, these may turn an illiquidity shock into an illiquidity spiral with systemic effects.

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Table 1: Descriptive statistics of illiquidity in the stock and FX markets

(a) *Descriptive statistics*

	ILLIQ EQ	ILLIQ FX
Mean	0.0121	0.0004
Median	0.0098	0.0004
Standard dev.	0.0064	0.0001
Minimum	0.0033	0.0001
Maximum	0.0425	0.0010
AC(1)	0.9778	0.6956
Correlation coeff.	75.02%	

(b) *Unit root tests*

	ILLIQ EQ	ILLIQ FX
Drift	-2.74	-6.31*
Drift + Trend	-3.91*	-9.10*

Notes: Panel a reports some descriptive statistics of the main data for the 1999-2012 sample period. ILLIQ EQ and ILLIQ FX are the average transaction costs across Nasdaq stocks and currencies, respectively. The last row reports the contemporaneous correlation coefficient between the stock and FX illiquidity measures. Panel b reports the test statistics of the ADF test for unit root. In the first column the test allows for a constant, while in the second column it allows for both a constant and a deterministic trend. * indicates significance at 5%.

Table 2: VAR model of stock and FX illiquidity

(a) *VAR estimation*

	ILLIQ EQ$_t$	ILLIQ FX$_t$
ILLIQ EQ $_{t-1}$	0.4006***	-0.0007
ILLIQ EQ $_{t-2}$	0.1712*	0.0045***
ILLIQ EQ $_{t-3}$	0.1411*	-0.0005
ILLIQ EQ $_{t-4}$	0.0777*	-0.0009
ILLIQ EQ $_{t-5}$	0.0925**	0.0007
ILLIQ EQ $_{t-6}$	0.0120	0.0026***
ILLIQ EQ $_{t-7}$	0.0246*	-0.0002
ILLIQ EQ $_{t-8}$	0.0471***	-0.0018*
ILLIQ FX $_{t-1}$	0.3232*	0.0975***
ILLIQ FX $_{t-2}$	0.2945	0.1165***
ILLIQ FX $_{t-3}$	-0.0667*	0.0946***
ILLIQ FX $_{t-4}$	0.2750*	0.0700***
ILLIQ FX $_{t-5}$	-0.0229	0.1704***
ILLIQ FX $_{t-6}$	-0.0618	0.0562***
ILLIQ FX $_{t-7}$	-0.0356	0.0900***
ILLIQ FX $_{t-8}$	0.2595	0.0874***
Constant	0.0371***	-0.0001
R^2	0.97	0.69

(b) *Innovation correlation*

	ILLIQ FX
ILLIQ EQ	4%**

(c) *Granger causality*

	ILLIQ EQ	ILLIQ FX
ILLIQ EQ	-	1024.06***
ILLIQ FX	18216.29***	-

Notes: Panel a reports the coefficients estimated for a VAR(8) of stock (ILLIQ EQ) and currency (ILLIQ FX) illiquidity for the period 1999-2012. Panel b shows the contemporaneous correlation coefficients of VAR innovations. Panel c reports the χ^2 statistics for the null of the column variables non Granger causing the row variables. Seasonal dummies are included in the model. * indicates significance at 10%, ** at 5% and *** at 1%.

Table 3: VAR models of stock and FX illiquidity for sub-sample periods

(a) *VAR estimation*

	Prior to crisis 1999-2006			Crisis episode 2007-2009	
	ILLIQ EQ$_t$	ILLIQ FX$_t$		ILLIQ EQ$_t$	ILLIQ FX$_t$
ILLIQ EQ $_{t-1}$	0.6243***	-0.0036	ILLIQ EQ $_{t-1}$	0.2384**	0.0003
ILLIQ EQ $_{t-2}$	0.2061***	0.0059*	ILLIQ EQ $_{t-2}$	0.1203	0.0040***
ILLIQ EQ $_{t-3}$	0.0709**	-0.0013	ILLIQ EQ $_{t-3}$	0.1508	0.0006
ILLIQ EQ $_{t-4}$	0.0643*	0.0015	ILLIQ EQ $_{t-4}$	0.1308	0.0006
ILLIQ EQ $_{t-5}$	-0.0109	-0.0018	ILLIQ EQ $_{t-5}$	0.1486	0.0023***
ILLIQ FX $_{t-1}$	0.1678	0.1548***	ILLIQ FX $_{t-1}$	1.5941***	0.0677*
ILLIQ FX $_{t-2}$	0.1383	0.1412***	ILLIQ FX $_{t-2}$	0.7626	0.1142***
ILLIQ FX $_{t-3}$	-0.0324	0.1518***	ILLIQ FX $_{t-3}$	0.6919	0.0872**
ILLIQ FX $_{t-4}$	-0.0644	0.0751***	ILLIQ FX $_{t-4}$	1.7987**	0.1179***
ILLIQ FX $_{t-5}$	0.0510	0.2051***	ILLIQ FX $_{t-5}$	0.8443	0.1211***
Constant	0.2033***	0.0230***	Constant	0.3690***	-0.0382***
R^2	0.98	0.71	R^2	0.62	0.48

(b) *Innovation correlation*

	Prior to crisis 1999-2006		Crisis episode 2007-2009
	ILLIQ FX		ILLIQ FX
ILLIQ EQ	2%	ILLIQ EQ	9%***

(c) *Granger causality*

	Prior to crisis 1999-2006			Crisis episode 2007-2009	
	ILLIQ EQ	ILLIQ FX		ILLIQ EQ	ILLIQ FX
ILLIQ EQ	-	0.62	ILLIQ EQ	-	15.53***
ILLIQ FX	6.24	-	ILLIQ FX	29.76***	-

Notes: Panel a reports the coefficients estimated for VAR(5) models of stock (ILLIQ EQ) and FX (ILLIQ FX) illiquidity for the periods prior and during the crisis. Panel b shows the contemporaneous correlation coefficients of VAR innovations. Panel c reports the χ^2 statistics for the null of the column variables non Granger causing the row variables. Seasonal dummies are included. * indicates significance at 10%, ** at 5% and *** at 1%.

Table 4: Descriptive statistics of stock illiquidity of market capitalization quintiles

	SMALLEST	2	3	4	LARGEST
Mean	0.0269	0.0156	0.0092	0.00540	0.0026
Median	0.0251	0.0128	0.0053	0.00293	0.0016
Standard dev.	0.0098	0.0089	0.0074	0.0048	0.0023
Minimum	0.0083	0.0029	0.0016	0.0010	0.0005
Maximum	0.0662	0.0541	0.0444	0.0426	0.0216
AC(1)	0.9701	0.9810	0.9804	0.9613	0.9673
correl w/ILLIQ FX	72.84%	74.26%	73.80%	71.24%	67.94%
Ave return	0.0005	-0.0002	-0.0003	-0.0005	-0.0007
Ave volatility	0.0290	0.0261	0.0261	0.0254	0.0239

Notes: The table reports some descriptive statistics of market capitalization quintiles for the sample period 1999-2012. Stocks are sorted by market capitalization at the beginning of each year and divided in five groups. The smallest cap stocks are included in the first column and the largest cap stocks are in the last column. The illiquidity measure of each quintile is obtained as the average across the percentage spreads in the group. The first six rows report descriptive statistics of the illiquidity measures. The last three rows include the correlation of each measure with FX illiquidity (ILLIQ FX), and the average returns and volatility of the stocks in the groups.

Table 5: VAR models of stock market capitalization quintiles and FX illiquidity

(a) *Innovation correlation*

Whole period 1999-2012

	ILLIQ FX
ILLIQ EQ - 1st	4%**
ILLIQ EQ - 5th	3%

Prior to the crisis 1999-2006		*Crisis episode 2007-2009*	
	ILLIQ FX		ILLIQ FX
ILLIQ EQ - 1st	1%	ILLIQ EQ - 1st	12%***
ILLIQ EQ - 5th	1%	ILLIQ EQ - 5th	6%*

(b) *Granger causality*

Whole period 1999-2012

	ILLIQ EQ	ILLIQ FX
ILLIQ EQ - 1st	-	19.69**
ILLIQ FX	50.19***	-
ILLIQ EQ - 5th	-	20.66**
ILLIQ FX	23.04***	-

Prior to the crisis 1999-2006			*Crisis episode 2007-2009*		
	ILLIQ EQ	ILLIQ FX		ILLIQ EQ	ILLIQ FX
ILLIQ EQ - 1st	-	5.56	ILLIQ EQ - 1st	-	11.03**
ILLIQ FX	5.90	-	ILLIQ FX	45.33***	-
ILLIQ EQ - 5th	-	5.21	ILLIQ EQ - 5th	-	23.67***
ILLIQ FX	9.33*	-	ILLIQ FX	18.02***	-

Notes: Panel a reports the contemporaneous correlation coefficient of the innovations of a VAR(10) of stock (ILLIQ EQ) and FX (ILLIQ FX) illiquidity for the period 1999-2012, and the subsamples prior and during the crisis episode. Stock illiquidity is measured as the average across all stocks, 1st and 5th market cap quintiles. According to the Schwarz criterion, VAR(5) are estimated for the subsamples, except for a VAR(4) for the 1st quintile in crisis. Panel b reports the χ^2 statistics for the null of the column variables non Granger causing the row variables. Seasonal dummies are included in the models. * indicates significance at 10%, ** at 5% and *** at 1%.

Table 6: VAR models of funding constraints and illiquidity

(a) *Innovation correlation*

	ILLIQ FX	UK TED	US TED
ILLIQ EQ	3%**	2%	6%***
ILLIQ FX	-1%	0%	
UK TED			12%***
ILLIQ EQ - 1st	4%**	4%**	5%***
ILLIQ FX		0%	0%
UK TED			12%***
ILLIQ EQ - 5th	2%	1%	5%***
ILLIQ FX		0%	0%
UK TED			11%***

(b) *Granger causality*

	ILLIQ EQ	ILLIQ FX	UK TED	US TED
ILLIQ EQ	-	12.33**	11.68**	12.07**
ILLIQ FX	67.34***	-	27.14***	24.62***
UK TED	15.51***	7.14	-	20.57***
US TED	12.71**	3.83	11.66**	-
ILLIQ EQ - 1st	-	10.02*	14.06**	15.24***
ILLIQ FX	64.87***	-	22.63***	19.46***
UK TED	13.31**	7.73	-	19.54***
US TED	14.33***	2.85	10.99**	-
ILLIQ EQ - 5th	-	13.72	12.63	15.14*
ILLIQ FX	24.52***	-	28.53***	24.32***
UK TED	22.86***	14.71*	-	26.45***
US TED	20.01**	9.15	15.03*	-

Notes: Panel a reports the correlation coefficients of VAR innovations. Panel b reports the χ^2 statistics for the null of the column variables non Granger causing the row variables. Funding constraints are proxied by TED spreads in the UK (UK TED) and US (US TED). Stock illiquidity (ILLIQ EQ) is measured as the average across all stocks, 1st and 5th market cap quintiles. ILLIQ FX is the average illiquidity across currencies. VAR(5) are estimated, except for a VAR(9) for the 5th quintile. The models include seasonal dummies. * indicates significance at 10%, ** at 5% and *** at 1%.

Table 7: VAR models of correlated trading activity and illiquidity

(a) *Innovation correlation*

	ILLIQ FX	TRADING EQ	TRADING FX
ILLIQ EQ	28%***	-13%*	-18%**
ILLIQ FX		3%*	-1%
TRADING EQ			80%***
ILLIQ EQ - 1st	27%***	-5%	-20%***
ILLIQ FX		4%	-1%
TRADING EQ			80%***
ILLIQ EQ - 5th	17%**	-7%	-18%**
ILLIQ FX		-1%	-3%
TRADING EQ			80%***

(b) *Granger causality*

	ILLIQ EQ	ILLIQ FX	TRADING EQ	TRADING FX
ILLIQ EQ	-	2.59	0.50	0.02
ILLIQ FX	14.85***	-	1.62	0.93
TRADING EQ	3.46*	0.50	-	3.61*
TRADING FX	0.45	0.95	0.36	-
ILLIQ EQ - 1st	-	7.72***	0.09	0.00
ILLIQ FX	27.72***	-	2.33	1.08
TRADING EQ	5.00**	0.22	-	3.49*
TRADING FX	0.46	0.94	0.33	-
ILLIQ EQ - 5th	-	0.06	1.85	1.32
ILLIQ FX	21.74***	-	3.39*	1.11
TRADING EQ	0.81	2.37	-	3.51*
TRADING FX	0.02	2.05	0.25	-

Notes: Tests of VAR(1) models of monthly stock (ILLIQ EQ) and FX (ILLIQ FX) illiquidity and funds flows to US domestic equity funds (TRADING EQ) and foreign equity funds (TRADING FX) for the period 1999-2012. Stock illiquidity is measured for all stocks, 1st and 5th market cap quintiles. Funds flows are scaled by 10^6. Panel a reports the contemporaneous correlation coefficients of VAR innovations. Panel b reports the χ^2 statistics for the null of the column variables non Granger causing the row variables. The models include seasonal dummies. * indicates significance at 10%, ** at 5% and *** at 1%.

Table 8: Robustness test - VAR models of stock and FX illiquidity measured with unscaled spreads

<table>
<tr><td colspan="6">(a) Whole sample 1999-2012</td></tr>
<tr><td colspan="2">Innovation correlation</td><td colspan="4">Granger causality</td></tr>
<tr><td></td><td>ILLIQ FX</td><td></td><td></td><td>ILLIQ EQ</td><td>ILLIQ FX</td></tr>
<tr><td>ILLIQ EQ</td><td>2%</td><td></td><td>ILLIQ EQ</td><td>-</td><td>19.46**</td></tr>
<tr><td></td><td></td><td></td><td>ILLIQ FX</td><td>41.52***</td><td>-</td></tr>
<tr><td colspan="6"></td></tr>
<tr><td colspan="6">(b) Prior to crisis 1999-2006</td></tr>
<tr><td colspan="2">Innovation correlation</td><td colspan="4">Granger causality</td></tr>
<tr><td></td><td>ILLIQ FX</td><td></td><td></td><td>ILLIQ EQ</td><td>ILLIQ FX</td></tr>
<tr><td>ILLIQ EQ</td><td>2%</td><td></td><td>ILLIQ EQ</td><td>-</td><td>2.14</td></tr>
<tr><td></td><td></td><td></td><td>ILLIQ FX</td><td>3.26</td><td>-</td></tr>
<tr><td colspan="6"></td></tr>
<tr><td colspan="6">(c) Crisis episode 2007-2009</td></tr>
<tr><td colspan="2">Innovation correlation</td><td colspan="4">Granger causality</td></tr>
<tr><td></td><td>ILLIQ FX</td><td></td><td></td><td>ILLIQ EQ</td><td>ILLIQ FX</td></tr>
<tr><td>ILLIQ EQ</td><td>9%**</td><td></td><td>ILLIQ EQ</td><td>-</td><td>10.67***</td></tr>
<tr><td></td><td></td><td></td><td>ILLIQ FX</td><td>4.52**</td><td>-</td></tr>
</table>

Notes: Panel a reports the correlation matrix and Granger causality tests for a VAR(10) model of stock (ILLIQ EQ) and FX (ILLIQ FX) illiquidity, measured by the equally-weighted average of unscaled bid-ask spreads of stocks and currencies. Panel b reports the test results for a VAR(5) model for the period prior to the crisis. Panel c reports the test results for a VAR(1) model for the period of the crisis. Seasonal dummies are included. * indicates significance at 10%, ** at 5% and *** at 1%.
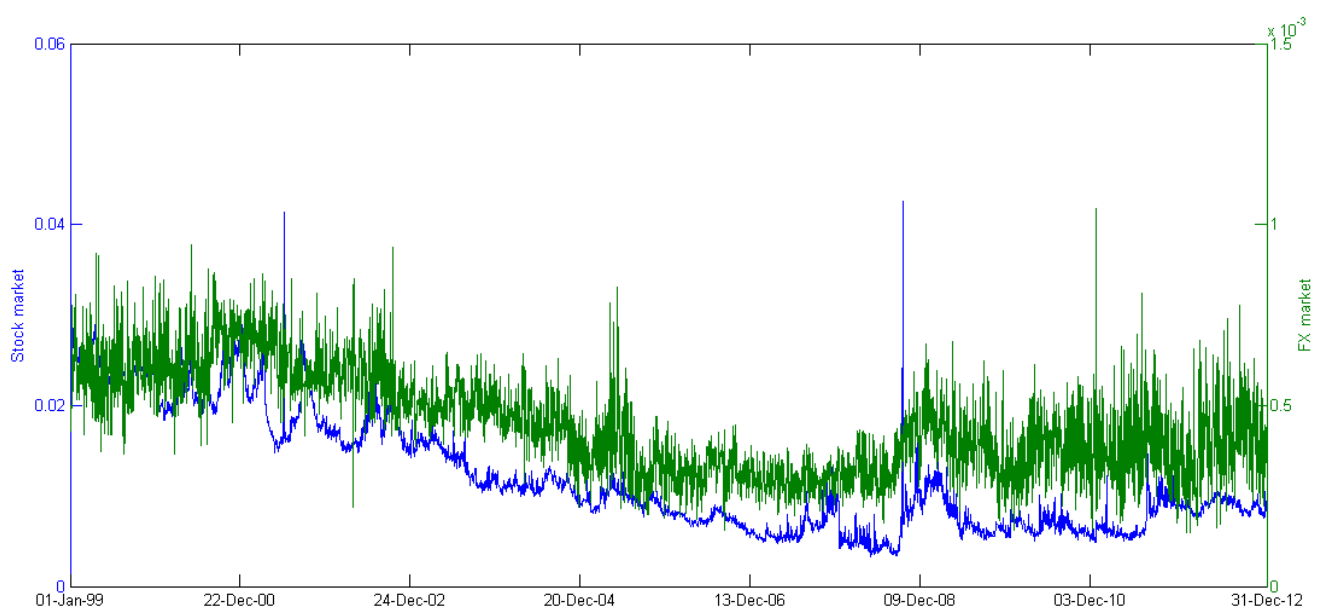
Figure I: Illiquidity level of the stock and FX markets. The figure plots the daily series of stock (left axis) and FX (right axis) illiquidity, estimated as the average of percentage bid-ask spreads across stocks and currencies, respectively.
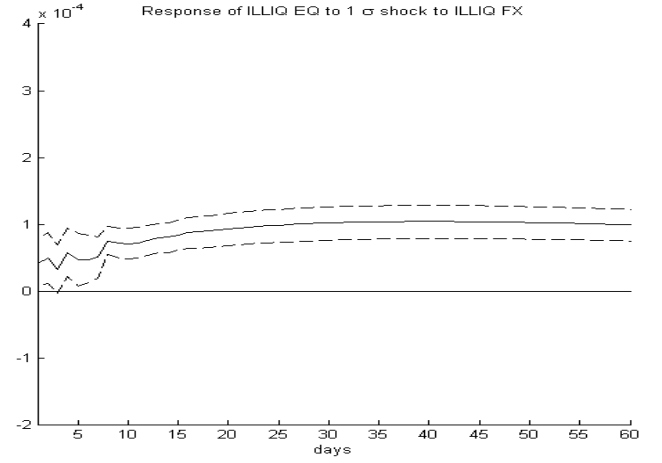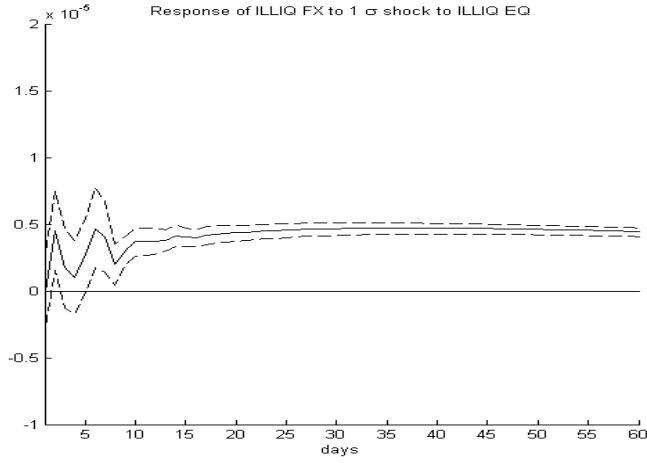
(a) *Whole period 1999-2012*
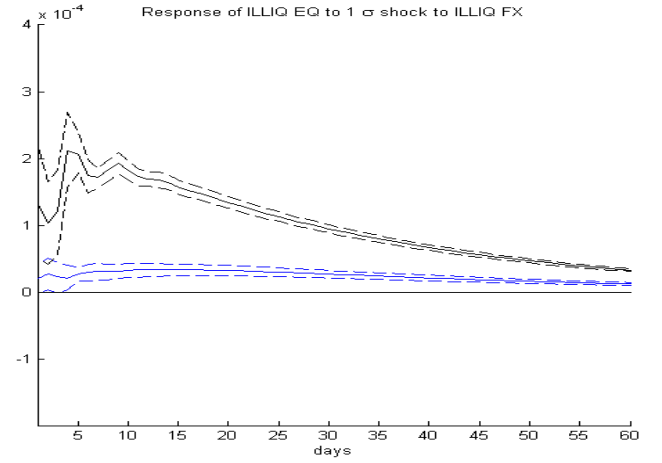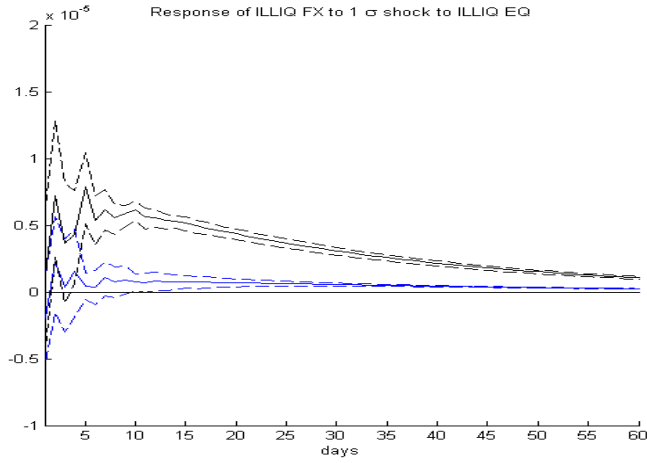
(b) *Prior to the crisis 1999-2006 (in blue) & crisis episode 2007-2009 (in black)*

Figure II: Responses of illiquidity across markets. The solid line represents the GIRFs 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. The endogenous variables of the VAR models are stock (ILLIQ EQ) and FX (ILLIQ FX) market illiquidity, estimated as the average percentage bid-ask spreads across stocks and currencies, respectively. According to the Schwarz criterion, VAR(8) are estimated for the whole sample period 1999 to 2012 (panel a), and VAR(5) for the two subsample prior and during the financial crisis (panel b). All VARs include seasonal dummies, such as day of the week, month in a year and a time trend.
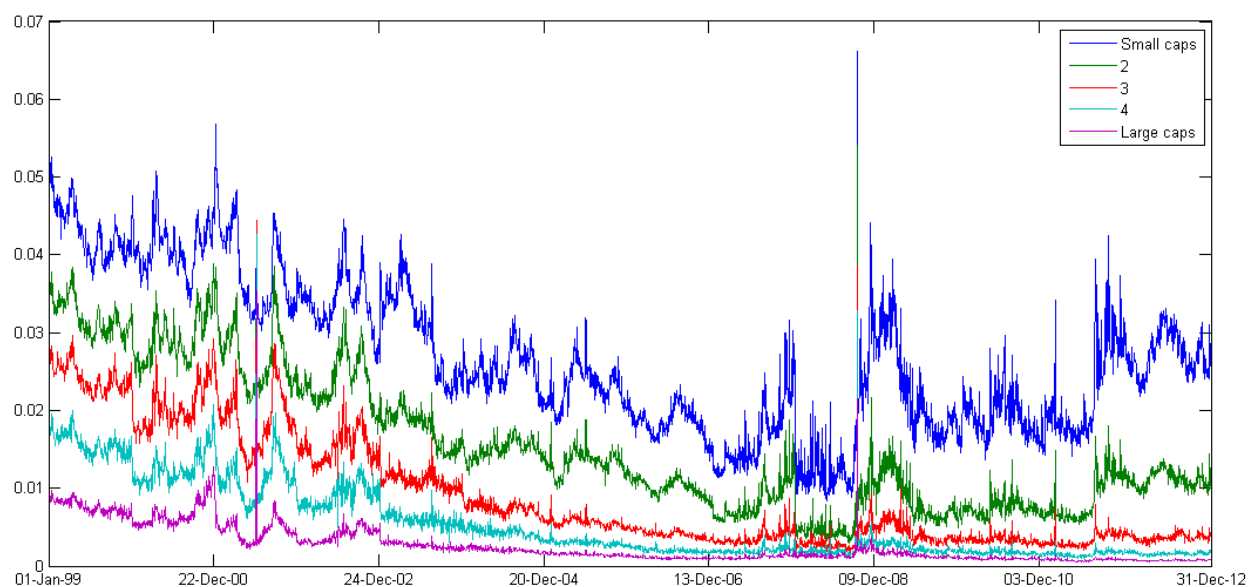
Figure III: Illiquidity level of stock market capitalization quintiles. The figure plots the daily series of illiquidity for stock market capitalization quintiles for the sample period 1999-2012. Stocks are sorted by market capitalization at the beginning of each year and divided in five groups. The illiquidity measure of each quintile is obtained as the average across the percentage spreads in the group.
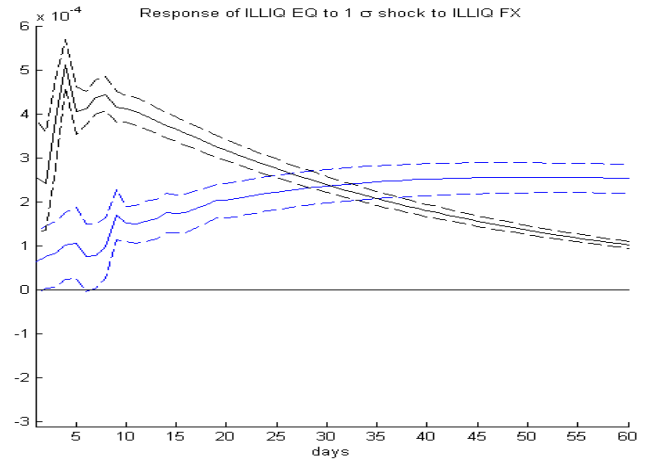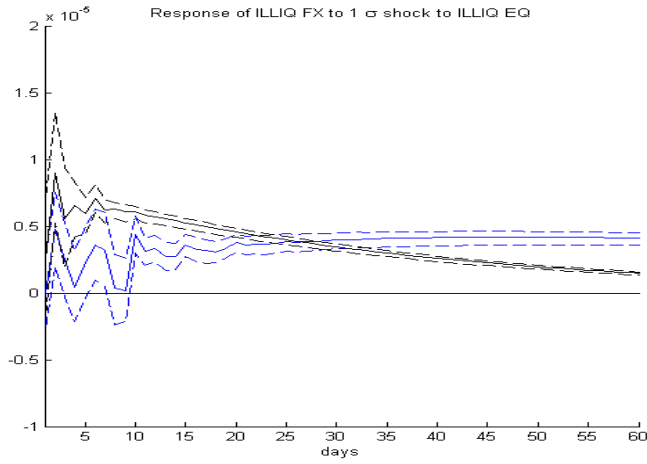
(a) *Small caps - Whole period (in blue) and crisis episode (in black)*
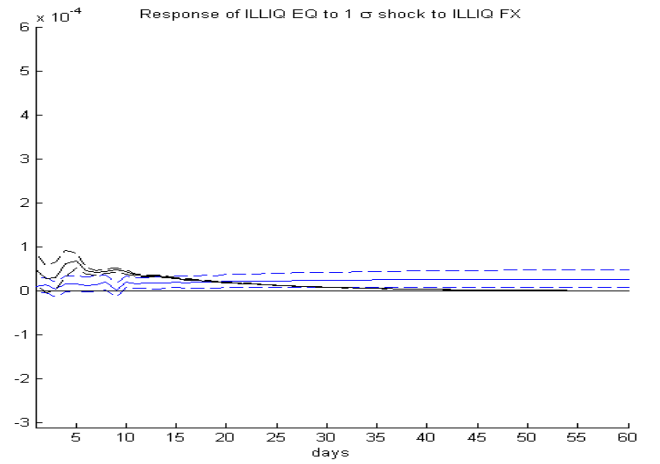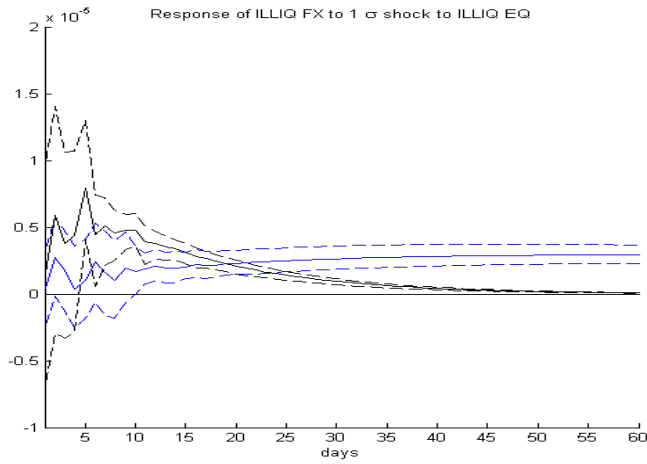
(b) *Large caps - Whole period (in blue) and crisis episode (in black)*

Figure IV: Responses across stock market caps and FX illiquidity. The solid line represents the GIRFs 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. The endogenous variables of the VAR models are stock (ILLIQ EQ) and FX (ILLIQ FX) market illiquidity. Small (panel a) and large (panel b) caps refer to the lowest and largest stock market capitalization quintiles, respectively. Stocks are sorted by market capitalization at the beginning of each year and divided in five groups. Illiquidity is estimated as the average percentage bid-ask spreads across stocks and currencies, respectively. According to the Schwarz criterion, VAR(5) are estimated, expect for a VAR(4) for small caps in crisis. All VARs include seasonal dummies, such as day of the week, month in a year and a time trend.
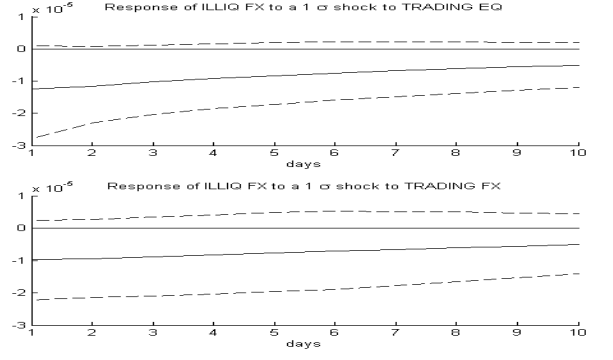
(a) *Whole sample*

(b) *Small caps*

(c) *Large caps*
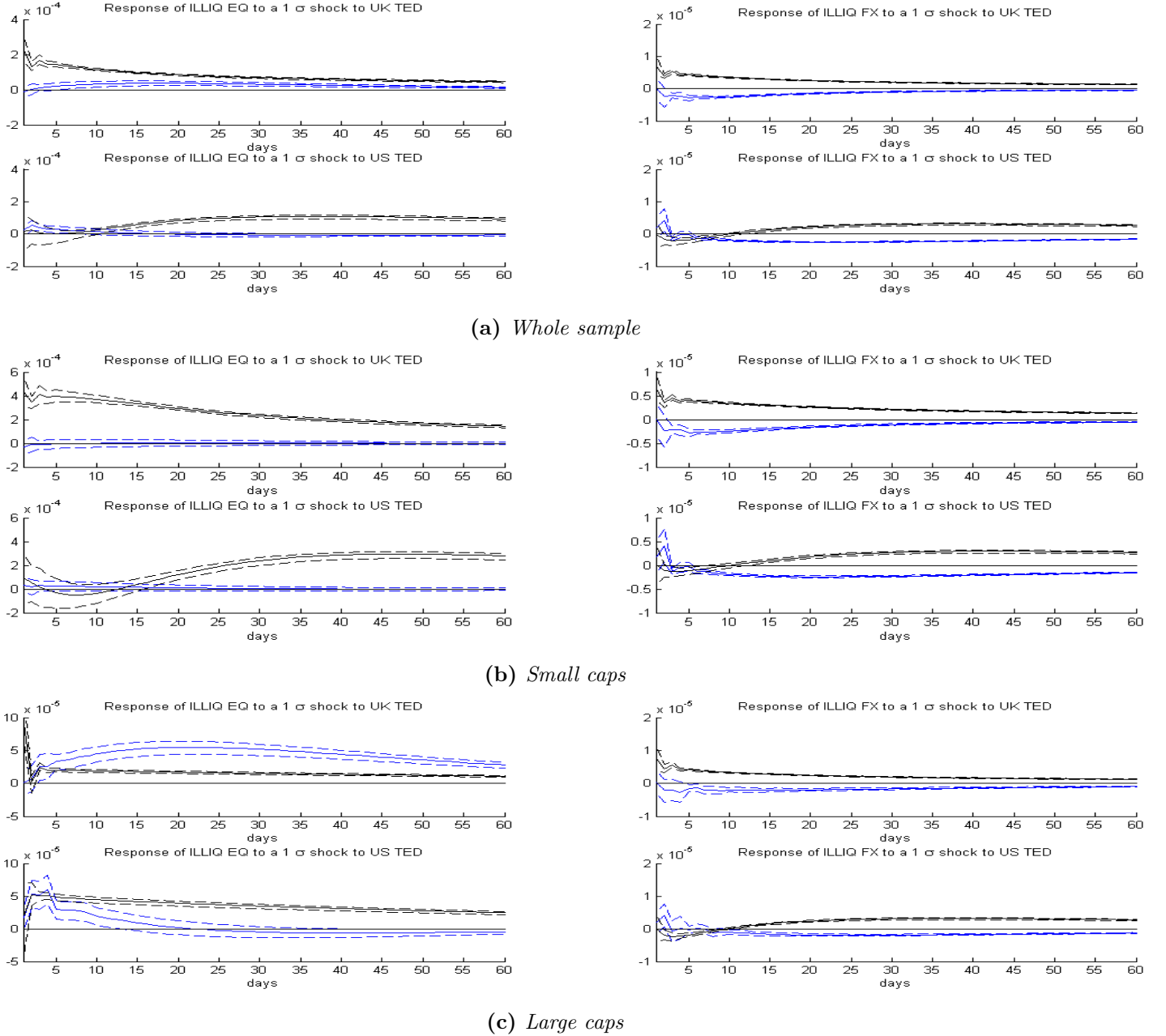
Figure V: Responses of illiquidity to funding shocks prior (in blue) and during the crisis (in black). The solid line represents the GIRFs of an endogenous variable of the VAR to a one time shock of one standard deviation in another variable. The dotted lines are bootstrap 95% confidence bands obtained with 1,000 bootstrap replications. The endogenous variables of the VAR models are stock (ILLIQ EQ) and FX (ILLIQ FX) market illiquidity, and UK (UK TED) and US (US TED) funding constraints. Whole sample (panel a), small (panel b) and large (panel c) caps refer to the overall, lowest and largest stock market capitalization quintiles, respectively. Stocks are sorted by market capitalization at the beginning of each year and divided in five groups. Illiquidity is estimated as the average percentage bid-ask spreads across stocks and currencies, respectively. According to the Schwarz criterion, VAR(5) are estimated, expect for a VAR(9) for large caps. All VARs include seasonal dummies, such as day of the week, month in a year and a time trend.
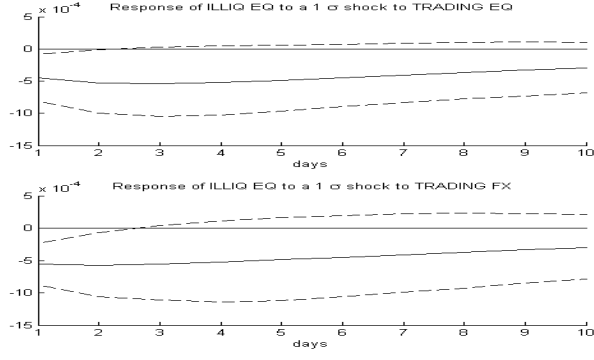
(a) *Whole sample*

**(b)** *Small caps*

(c) *Large caps*

Figure VI: Responses of funding to illiquidity shocks prior (in blue) and during the crisis (in black). The solid line represents the GIRFs 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. The endogenous variables of the VAR models are stock (ILLIQ EQ) and FX (ILLIQ FX) market illiquidity, and UK (UK TED) and US (US TED) funding constraints. Whole sample (panel a), small (panel b) and large (panel c) caps refer to the overall, lowest and largest stock market capitalization quintiles, respectively. Stocks are sorted by market capitalization at the beginning of each year and divided in five groups. Illiquidity is estimated as the average percentage bid-ask spreads across stocks and currencies, respectively. According to the Schwarz criterion, VAR(5) are estimated, expect for a VAR(9) for large caps. All VARs include seasonal dummies, such as day of the week, month in a year and a time trend.

**(a)** *Responses of illiquidity to trading shocks*
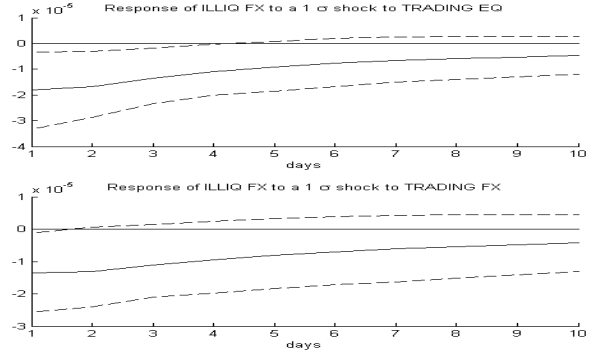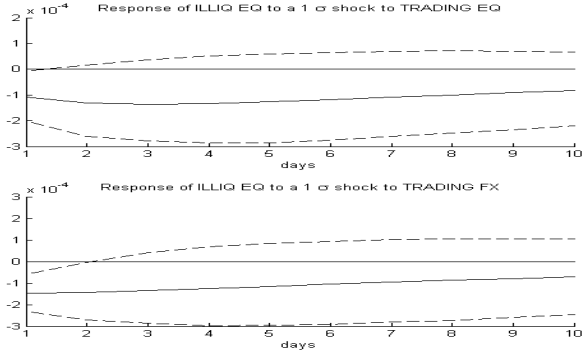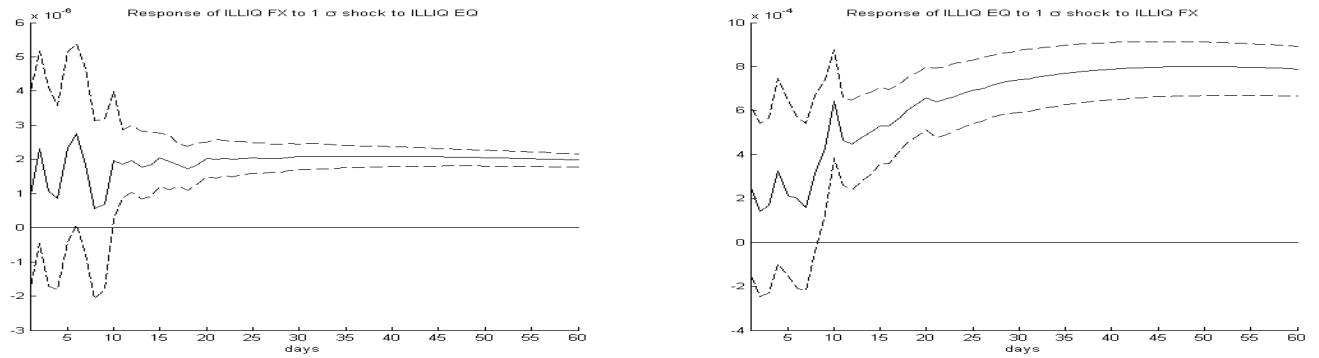

(b) *For large caps*
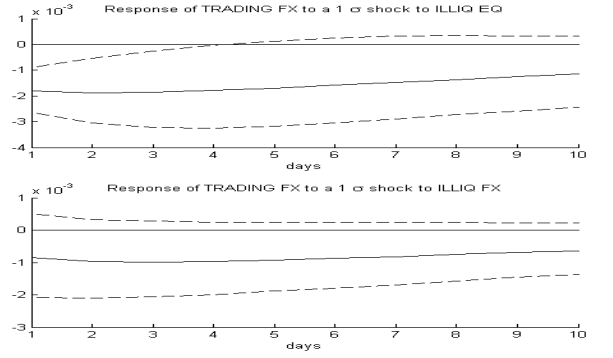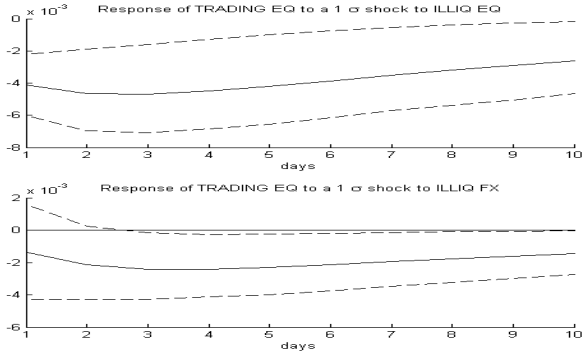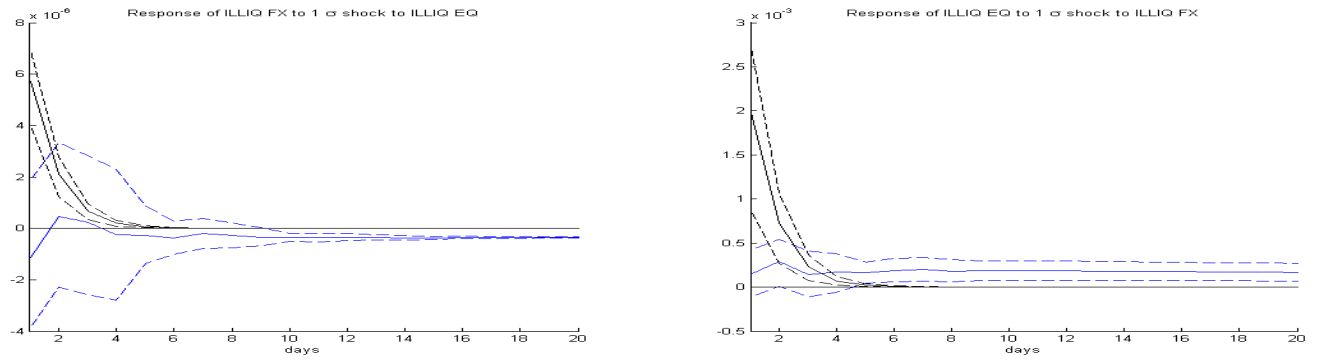

(c) *Responses of trading to illiquidity shocks*

Figure VII: Responses of illiquidity and trading. The solid line represents the GIRFs 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. The endogenous variables of the VAR models are stock (ILLIQ EQ) and FX (ILLIQ FX) market illiquidity, and correlated institutional trading in equity (TRADING EQ) and currencies (TRAD-ING FX). Illiquidity is estimated as the average daily percentage bid-ask spreads across stocks and currencies, respectively. Monthly measures are obtained as the last observation in a month. Correlated institutional trading is calculated as the sum of absolute inflows and outflows of mutual funds invested in US domestic equity and foreign equity, respectively. VAR(1) are estimated according to the Schwarz criterion and include seasonal dummies, such as month in a year and a time trend.
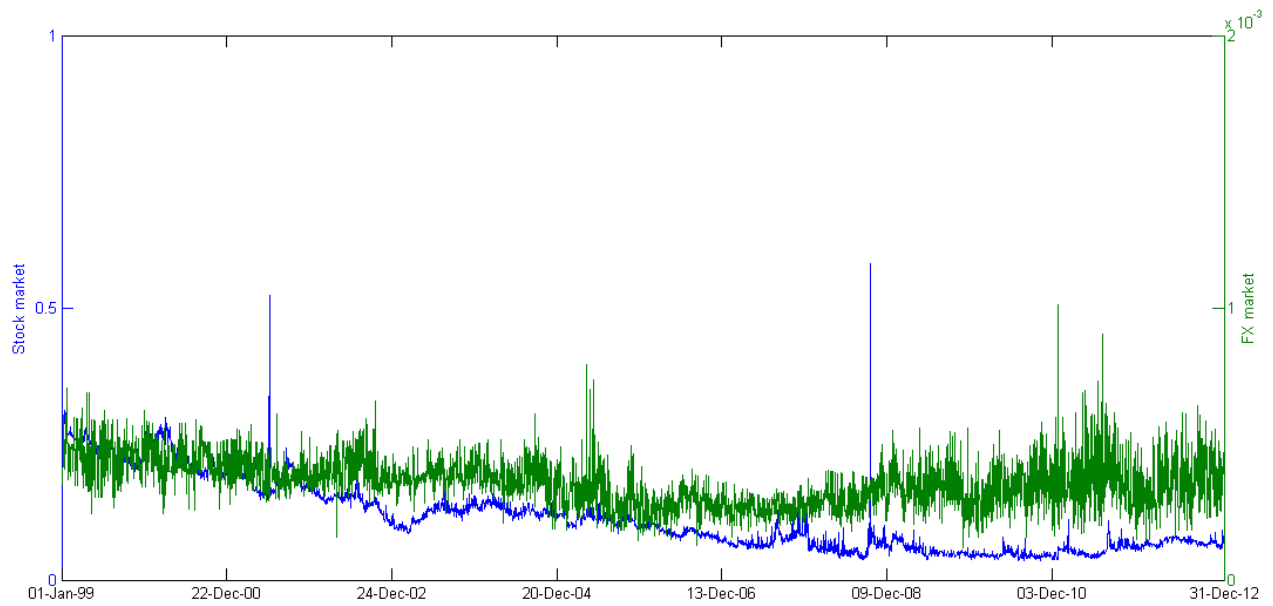
Figure VIII: Robustness test - Illiquidity level of the stock and FX markets measured by unscaled spreads. The figure plots the daily series of stock (left axis) and FX (right axis) illiquidity, estimated as the average of (unscaled) bid-ask spreads across stocks and currencies, respectively.

(a) *Whole sample 1999-2012*

(b) *Prior to the crisis 1999-2006 (in blue) & crisis episode 2007-2009 (in black)*

Figure IX: Robustness test - Responses of illiquidity measured by unscaled spreads. The solid line represents the GIRFs 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. The endogenous variables of the VAR models are stock (ILLIQ EQ) and FX (ILLIQ FX) market illiquidity, estimated as the average bid-ask spreads across stocks and currencies, respectively. According to the Schwarz criterion, VAR(10) are estimated for the whole sample period 1999 to 2012 (panel a), and VAR(5) and VAR(1) prior and during the financial crisis, respectively (panel b). All VARs include seasonal dummies, such as day of the week, month in a year and a time trend.