Funding Constraints and Market Liquidity in the European Treasury Bond Market*

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Abstract

Theoretical studies show that shocks to funding constraints should affect and be affected by market liquidity. However, little is known about the empirical magnitude of such responses because of the intrinsic endogeneity of liquidity shocks. This paper adopts an identification technique based on the heteroskedasticity of liquidity proxies to infer the reaction of one measure to shocks affecting the other. Using data for the European Treasury bond market, we find evidence that funding liquidity shocks affect bond market liquidity and of a weaker simultaneous feedback effect of market liquidity on funding liquidity. We also investigate the determinants of the magnitude of these effects in the cross-section of bonds characterized by different durations and default risk. We find that the market-to-funding liquidity effect is stronger for short-term bonds and for bonds used as collaterals in repo transactions, such as German bonds.

JEL classification:
Keywords: Liquidity, Asset Pricing, Identification, Heteroskedasticity.

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1 Introduction

Financial markets routinely experience a variety of frictions that hinder their efficient functioning by impacting price formation. These frictions are usually due to the organization of trading in a market, e.g. the design of a market structure or transaction costs, or to regulatory constraints, such as short-sale restrictions or market fragmentation. Several studies have recently exposed another source of friction: trading capital. As securities can be used as collaterals to relax borrowing constraints, there is a natural interplay between the ease with which traders can obtain funds (funding liquidity, henceforth) and the ease with which an asset is traded (market liquidity, henceforth)(see, Brunnermeier and Pedersen, 2009 and the references therein).

Despite the mounting theoretical and empirical evidence documenting the impact of both funding and market liquidity on asset prices (see, among others, Vayanos and Wang, 2012; Foucault *et al.*, 2013 and the references therein), little is known about the empirical relationship between the two dimensions of liquidity. In particular, albeit the growing evidence that funding constraints have an impact on market liquidity, the presence of a feedback effect of market liquidity on funding liquidity has not been documented.[1] This paper aims at filling this gap and proposes an empirical investigation of the dynamic relationships between funding and market liquidity measures in the context of the European Treasury bond market.

Our empirical investigation focuses on this market for several important reasons. First, the Treasury market is one of the largest and most liquid security market in the world, with a trading volume in 2015 of USD 6 trillion in the U.S., USD 5.9 trillion in Europe.[2] Second, as Treasury securities are most often used as high-quality collateral in repo transactions, it is reasonable to conjecture that liquidity of the Treasury market would therefore be the one

[1]For further details, see the selective review of the existing literature in Section 2.

[2]Source: SIFMA for the U.S., and MarketAxess for Europe.

that potentially exhibits the largest feedback effect to funding liquidity shocks, in the spirit of Brunnermeier and Pedersen's (2009) original argument. For instance, Krishnamurthy, Nagel, and Orlov (2014) find that the collateral backing the repos in the U.S. prior to the crisis was largely composed of government securities rather than riskier private sector assets. Third, trading of European Treasury securities falls under the jurisdiction of the European Central Bank and it is regulated by the same entity, the European Commission. They are traded in a large supranational secondary market whose liquidity condition respond to aggregate funding liquidity shocks, and they are denominated in the same currency. At the same time, these securities are issued by countries with different sovereign risk (and different ratings), which generates heterogeneity in the sample. In particular, notwithstanding the introduction of the Euro, bond markets in Europe are probably less homogenous than in the U.S., with multiple issuers, and country-specific tax considerations. Finally, the European repo market widely differs from the U.S. repo market along various dimensions, especially with regards to the proportion of triparty repo transactions, which in turn suggests that counterparty risk may play a more relevant role compared to the evidence reported in previous studies.[3]

In motivating our empirical investigation we start from noting that the analysis of the dynamic relationships between funding and market liquidity measures suffers from two major shortcomings. First, both market and funding liquidity are, by their very nature, difficult to define and even more difficult to estimate. This difficulty is reflected in the multitude of empirical proxies proposed in a vast number of studies that populated the extant literature in the past decade (see Goyenko *et al.*, 2009 and the references therein). In addition to this, recent studies suggest that any proxy may be a poor approximation of the same facet of liquidity as they all contain a common or systematic component which correlate across empirical proxies that is important for the pricing of liquidity risk (Korajczyk and Sadka, 2008). Second, existing studies investigating the impact of funding and/or market liquidity

[3] See Mancini, Ranaldo and Wrampelmeyer (2015) for a discussion on differences between the U.S. and the European repos markets.

on asset prices, usually employ empirical proxies that are recorded at the low frequency (usually monthly or even annual). This data limitation makes any statement regarding potential causation links between the two dimensions of liquidity dubious because of their intrinsic endogeneity and the fact that both market and funding liquidity may react to the same exogenous variables.

We tackle the first issue by carrying out the empirical analysis in the spirit of Korajczyk and Sadka (2008). More specifically, we use a panel of standard empirical proxies for both funding conditions and Treasury market liquidity.[4] For both panels, we compute across-measures (and in the context of market liquidity measures also across-securities) systematic components of liquidity and we use them in the subsequent empirical analysis.

In order to circumvent the second issue, we adopt an identification technique based on the heteroskedasticity of the liquidity measures that has been successfully used in other contexts (see, Rigobon, 2003, Rigobon and Sack, 2003; 2004 and the references therein). More specifically, we assume that changes in the variance of funding liquidity shocks relative to market liquidity shocks affect the covariance between market and funding liquidity in a way that depends on the responsiveness of market liquidity to and from funding liquidity. Thus, we exploit the existence of various volatility regimes in both funding and market liquidity to estimate the impact of funding (market) liquidity shocks to market (funding) liquidity shocks based on the observed shifts in that covariance matrix.[5]

We carry out our empirical investigation using a dataset containing all European Treasury bonds that are traded in the platform EuroMTS over the period October 1st, 2004 - February 28th, 2011. We find a host of interesting results. First, contemporaneous shocks to the systematic component of funding liquidity are found to significantly affect the sys-

[4]See Sections 3.1 and 3.2 of the main text for a detailed description of the liquidity measures used in the empirical estimations.

[5]In our empirical estimation, we select three volatility levels based on the volatility of vStoxx index returns, i.e. an index of the implied volatility in European stocks, and we document the behaviour of funding and market liquidity in each of these three regimes. Some robustness checks relative to this choice are carried out in Section 5.

tematic component of the liquidity of the European Treasury market also controlling for endogeneity. A one standard deviation shock to funding liquidity, that is a relaxation of funding constraints, generates a contemporaneous improvement of 0.17 standard deviation of market liquidity across Treasury bond markets. Second, contemporaneous shocks to the systematic component of market liquidity also significantly affect funding conditions: we find that one standard deviation shock to market liquidity, that is an improvement of market liquidity across European Treasury markets, generates a improvement of 0.07 standard deviation of funding liquidity. We thus document the presence of a positive feedback effect of the bond market liquidity on funding liquidity. Our results are robust to alternative definition of volatility regimes and alternative model specifications. These effects are sizable and economically significant.[6]

Third, after estimating the elasticities at the individual bond level, we find that the coefficients measuring the impact of funding liquidity shocks on the individual bonds' market liquidity are on average positive, but with different magnitudes across bonds. Interpreting this finding in Brunnermeier and Pedersen (2009)'s framework, this suggests that margins are on average destabilizing, or that the equilibrium is characterized by illiquidity spiral effects. We then explain the heterogeneity of parameter estimates by running a cross-sectional regression with the aim of disentangling the determinants of the individual bonds' elasticities. The results of this final exercise show that the elasticity of individual bonds' market liquidity to funding liquidity shocks is higher for long-term bonds, which are more capital intensive than short-term bonds. By contrast, the elasticity of funding liquidity to idiosyncratic market liquidity shocks is higher for bonds characterized by a shorter maturity and for German bonds, that is, bonds that are generally used as collaterals in repo transactions.

[6] For example, a one standard deviation decrease in the Euribor-OIS spread (a proxy for funding liquidity), generates a contemporaneous decrease of 0.20 bp of the effective spread in European Treasury bonds (a proxy for market liquidity), that is, an improvement of 5.5% of the average effective spread. Conversely, a one standard deviation decrease in the effective spread generates a contemporaneous decrease of 0.55 bp of the Euribor-OIS, that is, an improvement of 9% of the average Euribor-OIS spread.

The rest of the paper is organized as follows. Section 2 discusses the literature. Section 3 describes the empirical framework employed to investigate the relationship between market and funding liquidity and the measures of liquidity employed in this study. Section 4 describes the data used in this study, presents preliminary summary statistics and reports the results of the main estimations. Section 5 discusses various robustness checks. A final section concludes.

2 Related Literature

The theoretical literature dealing with the interplay between funding conditions and trading in security markets is vast and rich. Brunnermeier and Pedersen (2009) are among the first to elaborate on the relationship between funding liquidity and market liquidity. When a trader buys a security she can use it as collateral and then borrow a fraction of its value against it. The difference between the security price and the collateral value must be financed by traders' own capital. When this realistic feature of trading is taken into account, liquidity assumes a dual perspective: They show that the two notions of funding and market liquidity are mutually reinforcing, and are the first to suggest that market liquidity would also impact funding liquidity. In particular, endogenous variation of margin constraints by financiers at equilibrium may result in amplifying effects: under certain circumstances, margins can be destabilizing leading to cases of perverse liquidity spirals.

However, the idea that market liquidity is influenced by the risk-bearing capacity of market participants, which in turn is related to the amount of capital allocated to this activity, is not new. When investors need to trade and need immediacy, their orders would typically be matched with those of two types of financial institutions: market makers, who temporarily absorb imbalance by holding a possibly short term position in their inventory; or other intermediaries, like mutual or hedge funds, who may either absorb imbalance for a longer period, or to arbitrage prices. Various models suggest that these participants' wealth may be used directly to buy stocks or as collateral to borrow cash or securities and engage into these activities. This idea that is first found in "inventory" models of market making (see Demsetz, 1968, Stoll, 1978, or Ho and Stoll, 1981) has been formalized by Weill (2007), who analyzes the link between the cost faced by market makers to raise capital and liquidity provision.[7] More recently, D'Souza and Lai (2006) and Lescourret and Robert (2011) discuss how funding capital may impact the behavior of dealers and thus market liquidity in the context of bank consolidation or order preferencing.

More generally, capital is required to arbitrage markets. This is especially important when one needs to hold positions for some time or across large baskets of securities. The borrowing capacity of other financial institutions who typically absorb demand/supply pressure, like mutual funds or hedge funds, has also been shown to impact market liquidity. Shleifer and Vishny (1997) formalize this friction as limits to arbitrage. In particular, they show that investors' outflows from managed funds can amplify financial assets' negative 'sentiment' shocks. The literature has shed light on other mechanisms, like endogenous margin constraints (Gromb and Vayanos, 2002, Geanakoplos, 2003) or the role of repos (Huh and Infante, 2016), and analyzed their impact in various context, i.e., across markets (Kyle and Xiong, 2001) or during a financial crisis (He and Krishnamurthy, 2012 and 2013).

The empirical evidence of the effects of funding constraints on market trading is, however, rather scarce and usually indirect. Some studies explore the prediction that funding constraints would affect all the operations of traders, creating a systematic source of variation in liquidity across financial assets. Coughenour and Saad (2004), Comerton-Forde et al. (2010), Hameed, Kang, and Viswanathan (2010), or Jensen and Moorman (2010) document links between factors influencing market makers' capital constraints, such as its portfolio of

[7] Demsetz (1968) for instance writes that "this role of the specialist involves judgment, *investment*, and risk taking", while Stoll (1978) notes that "dealer inventory positions acquired in the process of providing immediacy are financed solely at the risk free rate of interest. (...) The *dealer's personal wealth (his investment account)* and the position in the trading account serve as collateral for the borrowing of cash or of shares."

stocks, losses, negative returns, or monetary conditions; and market liquidity. The results of Bessembinder *et al.* (2016) suggest that post-crisis regulations focused on banking may have unintended consequences on bond market liquidity, by comparing the participation between bank-affiliated dealers and non-bank dealers before and after post-crisis changes in regulation.

A few papers propose a different approach and investigate the impact of funding constraints on the persistence of limits to arbitrage, as evidenced for instance by deviations from Covered Interest Parity (CIP) (see, among others, Coffey *et al.*, 2009, Mancini Griffoli and Ranaldo, 2010) or noise (or predictability) in the cross section of bond returns, in particular across maturities (see for instance Adrian, Etula, and Muir, 2014, Garcia and Fontaine, 2012, Hu *et al.*, 2013, or Musto *et al.*, 2015.)

The use of non-conventional policies (such as quantitative easing) by central banks in the aftermath of the 2008-2009 financial crisis has also enabled to assess the impact of the relaxation of funding constraints on asset prices. The impact of these interventions is however debated.[8] Trebbi and Xiao (2015) find no evidence of structural deterioration in liquidity following these interventions in the U.S. corporate bond market. Deuskar and Johnson (2016) control for links between market and funding liquidity using the Identification by Heteroskedasticity approach, and find that bond market liquidity of the 10-year Indian government bond improves with greater funding liquidity provision by the central bank (RBI). Besides, Pelizzon, Subrahmanyam, Tomio, and Uno (2016) find that the Long-Term Refinancing Operations (LTRO) of the European Central Bank weakened the sensitivity of market makers' liquidity provision to credit risk, highlighting the importance of funding liquidity measures as determinants of market liquidity of the MTS European sovereign bond market.

Finally, other studies directly exploit differences on margin requirements across similar

[8]For example, some argue that the relaxation of funding constraints might have occurred at the expenses of market participants, as some have been evicted from the relevant markets.

assets, variations in margin policies, or shocks to the latter, in order to assess the impact of variations of funding constraints on market liquidity. Garleanu and Pedersen (2011) show that securities with (nearly) identical cash flows but different margin requirements can be traded at different prices. Aragon and Strahan (2012) use Lehman bankruptcy as an instrument and find that stocks held by Lehman-connected funds (that is, funds that used Lehman as prime broker) experienced greater declines in market liquidity following the bankruptcy than other stocks. Miglietta, Picillo, and Pietrunti (2015) document a significant and positive effect of variations of CCPs' initial margins on the Italian MTS GC repo rates. Hedegaard (2014) finds that following a margin increase, the price impact of trading increases for both the affected contract and for the remaining contracts in the market, documenting funding liquidity spillovers. Kahramand and Tookes (2016) employ a regression discontinuity design that exploits threshold rules that determine a stock's margin trading eligibility in India to identify a causal relationship between traders? ability to borrow and a stock's market liquidity. They find that liquidity is higher when stocks become eligible for margin trading. Finally, using a quasi-experiment, Jylh́a (2015) shows that changes in the computation of the margin requirements for portfolios of options traded in the U.S. which decreased the capital required to fund index option trading, significantly improved market liquidity relative to that of unaffected securities.

Consistently with most studies in this literature, we find evidence of a positive and significant impact of funding constraints on market liquidity, but our econometric model also enables us to investigate the reverse causality link. Our main contribution is to document the presence of a feedback effect of market liquidity on funding liquidity, that has been theoretically highlighted by Brunnermeier and Pedersen (2009), and to analyze the determinants of this effect. Two papers investigate a similar question, using a different approach than ours to address the endogeneity issue between market liquidity and funding liquidity. Boudt, Paulus, and Rosenthal (2013) rely on two natural instruments which are supposed to isolate the exogenous variation in equity market liquidity, namely a variable capturing the trend in average time between trades, and the change in yields for short-term AAA-rated corporate bonds versus change in Treasury bill rates. They find evidence of two regimes, one in which liquidity spirals are stabilizing, and in which they are destabilizing, over the period of July 2006? May 2011. Dick-Nielsen, Gyntelberg, and Lund (2013) use Granger causality tests from funding liquidity to market liquidity. They find that Euro spreads, their measure of funding liquidity, drive the changes in the market liquidity on the Danish bond market on the period spanning from November 2007 to December 2011. By contrast, we rely on an econometric approach, namely the Identification by Heteroskedasticity, that explicitly tackles the endogeneity issue between both aspects of liquidity, and we use the heterogeneity in government bonds characteristics across European countries to investigate the determinants of the loadings of market liquidity on funding liquidity.

Our results are in line with these findings; besides, we measure the elasticity of market liquidity to funding liquidity, we report evidence of a positive and significant feedback effect of market liquidity on funding liquidity, and we explain how bonds' characteristics influence the magnitude of the effects.

3 Empirical methodology

In this section, we first introduce the various empirical proxies for market and funding illiquidity used in the empirical investigation. Then we discuss the empirical framework adopted to identify the relationships between funding and market illiquidity based on the heteroskedasticity of illiquidity measures in the spirit of Rigobon (2003) and Rigobon and Sack (2003). It is worthwhile noting that the existing literature uses various measures to capture different aspects of market and funding illiquidity across markets. Most of these measures only proxy illiquidity along one dimension and cannot perfectly reflect its multifaceted nature. To tackle this issue, we define the two measures of market and funding illiquidity used in the empirical investigation as the first principal components computed across the following pool of potentially imperfect empirical proxies.

3.1 Market illiquidity measures

Since Amihud and Mendelson (1986), the bid-ask spread remains the most popular illiquidity measure. For each bond in our sample, we use intraday quote data to compute bid-ask spreads on daily basis. In particular, we compute for each bond j the difference between ask and bid quotes divided by the spread midpoint. We then take the average over all best quote revisions for day d as follows:

$$BAS_d^j = \frac{1}{NQ_d^j} \sum_{i=1}^{NQ_d^j} \frac{(Ask_i^j - Bid_i^j)}{(Ask_i^j + Bid_i^j)/2},$$

where Bid_i^j and Ask_i^j are the i-th bid and ask quote prices, NQ_d^j is the total number of quote revisions for day d. To avoid outliers we exclude quotes with the bid-ask spread greater than 100 basis points and those outside the trading hours (8:15 am - 5:30pm Central European Time). We then average daily measures at the weekly level as follows:

$$BAS_t^j = \frac{1}{D(t)} \sum_{d=1}^{D(t)} BAS_d^j,$$

where $D(t)$ is the number of trading days in week t.

Fleming (2003) suggests that the bid-ask spread is a valid measure in the U.S. government bond markets because it consistently captures the variations in market illiquidity. However, as the bid-ask spread is computed from the intraday data, it might be affected by the deterministic time-of-day effects described by Admati and Pfleiderer (1988). Furthermore, bid-ask spreads may not be a good measure of transaction costs if traders strategically trade when spreads are low. In order to take this issue into account, we follow Lee (1993) and compute the daily average effective spread of bond j, which measures the difference between the transaction price and the mid-quote price prevailing at the time of the trade:

$$ESPR_d^j = \frac{1}{NT_d^j} \sum_{\tau=1}^{NT_d^j} \frac{\left(TPrice_\tau^j - \frac{(Ask_\tau^j + Bid_\tau^j)}{2}\right)}{\frac{(Ask_\tau^j + Bid_\tau^j)}{2}} \times dir_\tau,$$

where Bid_τ^j and Ask_τ^j are the best ask quote prices prevailing before the τth trade, $TPrice_\tau^j$ is the execution price, NT_d^j is the total number of trades for day d, and dir_τ the direction of the trade that takes value 1 if the trade is initiated by a buy order, and -1 otherwise. Using the same notations as for the bid-ask spread, we similarly compute the weekly average effective spread as:

$$ESPR_t^j = \frac{1}{D(t)} \sum_{d=1}^{D(t)} ESPR_d^j.$$

Effective spreads abstract from intraday patterns since they are computed using the bid-ask spreads prevailing at the time when actual transactions occur. Besides, they successfully capture the (indirect) cost of an aggressive transaction, whatever its size, which indirectly accounts for market depth.

While these measures matter for brokers and investors, they may not perfectly reflect the capacity of the market to absorb orders without moving prices, therefore they may not be the most appropriate measures to capture the market illiquidity risk faced by market participants. Researchers and the industry therefore use a measure of the "price impact" of transactions, in the spirit of Kyle's lambda.[9] A market is considered less liquid if a small order can cause a large adverse impact on prices. Following Brennan and Subrahmanayam (1996), we measure the price impacts of a trade as in Hasbrouck (1991) using the following

[9]This practice has become common in the industry. This is in particular due to data availability, but also to the rise of algorithmic trading in the 2000s which has induced brokers to strategically split orders across time with the objective to soften the "price impact" of their trades. The SEC and the most recent literature similarly suggest to use the "price impact" of transactions as an alternative measure of illiquidity (see for instance Brogaard, Hendershott, and Riordan, 2014.) For instance, in the "Liquidity Management Rules For Mutual Funds And ETFs" released by the SEC on Sept 22nd, 2015, the SEC suggests a "classification of the liquidity of fund portfolio assets based on the amount of time an asset would be able to be converted to cash without a market impact".

Vector Autoregressive (VAR) for each bond j on a weekly basis:

$$
\begin{aligned}
qr_\tau &= \sum_{i=1}^{m} a_{t,i}^{j} qr_{\tau-i} + b_{t,0}^{j} x_\tau + \sum_{i=1}^{m} b_{t,i}^{j} x_{\tau-i} + v_{1\tau}, \\
x_\tau &= \sum_{i=1}^{m} c_{t,i}^{j} qr_{\tau-i} + \sum_{i=1}^{m} d_{t,i}^{j} x_{\tau-i} + v_{2\tau},
\end{aligned}
$$

where qr_τ is the change in mid-quote prices due to a trade at date τ and x_τ is the net aggregate buy and sell volume for all trades executed between transaction time $\tau - 1$ and time τ. $v_{1\tau}$ is the innovation in quote change, $v_{2\tau}$ is the unexpected component of the order flow, m is the order lags in the autoregression while a_t^j's, b_t^j's, c_t^j's and d_t^j's are the coefficients estimated for bond j in week t. The coefficient b_0^j measures the immediate price response to the trade and is used as our price impact measure.[10]

Another conventional empirical proxy for illiquidity is the *ILLIQ* measure developed by Amihud (2002). This measure is defined as the average of the daily ratio of bond j's absolute returns to the total trading volume over a period of D days in week t:

$$
ILLIQ_t^j = \frac{1}{D} \sum_{d=1}^{D} \frac{|r_d^j|}{V_d^j},
$$

where r_d^j is the daily return and V_d^j is the total trading volume on day d in week t. Similarly to Hasbrouck (1991)'s b_0 coefficient, *ILLIQ* measure captures the average price impact over D trading days. A bond is less liquid or, put differently, ILLIQ is high if a small trading volume can induce a large price change. The ILLIQ measure uses more aggregated information than the three measures defined above and may be less affected by microstructure noise.

3.2 Funding illiquidity measures

While funding liquidity is an increasingly relevant concept that extends and complements the one of market liquidity, the literature has still not converged on a unambiguous way to measure it. We acknowledge this potential limitation and use five variables to capture

[10] In our empirical exercise, we find that three is the appropriate order of lags m in the model.

funding illiquidity conditions in the European Treasury bond market.[11]

The first variable we consider is the spread between the Euro interbank offered rate (Euribor) and the overnight index swap rate (OIS) both with the maturity of one week. The Euribor-OIS spread has been discussed extensively in the literature as a proxy for funding liquidity (see, inter alia, Taylor and Williams, 2009; Baba and Packer, 2009 and the references therein). Offered rates are interest rates over unsecured deposits that a bank is willing to offer to another bank over a given maturity term. They can be high because of larger default/counterparty risk or because of poor interbank liquidity conditions. An overnight index swap is an agreement between two counterparts to pay the difference between a fixed interest rate and an average of overnight interest rates, i.e. the EONIA in the context of the euro area. By contrast to Euribor, OIS reflects little default or liquidity risk as the contract does not involve the exchange of principal while only net interest obligations are settled at maturity. The Euribor-OIS spread reflects the state of credit and funding conditions in the interbank market. We consider variations in Euribor-OIS spread as originating from liquidity conditions in light of the recent findings suggesting that liquidity conditions, not credit credit conditions, are the main drivers of short-term interbank spreads (Schwartz, 2016).

The second measure we use to proxy for funding liquidity relies on repo rates (see for instance Dunne, Flemming and Zholos, 2013). We consider the spread between the Euribor and the Eurepo. Eurepo is the rate at which a prime bank offers funds in euro to another prime bank against an accepted asset of suitable quality i.e. Eurepo General Collateral serving as the collateral in the transaction.[12] The Euribor spread over the Eurepo captures the state of funding conditions for *secured* money market transactions in the euro area. As indicated by Hördahl and King (2008), a higher repo spread is associated with higher risk aversion, a higher preference for cash as well as a greater uncertainty in the collateral value.[13]

[11]All measures discussed in this section are computed at the weekly frequency.

[12]According to Mancini *et al.* (2015), the repo market in the euro area is growing rapidly and is of a similar size as the U.S. market.

[13]Although European Money Markets Institute decided to discontinue to publish the Eurepo index

This measure therefore integrates and complements the Euribor-OIS spread by accounting for changes in funding conditions that are not captured by interbank interest rate spreads.

The third measure we consider in our empirical investigation is the difference between the average main refinancing operation (MRO) rate and the OIS rate. MRO remains one of the most important tools used by the European Central Bank to manage liquidity and implement monetary policies in the euro area (ECB, 2011). MRO involves weekly auctions at which banks borrow money with one week maturity, i.e. allotted liquidity, from the ECB secured against a collateral accepted by the central bank. Using proprietary data on individual demands by financial institutions during the ECB auctions between June 2005 and October 2008, Drehmann and Nikolaou (2012) show that an increase in auction rates in MROs is associated with higher funding constraints faced by banks and a reduction in market liquidity across stock, bond and money markets in the euro area.

We complement the funding illiquidity measures discussed above, with two additional ones that are not related to market interest rate spreads but have been found significant in explaining funding conditions in the US Treasury market. The first of these two additional measures considers the interest rate differential between on-the-run / off-the-run bonds with similar maturities. Vayanos and Weil (2008) explain that this differential is mainly due to liquidity, but also specialness [14]. As specialness is not a characterizing feature of the European bond market, we argue that variations in the on-the-run/off-the-run spread can be attributed mostly to changes in liquidity conditions. Fontaine and Garcia (2012) and Fontaine, Garcia and Gungor (2016) suggest that this measure is a suitable proxy for funding illiquidity and document, for the US market, that it is positively correlated to the market

from Jan 2015, an emerging benchmark for repo market in the euro area is RepoFunds Rate (see http://www.repofundsrate.com). This rate captures the repo transactions executed on the BrokerTec and MTS trading platform. However, due to the limited availability of historical data of RepoFunds Rate, we use Eurepo rate in our study.

[14] Loans that are collateralized by on-the-run bonds offer lower interest rates because the lender needs to return exactly the same bond, that is more difficult to find when the security is off-the-run than when it is on-the-run.

illiquidity of various portfolios.

We follow Fontaine and Garcia (2012) and assume that bond yields across maturities follow a Nelson Siegel yield curve and use it to price all bonds and specify the price differences between the on-the-run and off-the-run bonds in each country and maturity category as follows:

$$\zeta\left(L_t, Z_{n,t}\right) = L_t \times \beta_M \exp\left(-\frac{1}{\kappa} age_{n,t}\right),$$

where $age_{n,t}$ is the age (in years) of the government bond n at time t, L_t is the common liquidity factor that affects all bonds, β_M is the average premium at each fixed maturity M for each country, κ is the parameter that determines the variation of the liquidity premium with age and is fixed across all of the bonds. We obtain weekly measures of the common liquidity factor L_t from the price data of the French, German, Italian and Spanish government bonds. More precisely, we measure the common price factor for each country (Germany, France, Italy and Spain), then we compute Fontaine and Garcia's measure (hereafter FG) and average it across the whole Eurozone.

Our fifth and last proxy of funding illiquidity is the one introduced by Hu *et al.* (2013). This measure is based on the assumption that the availability of capital allows traders to engage in arbitrage activities and help smooth out yield differentials around an equilibrium yield curve. When funding constraints bind and arbitrage capital is curtailed, bond yields become more disconnected from each other. That, as a result, leads to bonds that are priced away from their equilibrium values. Put differently, when funding conditions deteriorate, bond prices become more noisy. According to Hu *et al.* (2013), this measure of noise can be empirically computed as the root-mean-squared-error of market yields and a given equilibrium model yields, across all bonds:

$$Noise_t = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}\left(y_t^i - y_{b,t}^i\right)^2},$$

where N_t is the number of bonds, y_t^j is the market yield of bond j and $y_{b,t}^j$ is the implied model bond yield at time t. In our empirical exercise, we first compute equilibrium yield curves by means of the Nelson and Siegel (1987) methodology using bonds with maturity ranging from 1 year to 10 years for France, Germany, Italy and Spain. We then compute a noise measure for each country on weekly basis and obtain an aggregate noise measure as the first principal component computed across the four countries.[15]

3.3 Identification through heteroskedasticity

In this section we discuss the framework adopted to investigate the relationship between funding illiquidity and market illiquidity, acknowledging that their dynamics are endogenously determined. Theories of financial intermediation suggest a direct dual causality between funding and market liquidity. Nonetheless, the empirical identification of this relationship is not a trivial task. In fact, as liquidity conditions are initially observed at different and potentially low frequencies, it difficult to empirically disentangle whether any shock to one of the two dimensions of liquidity causes changes in the other or whether both dimensions of liquidity are endogenously determined.

We do not take a specific stand on the direction of causality and investigate the dynamic interaction between market and funding illiquidity by adopting the methodology proposed in Rigobon (2003) and Rigobon and Sack (2003). More specifically, we assume that market and funding illiquidity follow the system of simultaneous equations:

$$m_t = \beta f_t + \epsilon_t \tag{1}$$

$$f_t = \alpha m_t + \eta_t, \tag{2}$$

where m_t and f_t are measures of aggregate market and funding illiquidity, respectively; ϵ_t and η_t are the structural shocks with zero mean and variances σ_ϵ^2 and σ_η^2, and β and α are the key

[15] We adopted a Nelson and Siegel (1987) methodology for simplicity and consistency with the methodology chosen to estimate the Fontaine and Garcia (2012) funding illiquidity measure. Nonetheless, Hu et al. (2013) show that their main results are not specific to a particular curve-fitting method employed.

parameters of interest in the model. We also assume that the shocks affecting market and funding illiquidity in the model are uncorrelated, i.e. $E(\epsilon_t \eta_t) = 0$.[16] Albeit very stylized, the two equations have a straightforward interpretation in light of Brunnermeier and Pedersen's (2009) theoretical framework. In fact, the first equation of the system captures the essence of Proposition 1 in Brunnermeier and Pedersen (2009, p. 2211) whereby any asset's market illiquidity is a function of common funding illiquidity. The second equation is less rooted into this specific theoretical framework. However, it can be viewed as a simplified counterpart of equation (14) in Brunnermeier and Pedersen (2009) where the shadow cost of capital, used as proxy for a common funding illiquidity measure, is a function of market illiquidity and endogenous margins, which are determined in Propositions 2 and 3.

Several studies have recorded that the parameter β of similar relationships is different from zero and usually statistically significant at conventional level. A couple of studies have noted that α was also different from zero. However, existing studies did not explicitly take into account the endogeneity of the liquidity variables. In fact, the system above cannot be estimated, unless further information is incorporated. This is because an identification problem occurs, as the covariance matrix of the reduced form of the above system of equation provides only three moments (variance of funding and market liquidity and the covariance of their shocks), but four parameters have to be estimated.

Rigobon (2003) suggests that if the variance of the structural shocks is subject to regimes, then the identification problem can be solved.[17] If we assume for simplicity that the variance of both structural shocks ϵ and η is subject to only two regimes (i.e. variances of both shocks are either high or low) and, most importantly, the structural parameters α and β are stable across regimes then the covariance matrix of the reduced form, as it is regime-specific, will

[16] For the sake of exposition, we use a simple model where there are no exogenous variables affecting the dynamics of both dimensions of liquidity. However, this assumption is relaxed later.

[17] The identification through heteroskedasticity is not the only solution to the identification problem highlighted above. In fact, the parameter α and β can still be estimated by 1) imposing zero or sign restrictions on the parameters, 2) assuming long-run constraints, or 3) imposing constraints on variances. See Rigobon (2003) and the references therein.

provide six moments (three per regime) for six parameters to be estimated (namely α, β, and four variances), which solves the identification problem.

It is instructive to note that this identification procedure can be intuitively explained. In fact, the estimation of the two structural parameters assumes that both variances of market and funding illiquidity shocks change over time. For example, consider a sudden increase in the variance of funding illiquidity shocks. If an econometrician observes a contemporaneous increase in market illiquidity, given the assumption that the covariance between funding and market illiquidity shocks is zero, the change in market illiquidity is exclusively due, in light of the above system of equations, to the effect of funding illiquidity on market illiquidity (i.e. $\beta\ f_t$). By observing the changes in market and funding illiquidity in this specific volatility regime, then it is possible to back out the value of the parameter β. A similar narrative applies for the estimation of the other parameter α.

More formally, under the assumption of two regimes, the regime-specific covariance matrix of the reduced form can be written as follows:

$$\begin{aligned}\Omega_s &= \frac{1}{(1-\alpha\beta)^2}\begin{bmatrix} \beta^2\sigma^2_{\eta,s}+\sigma^2_{\epsilon,s} & \beta^2\sigma^2_{\eta,s}+\alpha\sigma^2_{\epsilon,s} \\ \cdot & \sigma^2_{\eta,s}+\alpha^2\sigma^2_{\epsilon,} \end{bmatrix} \\ &= \begin{bmatrix} \omega_{11,s} & \omega_{12,s} \\ \cdot & \omega_{22,s} \end{bmatrix}. \end{aligned} \tag{3}$$

where $s \in \{1,2\}$. Solving for the variances in the regime-dependent reduced form, leads to the definition of the estimates of the parameters β and α (see Appendix 1 for more details). The β parameter is estimated as:

$$\beta = \frac{\omega_{12,s}-\alpha\omega_{11,s}}{\omega_{22,s}-\alpha\omega_{12,s}},$$

and the parameter α solves the following quadratic equation:

$$[\omega_{11,1}\omega_{12,2}-\omega_{12,1}\omega_{11,2}]\alpha^2-[\omega_{11,1}\omega_{22,2}-\omega_{22,1}\omega_{11,2}]\alpha+[\omega_{12,1}\omega_{22,2}-\omega_{22,1}\omega_{12,2}]=0.$$

The identification through heteroskedasticity fails if the two covariance matrices are proportional, i.e. the relative variances are constant across regimes. Appendix 2 presents the Identification by Heteroskedasticity when the two equations include a set of exogenous variables x_t and latent variables z_t. Our main analysis in Section 4 includes exogenous variables, and the model with latent variables is estimated as a robustness check in Section 5.

4 Empirical analysis

In this section, we first present the data and the descriptive statistics of our liquidity measures. Prior to estimating the reduced-form model and adopt the identification-through-heteroskedasticity methodology, we formally test that all series used in this empirical investigation are indeed subject to heteroskedasticity. We finally explore the dynamic relationship between funding and market liquidity using this framework.

4.1 European government bonds and the trading environment

Our study examine bonds issued by the central governments of the ten Euro area countries including Austria, Belgium, Germany, Finland, France, Greece, Italy, the Netherlands, Portugal and Spain with maturities between one year and thirty years.[18] Similarly to Beber et al. (2009), we only select fixed-rate and zero coupon bonds and exclude those with special fixed-income features such as floating rate coupons, inflation-linked or inflation-indexed indexed bonds, securities traded prior to issue (when issued).[19]

A report published in 2006 by the European Securities Markets Expert Group (ESME) presents an overview of the bond market at the time of our study. To summarize, bond markets in Europe are usually dealer markets with investment banks committing their own capital and providing liquidity to facilitate trading. However, by contrast to corporate bond

[18] The Euro Bond Market Study of the European Central Bank published in December 2004 shows that three countries, namely Italy, Germany, and France, account for more than 70% of the total outstanding amount of government bonds in the euro area. The same report shows that Luxembourg has no debt outstanding, while the sovereign of Ireland was very small.

[19] According to the study by ECB (2004), fixed-rate coupon bonds remain the most popular instrument capturing a 65% share of the total outstanding amount.

markets, members of the Securities Industry and Financial Markets Association indicated that only around 50% of trading in government bonds was conducted over the telephone (according to their response to CESR's call for evidence in 2005). The European government bond market is thus reputed transparent *ex ante* with dealers advertising the prices at which they are prepared to trade, but not *ex post*.[20] In particular, closing prices are available through data vendors but there is little information about trade size.

Like for many other securities, European Treasury markets have experienced growing electronification. A report by Greenwich Associates based on interviews with investment grade institutional investors indicates that % 39% (resp. 47%) of European government bonds are traded electronically in 2008 (resp. 2012).[21] A report published in 2016 by the BIS however suggests that intermediation in the off-the-run Treasury market is still almost exclusively provided by traditional bank dealers, with little involvement of non-bank market-makers.[22]

The bond market data used in this study is from MTS Data, a product of EuroMTS that is the major platform for fixed-income securities in Europe[23]. A report on price discovery published in August 2010 by the Association for Financial Markets in Europe (AFME) indicates an average daily turnover on MTS of 85 billion euros (single counted and including repo).

EuroMTS is an inter-dealer, fully-electronic and quote-driven market characterized by a high degree of transparency.[24] There are two types of market participants on the MTS

[20] An investor looking to buy or sell a bond can, again with a few exceptions, come to a bank and obtain a price at which the dealer is willing to sell or buy that bond.

[21] Source: https://www.greenwich.com/blog/electronic-trading-bonds-growing-%E2%80%93-sort-of%E2%80%A6.

[22] The report however notes that the situation in US secondary markets is quite different in that inter-dealer platforms have granted more lenient access to non-bank players, including PTFs (Principal Trading Firms).

[23] Persaud (2006) shows that EuroMTS captures a 71.9% share of the electronic trading volume of European cash government bonds. The MTS Data database has been extensively analyzed in previous studies (See Beber, Brandt and Kavajecz, 2009; Dufour and Nguyen, 2012; Pelizzon et al., 2016 and the references therein).

[24] All platforms publish post-trade prices for trades conducted on their platforms on a realtime basis. In

platform: ”market makers” and ”market takers”. The liquidity is provided by dealers with specific market-making obligations. Market makers have to post firm two-sided quotes for a minimum size, a maximum spread and a minimum number of hours during the trading day. Once a quote is submitted to the network, it is ranked in the book according to price-time priority rules and EuroMTS publishes the best five quotes on either side of the book. Although EuroMTS is considered as an “inter-dealer”platform, some participants like hedge funds do not meet the requirements to be “market makers”and hence can only be eligible for a market taking status. EuroMTS requires market takers to have net assets of at least 10 million euros. These participants can only use market orders to hit the best outstanding quotes. The minimum quantity for quotes and trades on EuroMTS is one million euros. Executed trades are immediately and automatically reported.

4.2 Data and summary statistics

We focus on bonds that are traded at least 15 days in each of the three volatility regimes defined in the previous section. Our sample period spans from October 1st, 2004 to February 28th, 2011 (due to the availability of data). [25]

We first collect the daily trading summaries of all European Treasury bonds that are traded in the platform EuroMTS provided by MTS Data. It involves the closing bond prices, yield, year-to-maturity, bond duration, the total trading volume as well as the number of market participants during the day. We then focus on bonds that are traded in the platform EuroMTS at least fifteen days in each of the three volatility regimes.

Table 1 reports the descriptive statistics of the government bonds over the whole sample period. Overall, we have 149 unique securities across the ten countries. Panel A describes the statistics by country. Bonds of most countries have an average duration between five

the case of inter-dealer platforms, these prices can only be viewed by platform participants. Exception is inter-dealer platform MTS, which makes post trade prices available to third parties through data vendors.

[25](Note that our sample period includes the financial crisis (in particular, Lehman’s bankrupcy on September 15, 2008) but not the downgrade of Spain and Italy that took place on October 7, 2011.)

and seven years. German bonds exhibits the lowest yields while those from Greece record the highest. Italian Treasury bonds have the highest trading volume. This may not be surprising since MTS (Mercato dei Titoli de Stato), the first electronic bond market, was indeed initially launched in 1988 by the Italian Treasury and Bank of Italy, before EuroMST began its expansion across Europe in 1997. Bonds from Belgium, Finland, France, Germany, Greece and Italy exhibit a higher activity than bonds from other countries, measured in number of trades as well as in the number of participants. With the exception of Finland, this is in line with the fact that the amounts of debt outstanding of those countries are larger than those of the other countries.[26]

Panel B provides statistics on the cross-sectional distribution. The average time to maturity is 9.37 years, the average duration is 6.75 years, and the average trading volume is 21 trades per week. However, bonds in our sample are characterized by a large heterogeneity, with a time to maturity spanning from 0.49 to 30.09 years, or a number of trades per week spanning from almost 0 to 562.

We use the daily data to construct the weekly time series of the ILLIQ measure for each bond. Our three other proxies of market liquidity are based on intraday data. In addition to these daily data, the MTS Data database indeed contains details of quotes and trades electronically recorded with time stamps accurate to the millisecond. The trades dataset records the execution price, quantity and the buy or sell direction for each transaction. The quotes dataset includes the proposed price and quantity up to the best three levels. In this study, we only consider quotes and trades during the trading hours (8:15 am - 5:30pm Central European Time). Overall, the dataset provides us with more than 500 million quote and trade observations (intraday) and 75,810 bond-weeks. From these intraday data, we construct the weekly time series of bid-ask spreads, effective spreads, and price impacts for

[26]The ECB (in its Euro Bond and Derivatives report of June 2007), publishes the following statistics on the outstanding nominal amounts of euro denominated public debt securities as of 2004, in billion euros: Austria 114.4, Belgium 254.2, Finland 54.8, France 891.9, Germany 1,006.6, Greece 158.8, Ireland 31.3, Italy 1,144.2 , Netherlands 215.4, Spain 330.9, Portugal 72.9.

each bond in the sample.

Table 2 reports summary statistics of the market liquidity measures discussed in Section 3. In Panel A, we report the mean and standard deviation across bonds by country. Both spread measures seem to be in line, but they do not rank countries in terms of market liquidity similarly as Amihud's and the price impact measures. This suggests that various measures may capture different aspects of market liquidity. Quite intuitively, the effective spread seems to be higher in countries that are characterized by a higher average yield, a longer average time-to-maturity, or a lower number of trades per week. Interestingly, more participants do not seem to be linked to higher market liquidity.

Panel B reports the statistics of the distribution of the cross-section of bonds. In line with strategic order submission, effective spread are on average lower than quoted spreads. Note that spreads are measured in basis points: an average effective spread of 3.74 bp on an average transaction size of 7.11 million euros corresponds to a transaction cost of $2,659$ euros. The large heterogeneity across bonds' liquidity measures in our sample echoes the heterogeneity on their characteristics documented in Table 1.

Correlations reported in panel C indicate that all market liquidity measures are highly correlated. Amihud's illiquidity measure is less correlated with the other measures than any other pair, with correlation coefficents with the three other measures ranging from 0.63 to 0.66.

4.3 Data Funding Liquidity

Data on OIS, Euribor and Repo rates used to compute the first three funding liquidity proxies come from Thomson Reuters' Datastream. We use our dataset containing all bonds traded in EuroMTS to compute the last two proxies, namely the Noise measure and the on-the-run/off-the-run spread. Funding liquidity measures are reported in Table 3, panel A. Only the first two measures can be directly compared. The Repo-OIS spread is on average higher than the Euribor-OIS spread, which reflects that the former measure may reflect changes in funding conditions that may not be only related to the counterparty risk of the institution but to changes in market conditions. All measures exhibit large standard deviations.

Correlations across measures are reported in Panel B. All variables are significantly correlated at 1% level. The correlations between FG and noise measures and the Euribor-OIS spread are small, but they are highly correlated with the MRO, i.e. the central bank rate spread. In the time series (not reported here), all measures increase at the end of 2009, which seem to reflect the European sovereign bond crisis.

4.4 Systematic components

We then construct systematic components $FLIQ$ and $MLIQ$ from both panels of funding and market liquidity measures across proxy measures and Treasury bond markets by a adopting principal components approach. The results reported in Table 4, Panel A suggest that this first principal component of both panels is sufficient to capture 54 and 81 percent of the cross-sectional variability of the funding and market liquidity measures, respectively. This result echoes and corroborates the one reported in Korajczyk and Sadka (2008) where a single factor can explain between 4 and 26 percent of the variability of the cross-section of market liquidity proxies computed for individual equities. This result also suggests that there are significant systematic components driving the time-series variation of funding and market liquidity in the European Treasury bond market. Besides, correlations with the standard liquidity measures reported in panel B all stand within an interval $[0.60, 0.96]$. The Hu et al. noise measure seems to be the most correlated with the systematic funding liquidity measure (i.e., with correlation coefficient of 0.84), while the effective spread seems to be the most correlated with the systematic market liquidity measure (i.e., with a correlation coefficient of 0.96).

Figure 1 plots the time series of the $MLIQ$ (panel A) and $FLIQ$ (panel B) measures.

Comparing panels A and B in Figure 1, it is worth noticing that the estimated proxies for the two dimensions of liquidity, $MLIQ$ and $FLIQ$, seem to be correlated over time. In fact, the contemporaneous correlation between market and funding liquidity measures is equal to 0.81 and is statistically significant at 1 percent level. [27] However, as highlighted in the previous sections, the intrinsic endogeneity between two variables may lead to spurious conclusions. We address and discuss this important issue below.

4.5 Empirical Results

Prior to estimating the reduced-form model, we first formally test that all series used in this empirical investigation are indeed subject to heteroskedasticity. To this aim we use two tests that are routinely used to assess the null hypothesis of homoskedasticity: the White (1980) test and the Breusch-Pagan (1979) test. The results of the test are reported in Table 5, Panel A and there is a unambiguous evidence that the liquidity proxies exhibit heteroskedasticity over the sample period. We are therefore legitimately allowed to apply the procedure discussed in Section 3.3.

Panel B reports the variances and covariances of the market and funding liquidity measures in the three regimes. The "low vStoxx" regime (9.80% of our observations) is characterized by a low volatility of both market and funding liquidity measures. The "high vStoxx" regime (11.63% of our observations) is characterized by a high volatility of both market and funding liquidity measures. The intermediate regime is characterized by a high volatility of funding liquidity (namely 0.23, similar to that of the high vStoxx regime which was 0.26) but a relatively low volatility of market liquidity (namely 0.24 relative to 0.68 in the high vStoxx regime). The three regimes thus exhibit the variation in volatilities that is required to identify our parameters of interest.

[27] Similar correlation coefficients computed for the measures BAS, EBAS, IMP and ILLIQ against FLIQ are equal to 0.82, 0.78, 0.62 and 0.67, respectively. Conversely, correlation coefficient computed for the Euribor-OIS spread, the Repo-OIS spread, the MRO-OIS spread, FG measure and the noise measure against MLIQ are equal to 0.40, 0.47, 0.78, 0.56 and 0.72 respectively.

We finally estimate the reduced-form model defined in (3). In this study, the exogenous variables, x_t, include the mutual fund flows, the variations in M2 money supply component and the changes in the implied volatility obtained from stock market option prices in the euro-area, i.e the vStoxx index and the stock returns from financial companies. These variables aim at accounting for factors known to impact liquidity. The first two variables (i.e., mutual funds' flows and M2 money supply) aim at capturing variations in the borrowing capacities of financial institutions/arbitrageurs, either due to the size of the assets under management or to monetary policy. We proxy mutual funds' flow by inflows/outflows in billion USD in government bonds with intermediate and long maturities for the European countries, from EFPR reports.[28] As the time series is reported in a monthly frequency, we use linear interpolation to transform the variable to weekly data. The data on variations in money supply M2 come from ECB's monetary statistics. We control for volatility since many market microstructure models suggest that volatility negatively impacts market liquidity (e.g., either due to inventory management or to adverse selection costs). Finally, we introduce an end-of-the-month dummy to control for the jump or European repo rates on the last trading day of each month that is mainly due to the fact that European banks are required to report that day's positions to the European Central Bank. We also use the lagged funding and market liquidity variables up to the order of three as the control variables.

The results are reported in Table 5, Panel C. Contemporaneous shocks to the systematic component of funding liquidity are found to significantly affect the systematic component of market liquidity across all local European Treasury bond markets. The reverse causality link also applies as contemporaneous shocks to the systematic component of market liquidity significantly affects funding liquidity in the European Treasury market. Both effects are sizable and economically significant as one standard deviation shock to funding liquidity (i.e. relaxation of funding constraints) generates a contemporaneous improvement of market

[28] Flows for short term bonds are indeed reported only from April 2007.

liquidity of 16.9bps across Treasury bond markets in Europe, while one standard deviation shock to systematic market liquidity generates a contemporaneous improvement of funding liquidity of 7.3 bps. To help interpreting the economic magnitude of these coefficients, we estimate the same model using alternative measures of funding and market liquidity, namely the Euribor - OIS spread and the effective bid-ask spread respectively. Results provided in the last two columns of Table 5, Panel C shows that one standard deviation decrease of the Euribor-OIS spread (that is, a decrease by 9.92 basis points) generates a contemporaneous decrease 0.20 bps of the effective bid-ask spreads across Treasury bond markets in Europe (that is, 0.07 times 2.92 bp), which correspond to an improvement of 5.5% relative to the average effective spread. A one standard deviation decrease in effective bid-ask spreads (that is, 2.92 bp) generates a contemporaneous decrease of the Euribor-OIS spread of 0.55 bps (that is, 0.055 times 9.92 bp), which corresponds to an improvement of 9% relative to the average Euribor-OIS spread.

Mutual funds' net inflows and an increase in M2 money supply significantly reduce market illiquidity. Both signs would be consistent with the prediction that higher macro liquidity would increase market liquidity. Their impact on funding liquidity is however not significant. Stock market volatility is positively and significantly related to bond market liquidity but not to funding liquidity. Funding illiquidity significantly increases at the end of the month. This supports the argument that European banks are reluctant to lend to each other at the end of the month for reporting reasons, therefore, funding liquidity is reduced.

4.6 Bonds' characteristics and elasticities: a cross-sectional analysis

The results reported in Table 5 provide evidence that, after controlling for possibly simultaneity issues, funding liquidity positively impacts market liquidity, and vice-versa. Two mechanisms could be at play to explain this finding. First, constraints on access to capital of market makers would impact the risk premium required to hold an inventory position.

Second, constraints on access to capital of hedge funds or arbitrageurs may decrease market liquidity because they use to absorb the investors' demand. In particular, Garleanu and Pedersen (2011) show that market liquidity may depend on margin requirements. In this section, we take advantage of the existence of different margin requirements across maturities or across countries to test the link between margin conditions and the strength of the relationship between funding and market liquidity.

To this end, we first define a measure of idiosyncratic bond market il-liquidity per bond as follows. We consider the $MLIQ_t$ variable defined in section **??** as the first principal component of the cross-sectional averages of our four proxies for market liquidity, as the Systematic component of each bond's market liquidity. For each individual bond j, we compute the total market (il-)liquidity measure $MLIQ_{j,t}$ as the first principal component of the four proxies of market liquidity, namely the bid-ask spread, the effective spread, Amihud's illiquidity and the price impact, measured at the individual bond level. Finally, we define the idiosyncratic market liquidity of bond j, $IdioMLIQ_{j,t}$, as follows:

$$IdioMLIQ_{j,t} = MLIQ_{j,t} - MLIQ_t$$

We use the variable $IdioMLIQ_{j,t}$ to carry out the estimations in the bi-variate system (3) a la Rigobon, 2003. We use the same specification that includes lags and the set of control variables. This provides us with a cross-sectional bond panel of contemporaneous coefficients (α_j, β_j). Hence, we do not have to estimate the reaction for each bond for the systematic component as it is assumed to be the same for all bonds.

Table 6, panel A reports statistics on the distribution of (α_j, β_j), that is, the idiosyncratic market liquidity effects and the impact of funding liquidity on idiosyncratic market liquidity. The average of individual β_j's is much smaller than the estimate of β in the global estimation. It thus seems that funding liquidity mainly impacts the systematic component of market liquidity, $MLIQ$, rather than the idiosyncratic liquidity of each bond. Coefficients

α_j are significantly positive in 56% of the regressions and significantly negative in 38%, while coefficients β_j are significantly positive in 46% of the regressions and significantly negative in 42%. Coefficients α_j and β_j have the same sign in 85% of the cases.

The Table also report statistics on the distribution of the control variables in the MLIQ equations.[29]

We then use the estimates of s (α_j, β_j) to analyze what variables impact the two elasticities in the cross section of bonds. To this end, we run the two following regressions on the bond panel :

$$\alpha_j = a_0 + a_1 \times Duration + \sum_{i=2}^{5} a_j Country_j + \varepsilon_j \tag{4}$$

$$\beta_j = b_0 + b_1 \times Duration + \sum_{i=2}^{5} b_j Country_j + \varepsilon'_j \tag{5}$$

We chose four dummy variables i.e. Germany, France, Italy and Spain which in total account for 80% of the market share in the market. Haircuts could significantly explain the variations in beta and alpha. We only have data on valuation haircuts after February 2001; however, we find that haircuts are highly correlated with bond duration (with a correlation coefficient of 0.6 that is significant at the 1% level). We therefore include bond duration as a proxy for haircuts.

The results of the two cross-sectional regressions are reported in Table 6, panel B. The impact of funding liquidity on market liquidity (β) significantly increases with duration. Bonds with a longer duration are less liquid and thus more affected by variations in funding liquidity. By contrast, we find that the impact of the idiosyncratic market liquidity on funding liquidity (α) significantly decreases with duration. This is consistent with the fact that bonds that have a longer duration are probably used less frequently as collateral, so that variations in market liquidity for the latter impact less funding liquidity.

[29]Note that the coefficients of the control variables in the FLIQ equations are the same for every bond, and they are reported in Table 5.

We expect the country to play a role if default risk (and thus probably margin requirements) differ. We find that the sign of the coefficients of the country dummies of sovereign bonds which are characterized by a higher (resp. lower) counterpart risk such as Spain (resp. Germany) is the same (resp. opposite) to that of bonds with a longer (resp. shorter) duration.

5 Robustness checks

We perform a number of additional tests and find that our baseline results are robust to various modeling choices.

5.1 Sample of bonds

As described in section 4.2, our analysis focuses on a subsample of 149 bonds that are traded in the platform EuroMTS at least fifteen days in each of the three volatility regimes, defined exogenously based on variation in the vStoxx index. This restriction enables us to compare estimates of α_j and β_j in the cross-section of bonds since all the estimations are based on the same volatility regimes. However, it induces us to restrict our attention to a subsample of bonds. In this section, we check the robustness of our global results to the sample of bonds, by estimating the reduced-form model defined in (3) on the full sample of 452 bonds traded in EuroMTS over the sample period.

Table 7, panel A reports some descriptive statistics on the full sample, by country. The comparison with Table 1, panel A shows that the characteristics of the bonds by country in the subsample are similar to those in the full sample, except for the fact that they have on average shorter years-to-maturity and duration. Given that the subsample requires trades in each volatility regime, it may not be surprising to observe that the condition mainly excludes bonds with shorter maturities. Including more bonds with shorter maturities increases the trading volume of all but Finish bonds.

We then construct systematic components $FLIQ$ and $MLIQ$ from both panels of funding and market liquidity measures across proxy measures and Treasury bond markets by a adopting principal components approach. The results (omitted for brevity) suggest that the first principal component of both panels is sufficient to capture 54 and 75 percent of the cross-sectional variability of the funding and market liquidity measures, respectively. Besides, the heteroskedasticity tests also reject the null for both FLIQ and MLIQ at the 1% level.

Table 7, panel B reports the estimates of the reduced-form model defined in (3). The results, whether relative to our variables of interest or on control variables, are perfectly in line with those reported in 5, Panel C on the subsample, although slightly less economically significant. In particular, both effects of funding to market liquidity and vice-versa are positive and significant, with coefficients of 0.081 for β and 0.049 for α respectively.

5.2 Different Volatility-regime Classification

As a robustness check, we decide to be agnostic and identify the volatility regimes directly from the time-series data. In line with Rigobon and Sack (2003), we define the various regimes globally from the reduced-form residuals by computing rolling-window variances of N-week worth of observations for each variable. A high (low) volatility regime is assigned if the volatility of that variable is larger (smaller) than its average value plus the value of the average volatility times a coefficient c. We report the results of the estimation using a moving-average estimate of volatility for the various time series of $N = 20$ weeks with a threshold parameter $c = 0.5$.[30] Table 8 A reports the results of the estimation of the reduced-form model defined in (3) on the sample of 149 bonds and on the full sample. Again, both effects of funding to market liquidity and vice-versa are positive and significant.

[30] We have used additional rolling windows of 10, 30 and 40 weeks to estimate the volatility of the various time series and additional thresholds of $c = 0.25, 0.75, 1.0$ to classify high-volatility regimes. The results of this robustness check are available upon request. In all cases, the results of our baseline estimations are confirmed.

The coefficients of 0.156 for β and 0.02 for α for the subsample, and of 0.111 for β and 0.03 for α for the full sample, are very close from the values obtained with the alternative definition of volatility regimes.

5.3 Alternative models

As an additional robustness check we estimate an alternative model, based on Rigobon and Sack (2003). The model includes an unobservable common shock, which accounts for potential omitted control variables, but prevents from estimating the parameter α, measuring the impact of market liquidity on funding liquidity. Instead, the model provides an estimate of a parameter θ, which is defined as

$$\theta = \frac{(1 + \alpha \times \gamma)}{\beta + \gamma},$$

where γ is the coefficient of the unobserved variable. Table 9 reports the estimates of this model, for both the subsample of 149 bonds and the full sample. In both cases, the effects of funding to market liquidity and vice-versa are positive, significant, and relatively close to that obtained in our model based on Rigobon (2003).

6 Conclusions

This paper adopts an identification technique based on the heteroskedasticity of liquidity proxies to infer the magnitude of the impact of market liquidity to and from funding liquidity, that enables to explicitly take the endogeneity into account. Using data for the European Treasury bond market, we find evidence that funding liquidity shocks affect bond market liquidity, with is consistent with the theory and with the existing literature. We also document the existence of a positive and significant feedback effect of market liquidity on funding liquidity: market illiquidity seems to tighten funding contraints. We exploit the heterogeneity of our sample of bonds, characterized by different durations and default risk, to investigate the determinants of the magnitude of these effects. We find that the market to funding liquidity effect is stronger for short-term bonds and for bonds used as collaterals in repo transactions, such as German bonds. Our results are robust to alternative definitions of the volatility regimes, alternative samples of bonds, and alternative model specifications. Our findings suggests the presence of destabilizing liquidity spirals. As shown by Brunnermeieir and Pedersen (2009), central banks can help mitigate market liquidity problems in such equilibria by boosting speculators' funding conditions during a liquidity crisis.

7 Appendix 1

The appendix follows the identification strategy in the Section 3.3. The covariance matrix of the reduced-form residuals in (1) model in each regime i ($i = 1, ..., I$ volatility regimes) can be given as:

$$\Omega_i \equiv \begin{bmatrix} \varpi_{11,i} & \varpi_{12,i} \\ . & \varpi_{22,i} \end{bmatrix} \tag{6}$$

$$= \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} \beta^2\sigma^2_{\eta,i} + \sigma^2_{\epsilon,i} & \beta^2\sigma^2_{\eta,i} + \alpha\sigma^2_{\epsilon,i} \\ . & \sigma^2_{\eta,i} + \alpha^2\sigma^2_{\epsilon,i} \end{bmatrix}, \tag{7}$$

where $\alpha\beta \neq 1$. In each regime, the covariance matrix provides three equations to solve the unknown variables. The three equations can be written as follows:

$$\beta^2\sigma^2_{\eta,i} + \sigma^2_{\epsilon,i} = (1-\alpha\beta)^2 \varpi_{11,i} \tag{8}$$

$$\beta^2\sigma^2_{\eta,i} + \alpha\sigma^2_{\epsilon,i} = (1-\alpha\beta)^2 \varpi_{12,i} \tag{9}$$

$$\sigma^2_{\eta,i} + \alpha^2\sigma^2_{\epsilon,i} = (1-\alpha\beta)^2 \varpi_{22,i} \tag{10}$$

Solving these equations leads to the following moment condition:

$$\frac{\varpi_{12,i} - \beta\varpi_{22,i}}{\varpi_{11,i} - \beta\varpi_{12,i}} - \alpha = 0, \tag{11}$$

When the number of volatility regimes I is exactly the same as the number of endogenous variables, i.e. two in our case, β needs to statistfy the following condition:

$$\frac{\varpi_{12,1} - \beta\varpi_{22,1}}{\varpi_{11,1} - \beta\varpi_{12,1}} = \frac{\varpi_{12,2} - \beta\varpi_{22,2}}{\varpi_{11,2} - \beta\varpi_{12,2}}, \tag{12}$$

After some algebra, β solves the quadratic equation[31]:

[31] The quadratic equation has two solutions. One is the values of α and β in the system of equation. The other is given as the system in which the order of funding liquidity is first and then market liquidity. In that case, the solution gives the values $\alpha^* = 1/\beta$ and $\beta^* = 1/\alpha$.

$$a\beta^2 - b\beta + c = 0, \tag{13}$$

where

$$\begin{aligned} a &= \varpi_{22,1} \times \varpi_{12,2} - \varpi_{22,2} \times \varpi_{12,1} && (14) \\ b &= \varpi_{22,1} \times \varpi_{11,2} - \varpi_{22,2} \times \varpi_{11,1} && (15) \\ c &= \varpi_{12,1} \times \varpi_{11,2} - \varpi_{12,2} \times \varpi_{11,1} && (16) \end{aligned}$$

When the regimes of volatility I is exactly greater than the number of endogenous variables, GMM estimation can be used with the moment condition specified as above.

8 Appendix 2

We do not take a specific stand on the direction of causality and investigate the dynamic interaction between market and funding liquidity by adopting the methodology proposed in Rigobon (2003) and Rigobon and Sack (2003). More specifically, we start from the observation that market and funding liquidity are determined simultaneously and we model their time-series dynamics by using the following structural form:

$$\begin{aligned} m_t &= \beta f_t + \theta x_t + \gamma z_t + \epsilon_t, & (17) \\ f_t &= \alpha m_t + \phi x_t + z_t + \eta_t, & (18) \end{aligned}$$

where m_t is the first principal component of market liquidity variables, f_t is the first principal component of funding liquidity variables, x_t is a vector of exogenous variables, z_t is the latent variable, ϵ_t and η_t are structural shocks in each equation. The parameter of the common shock z_t is normalized to one in the second equation while β, α, θ, ϕ are the parameters in the model.

The equations can be written in a reduced-form model as follows:

$$\begin{pmatrix} m_t \\ f_t \end{pmatrix} = \Phi x_t + \begin{pmatrix} \nu_t^m \\ \nu_t^f \end{pmatrix},$$

where the reduced form residuals $\left(\nu_t^m \text{ and } \nu_t^f\right)$ are related to the structural shocks as follows:

$$\begin{aligned} \nu_t^m &= \frac{1}{1-\alpha\beta}\left[\left(\beta+\gamma\right) z_t + \beta\eta_t + \epsilon_t\right], & (19) \\ \nu_t^f &= \frac{1}{1-\alpha\beta}\left[\left(1+\alpha\gamma\right) z_t + \eta_t + \alpha\epsilon_t\right] & (20) \end{aligned}$$

The covariance matrix of the reduced-form residuals can be given as:

$$\Omega = \frac{1}{(1-\alpha\beta)^2}\left[\begin{array}{cc} (\beta+\gamma)^2\sigma_z^2+\beta^2\sigma_\eta^2+\sigma_\epsilon^2 & (1+\alpha\gamma)(\beta+\gamma)\sigma_z^2+\beta^2\sigma_\eta^2+\alpha\sigma_\epsilon^2 \\ . & (1+\alpha\gamma)^2\sigma_z^2+\sigma_\eta^2+\alpha^2\sigma_\epsilon^2 \end{array}\right], \quad (21)$$

We assume that the data exhibits $i = 1, ..., I$ volatility regimes, of which the covariance matrix of the reduced form residuals in regime i can be written as Ω_i. Let $\theta = (1+\alpha\gamma)/(\beta+\gamma)$. and $\Delta\Omega_{ij,km}$ denote element *(k, m)* of the matrix $\Delta\Omega_{ij}$, , which is the difference between the covariance matrix in regime i and regime *j*. If $\theta\beta \neq 1$, which assures finite variance, Rigobon and Sack (2003) suggests the following moment conditions with regime i ($i \neq 1$):

$$\frac{\Delta\Omega_{i1,12}-\beta\Delta\Omega_{i1,22}}{\Delta\Omega_{i1,11}-\beta\Delta\Omega_{i1,12}}-\theta=0, \quad (22)$$

When the number of volatility regime I is exactly the same as the number of endogenious variables plus the number of common shock, Rigobon and Sack (2003) shows that the parameter β can be obtained by solving the quadratic equation:

$$a\beta^2 - b\beta + c = 0,$$

where

$$a = \Delta\Omega_{31,22}\Delta\Omega_{21,12} - \Delta\Omega_{21,22}\Delta\Omega_{31,12} \quad (23)$$

$$b = \Delta\Omega_{31,22}\Delta\Omega_{21,11} - \Delta\Omega_{21,22}\Delta\Omega_{31,11} \quad (24)$$

$$c = \Delta\Omega_{31,12}\Delta\Omega_{21,11} - \Delta\Omega_{21,12}\Delta\Omega_{31,11} \quad (25)$$

If the number of I is greater than the number of endogenious variables plus the number of common shock, GMM estimation technique needs to be applied. Using the rolling-variance method, we specify $I = 4$ volatility regimes, one where the two liquidity measures demonstrate high conditional volatility, two regimes where one variable remains in low volatility state, one regime where all variables stay in low volatility state. We obtain the parameters by using the (22) moment conditions in the GMM estimation. We establish the distributions of the estimated coefficients and perform significance tests in 1000 replications.

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Table 1: The table reports the average statistics for the ten Euro-area government bond markets. We only consider fixed-rate coupon bonds with maturity between one year and thirty years, issued by the central government and traded on the MTS platform from Oct 1, 2004 to Feb 28, 2011. We focus on the bonds that are traded at least 15 days in each of the three volatility regimes. In this table, *No.* denotes the total number of bonds for each country, *Yield* is the end-of-day miquote bond yield (in percentage), *YTM* is the years to maturity (in years), *Duration* is the bond duration (in years), *Coupon* is the coupon rate (in percentage), *Part.* is the number of active participants over the whole sample period, *Trades* is the average weekly number of transactions per bond over the whole sample period and *Size* is the average trade size in million euros over the whole period. Panel A reports the country average statistics, and Panel B reports the mean, median, standard deviation, min and max of the cross-section of individual bonds.

Statistics by country

(a)

Country	**No.**	**Yield**	**YTM**	**Duration**	**Coupon**	**Part.**	**Trades**	**Size**
Austria	10	3.82	9.96	7.45	4.51	56	34	8.34
Belgium	12	3.71	10.04	7.20	4.72	37	124	8.25
Finland	4	3.38	6.27	5.19	4.90	46	143	9.47
France	29	3.52	9.80	7.01	4.80	39	133	7.06
Germany	23	3.27	7.55	5.73	4.32	65	146	6.66
Greece	14	4.11	8.28	6.30	5.15	42	132	7.58
Italy	29	3.97	11.21	7.44	2.44	85	1,219	5.67
Netherlands	11	3.50	8.77	6.48	4.74	46	54	9.02
Portugal	5	3.80	7.11	5.85	4.27	49	70	9.09
Spain	12	3.73	8.74	6.49	4.76	46	92	8.74

Cross-sectional statistics

(b)

Panel	**No.**	**Yield**	**YTM**	**Duration**	**Coupon**	**Part.**	**Trades**	**Size**
Mean	149	3.68	9.37	6.75	0.09	55	21	7.11
Median		3.90	7.49	6.16	0.00	50	8	7.00
Std Dev		0.93	6.63	3.47	0.66	19	38	3.23
Min		0.12	0.49	0.49	0.00	20	0	0.50
Max		6.18	30.09	17.22	8.50	130	562	230.50

Table 2: The table reports the summary statistics of market liquidity variables across European Treasury bond markets for the same sample period . Market liquidity variables include the bid-ask spread (BAS, in bp), the effective spread (EBAS, in bp), price-impact (IMP) and Amihud's ILLIQ measure. The definition of all measures is discussed in Section 3. The market liquidity variables are equal-weighted averages across all bonds and markets on a weekly basis. Panel A reports the country average statistics (the mean and the standard deviation in parenthesis), and Panel B reports the mean, median, standard deviation, min and max of the cross-section of individual bonds. Panel C reports the correlations between the four market liquidity measures.

Descriptive statistics of market liquidity variables by country

(a)

	Market Liquidity Measure			
Country	**BAS**	**EBAS**	**ILLIQ**	**IMP**
Austria	8.52 (5.20)	4.65 (4.54)	2.14 (1.58)	0.79 (1.45)
Belgium	7.32 (4.61)	3.89 (3.52)	1.78 (1.22)	0.61 (0.87)
Finland	6.08 (4.79)	3.03 (3.39)	1.17 (1.07)	0.50 (0.92)
France	7.37 (3.43)	3.24 (2.19)	2.38 (1.25)	0.70 (0.98)
Germany	5.88 (2.06)	2.42 (1.12)	1.61 (1.03)	0.97 (1.44)
Greece	6.53 (4.62)	3.87 (4.72)	1.74 (1.55)	1.30 (2.58)
Italy	7.14 (4.31)	3.50 (2.97)	1.40 (0.82)	0.64 (0.65)
Netherlands	6.77 (3.14)	2.97 (2.03)	1.67 (0.72)	0.46 (0.46)
Portugal	6.90 (5.45)	4.50 (6.78)	1.25 (1.69)	0.68 (1.56)
Spain	7.55 (5.12)	4.42 (4.61)	1.74 (1.26)	0.67 (0.93)

Cross-sectional statistics of market liquidity variables

(b)

	Market Liquidity Measure			
Panel	**BAS**	**EBAS**	**ILLIQ**	**IMP**
Mean	7.90	3.74	1.92	0.72
Median	4.53	2.07	1.79	0.42
Std Dev	4.73	2.92	0.69	0.70
Min	3.19	1.02	0.77	0.21
Max	16.08	11.32	4.46	3.80
AC(1)	0.96	0.95	0.69	0.86

Correlations of market liquidity measures

(c)

	Market Liquidity Measure			
Variables	**BAS**	**EBAS**	**ILLIQ**	**Impact**
BAS	1	0.92	0.64	0.75
EBAS		1	0.66	0.85
ILLIQ			1	0.63
Impact				1

Table 3: The table (Panel A) reports the summary statistics of European funding liquidity variables from Oct 1, 2004 to Feb 28, 2011. Funding liquidity variables include the spreads (in basis points) between Euribor, General Collateral Repo, the ECB's Main-Refinancing Operation Rates over the overnight-index-swap (OIS) rate or the Euribor, Fontaine and Garcia (2012)'s measure based on the spread between on-the-run and off-the-run securities, and the Hu, Pan and Wang (2013) measure of noise. The definition of all measures is discussed in Section 3. The funding liquidity variables are equal-weighted averages across markets on a weekly basis. Mean, Std, Min, Max denote the average, standard deviation, minimum and maximum of the variables. AC(1) denotes the first-order autocorrelation coefficients of the variables. Panel B reports the correlations between the five funding liquidity measures.

Descriptive statistics on Funding Liquidity measures

(a)

	Funding Liquidity Measure				
	EURIBOR-OIS	**EURIBOR-Repo**	**MRO-OIS**	**On/off spd**	**Noise**
Mean	6.07	6.36	18.16	0.22	0.19
Median	2.80	3.20	2.15	0.16	0.03
Std Dev	9.92	9.34	26.00	0.12	0.22
Min	-17.00	-7.50	-8.50	0.05	0.03
Max	98.90	85.00	111.00	0.72	1.02
AC(1)	0.75	0.86	0.94	0.85	0.92

Correlations of funding liquidity measures

(b)

	Funding Liquidity Measures				
Variables	**Euribor**	**Repo**	**MRO**	**FG**	**Noise**
Euribor	1	0.94	0.24	0.11	0.14
Repo		1	0.29	0.24	0.28
MRO			1	0.51	0.64
FG				1	0.89
Noise					1

Table 4: The table (panel A) reports the results from the principal component analysis of funding and market liquidity variables. Panel B reports the correlations of the FLIQ and MLIQ measures with the standard liquidity measures defined in Section 3.

Principal component analysis of funding liquidity variables

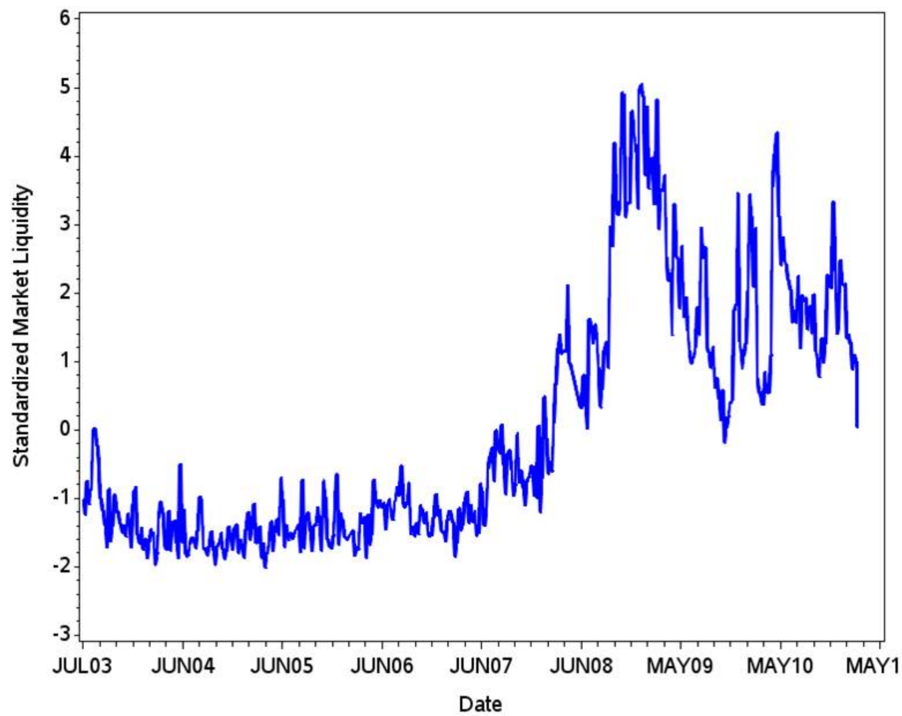
(a)

	Funding Liquidity Measures			**Market Liquidity Measures**		
	Eigenvalue	Proportion	Cumulative	Eigenvalue	Proportion	Cumulative
PC1	2.72	0.54	0.54	3.25	0.81	0.81
PC2	1.61	0.32	0.87	0.44	0.11	0.92
PC3	0.52	0.10	0.97	0.26	0.06	0.99

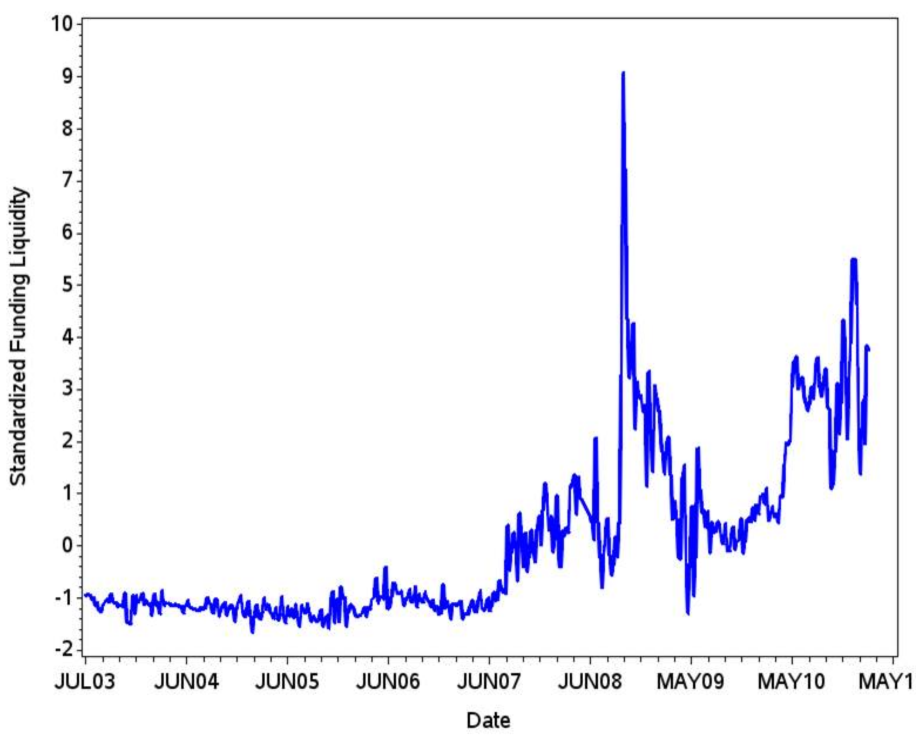
Contemporaneous Correlation Coefficients Across Liquidity Measures

(b)

	Funding Liquidity Measures					**Market Liquidity Measures**			
Correlation	**Euribor**	**Repo**	**MRO**	**FG**	**Noise**	**BAS**	**EBAS**	**ILLIQ**	**Impact**
FLIQ	0.60	0.70	0.75	0.79	0.84				
MLIQ						0.93	0.96	0.80	0.90



(a)



(b)

Figure 1: *This Figure plots the time series of the market liquidity measure, MLIQ, in Panel A, and of the funding liquidity measure, FLIQ, in Panel B. Both measures are computed as the first principal component of a panel of liquidity proxies as defined in Section 3*

Table 5: The table (Panel A) reports the results from the White heteroskedasticity test for funding and market liquidity variables over the sample period from Oct 1, 2004 to Feb 28, 2011. From the vStoxx index, we classify three volatility regimes. Panel B reports the variances and covariances of the market and funding liquidity measures in the three regimes. Panel C shows the coefficients and the standard errors (in parentheses) of the parameters of the structural model based on Rigobon (2003). FLIQ is the first principal component of the changes in the five funding liquidity variables. MLIQ denotes the first principal component of the changes in the four market liquidity variables. p-values are obtained from bootstrap with 1,000 replications. *** indicates that coefficients are significantly different from zero at the 1% level.

Tests for Heteroskedasticity

(a)

Variables	**White Statistic**	**Breusch-Pagan Statistic**
FLIQ	24.33	20.67
MLIQ	43.77	34.99

Variance-Covariance of the innovations under different regimes

(b)

Variables	**Low** σ_{FLIQ}, **Low** σ_{MLIQ}	**High** σ_{FLIQ} **Low** σ_{MLIQ}	**High** σ_{FLIQ} **High** σ_{MLIQ}
Variance of MLIQ	0.10	0.24	0.68
Variance of FLIQ	0.06	0.23	1.78
Covariance MLIQ, FLIQ	0.02	0.02	0.26
Freq. of obs.	9.80%	80.72%	11.63%

Heteroskedasticity identification

(c)

	First Principal Components		**Direct proxies**	
	MLIQ	**FLIQ**	**EBAS**	**Euribor-OIS**
β (funding to market)	0.169***		0.07***	
	(48.06)		(20.83)	
α (market to funding)		0.073***		0.0553***
		(19.40)		(3.16)
Implied volatility (vStoxx)	0.011***	0.0034	0.0326***	0.0641
	(4.35)	(0.63)	(5.25)	(1.16)
Variation in M2 money supply	−0.149***	−0.052	−0.151***	0.07
	(−4.14)	(−1.29)	(−3.69)	(0.18)
Mutual funds' flows	−0.48***	−0.024	−0.44*	−0.465
	(−2.55)	(−0.18)	(−1.86)	(−0.19)
End-of-month dummy	−0.0246	0.193***	1.27	1.84***
	(-0.28)	(2.84)	(1.52)	(2.39)

Table 6: The table reports the results of the analysis at the individual bond level. We estimate the Reduced-form model (3). Our Funding Liquidity measure $FLIQ$ is defined in Section 3. The idiosyncratic market liquidity measure $IdioMLIQ_j$ is defined as the difference between the individual market liquidity measure $MLIQ_j$, which is the first principal component of the four proxies of market liquidity, namely the bid-ask spread, the effective spread, Amihud's illiquidity and the price impact measured at the individual bond level, and the systematic market liquidity measure $MLIQ$ defined in Section 3. Panel A reports the cross-sectional averages and standard deviations of the estimates of α_j, β_j and control variables. Panel B reports the estimates of the cross-sectional regression $Y_j = a_0 + a_1 \times Duration + \sum_{i=2}^{5} a_j Country_j + \varepsilon_j$.

Bond-by-bond estimations

(a)

			Control variables in the MLIQ equation			
	α	β	**vStoxx**	**M2**	**MFF**	**EoM**
No Bonds				149		
Mean	0.01	0.02	−0.01	0.19	0.21	0.03
Std	0.08	0.12	0.01	0.07	0.23	0.11
Min	−0.49	−0.15	−0.04	−0.01	−0.42	−0.31
Max	0.22	0.85	0.02	0.53	0.85	0.46

Explaining liquidity exposure in the cross-section of bonds

(b)

	β		α	
Intercept	−0.027	(−0.91)	0.055	(2.68)
Duration	0.007***	(2.18)	−0.008***	(−3.82)
Germany	−0.026	(−0.95)	0.039***	(2.02)
Spain	0.093***	(2.61)	−0.008	(−0.31)
France	−0.028	(−1.07)	0.032	(1.79)
Italy	−0.028	(−1.09)	0.07***	(3.93)
R^2	10.33%		17.92%	

Table 7: The table reports the country average statistics for the full sample of the ten Euro-area government bond markets. We only consider fixed-rate coupon bonds with maturity between one year and thirty years, issued by the central government and traded on the MTS platform from Oct 1, 2004 to Feb 28, 2011. In this table, *No.* denotes the total number of bonds for each country, *Yield* is the end-of-day miquote bond yield (in percentage), *YTM* is the years to maturity (in years), *Duration* is the bond duration (in years), *Coupon* is the coupon rate (in percentage), *Part.* is the number of active participants over the whole sample period, *Trades* is the average weekly number of transactions per bond over the whole sample period and *Size* is the average trade size over the whole period. Panel B shows the coefficients and the standard errors (in parentheses) of the parameters of the structural model based on Rigobon (2003), estimated on the full sample of bonds. FLIQ is the first principal component of the changes in the five funding liquidity variables. MLIQ denotes the first principal component of the changes in the four market liquidity variables. p-values are obtained from bootstrap with 1,000 replications. *** indicates that coefficients are significantly different from zero at the 1% level.

Statistics by country on the full sample of bonds

(a)

Country	**No.**	**Yield**	**YTM**	**Duration**	**Coupon**	**Part.**	**Trades**	**Size**
Austria	19	3.65	8.14	6.29	4.63	55	61	4.46
Belgium	34	3.46	7.20	5.63	5.01	35	226	5.02
Finland	13	3.27	5.66	5.16	4.37	61	79	4.76
France	70	3.32	8.19	5.68	4.70	45	256	4.39
Germany	104	3.16	7.24	4.53	4.26	45	256	4.39
Greece	35	3.84	7.21	5.53	5.02	38	212	4.27
Italy	86	3.62	7.75	5.06	2.36	42	2,476	3.28
Netherlands	31	3.29	7.45	5.79	4.35	87	105	5.78
Portugal	21	3.65	7.28	5.49	4.50	44	215	4.89
Spain	39	3.56	8.56	5.28	4.65	46	187	4.88

Heteroskedasticity identification on the full sample of bonds

(b)

	MLIQ	**FLIQ**
β (funding to market)	0.081***	
	(28.96)	
α (market to funding)		0.049***
		(20.44)
Implied volatility (vStoxx)	0.015***	0.0016
	(3.99)	(0.74)
Variation in M2 money supply	−0.106***	−0.064
	(−2.36)	(−1.13)
Mutual funds' flows	−0.32***	−0.000
	(−2.40)	(−0.09)
End-of-month dummy	0.041	0.159***
	(0.70)	(2.15)

Table 8: In line with Rigobon and Sack (2003), we define the various regimes globally from the reduced-form residuals by computing rolling-window variances of 20-week worth of observations for each variable. A high (low) volatility regime is assigned if the volatility of that variable is larger (smaller) than its average value plus the value of the average volatility times a coefficient $c = 0.5$. The Table reports the results of the estimation of the reduced-form model a la Rigobon (2003) defined in (3), on the subsample of 149 bonds as well as on the full sample. Values in brackets denote the standard deviations obtained by bootstrapping with 1,000 replications.

Volatility regimes defined based on rolling-window variances

(a)

	Subsample of 149 bonds		**Full sample**	
Variables	**MLIQ**	**FLIQ**	**MLIQ**	**FLIQ**
beta	0.156*** (61.92)		0.111*** (52.91)	
alpha		0.02*** (3.36)		0.03*** (10.86)

Table 9: The Table reports the estimates of an identification model based on Rigobon and Sack (2003). The model controls for an unobservable common shock, but prevents the complete characterisation of the alpha parameter. Instead, we obtain theta = (1+alpha*gamma)/(beta+gamma). Values in brackets denote the standard deviations obtained by bootstrapping with 1,000 replications.

Rigobon and Sack (2003) identification

(a)

	Subsample of 149 bonds		**Full sample**	
Variables	**MLIQ**	**FLIQ**	**MLIQ**	**FLIQ**
beta	0.167*** (16.45)		0.0718*** (10.2)	
theta		0.203*** (14.05)		0.1307*** (9.30)