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Sophie Moinas, Minh Nguyen and Giorgio Valente

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

Sophie Moinas

Toulouse School of Economics

Minh Nguyen

University of Newcastle Business School

Giorgio Valente

Hong Kong Institute for Monetary Research

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Abstract

Theoretical studies show that shocks to funding constraints should aﬀect and be af-fected by market illiquidity. However, little is known about the empirical magnitude of such responses because of the intrinsic endogeneity of illiquidity shocks. This paper adopts an identification technique based on the heteroskedasticity of illiquidity proxies to infer the reaction of one measure to shocks aﬀecting the other in a joint setting. Using data for the European Treasury bond market, we find evidence of a two-way re-sponse occurring between funding and market illiquidity shocks. In the cross-section, we show that individual bonds' illiquidity responses to funding or market illiquidity shocks vary with with bond maturity, the credit risk of the issuer, haircuts, and the number of bonds issued by the country.

Keywords: Illiquidity, Asset Pricing, Identification, Heteroskedasticity.

JEL Classification: G10, G28

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*Email addresses: Corresponding Author: Moinas : sophie.moinas@ut-capitole.fr , Nguyen: minh.nguyen@newcastle.ac.uk , Valente: gvalente@hkma.gov.hk

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1 Introduction

Financial markets routinely experience a variety of frictions impacting price formation that hinder their efficient functioning. 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).

Despite the mounting theoretical and empirical evidence documenting the impact of both funding and market illiquidity on asset prices (see, among others, Vayanos and Wang (2012); Foucault, Pagano, and Roell (2013)), less is known about the empirical relationships jointly linking the two dimensions of illiquidity. This paper aims at filling this gap and proposes an empirical investigation of the dynamic relationships between funding and market illiquidity in the context of the European Treasury bond market. We focus on this market because of its large size, the wide use of the traded Treasury securities in repo transactions[1], and its institutional features whereby trading occurs in a large supranational secondary market whose liquidity conditions respond to aggregate funding illiquidity shocks.

We take explicitly into account the endogeneity that naturally arises between the two dimensions of liquidity and adopt an empirical methodology, i.e. Identification through Heteroskedasticity (ITH henceforth), that has been successfully used in other contexts (Rigobon (2003), Rigobon and Sack (2003), Rigobon and Sack (2004)). We then quantify economically the responses of market illiquidity to and from funding illiquidity shocks and exploit

[1]It is important to note that the European repo market differs substantially from the U.S. repo market along various dimensions. This in turn suggests that counterparty risk may play a different role compared to the evidence reported in previous studies. See, for example, Mancini, Ranaldo, and Wrampelmeyer (2016) for a discussion on differences between the U.S. and the European repos markets, and their potential impact on the resiliency of the repo market.

the heterogeneity in the cross-section of government bonds' characteristics, across European countries, to investigate the determinants of the liquidity responses.

Using a dataset containing all European Treasury bonds that are traded on the Mercato Telematico dei Titoli di Stato (MTS henceforth) platforms over the period October 1st, 2004 - February 28th, 2011,[2] we carry out our estimation and find a host of interesting results.

First, we show that shocks to funding illiquidity significantly and positively affect the market illiquidity of the European Treasury market, after controlling for endogeneity. A one standard deviation shock to funding illiquidity, denoting increased funding constraints, increases market illiquidity by 0.15 standard deviation. This positive impact is consistent with most studies in this literature.[3] Furthermore, and unlike in the previous literature, our econometric model uncovers evidence of a positive and significant feedback effect whereby one standard deviation shock to market illiquidity across European Treasury markets generates a increment of 0.08 standard deviation of funding illiquidity. This latter result is crucial for two reasons. First, it shows the presence of a feedback effect from market illiquidity to funding illiquidity, which has been theoretically formalized by Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2010) but never formally tested in a joint setting[4]. Second, it sheds further light on the direction of this impact, since both theoretical models suggest

[2]MTS is the most important electronic platform for euro-denominated government bonds and it consists of number of domestic markets (i.e., local MTS) and a centralized European marketplace (i.e., EuroMTS).

[3]See, among others, Chordia, Roll, and Subrahmanyam (2001), Chordia, Sarkar, and Subrahmanyam (2005), Coughenour and Saad (2004), Comerton-Forde, Hendershott, Jones, Moulton, and Seaholes (2010), Hameed, Kang, and Viswanathan (2010), Jensen and Moorman (2010), Bessembinder, Jacobsen, Maxwell, and Venkatamaran (2016), Rapp (2017)), Coffey, Hrung, and Sarkar (2009), Mancini Griffoli and Ranaldo (2010), Adrian, Etula, and Muir (2014), Fontaine and Garcia (2012), or Hu, Pan, and Wang (2013), Trebbi and Xiao (2015), Pelizzon, Subrahmanyam, Tomio, and Uno (2016) and Deuksar and Johnson (2017). Our results also complement studies that address differently the endogeneity issue by exploiting Lehman bankruptcy as instrument (Aragon and Strahan (2012)), natural experiments such as variations or shocks to margin requirements (Miglietta, Picillo, and Pietrunti (2015), Hedegaard (2014), Jylhä (2017)), or a regression discontinuity design (Kahramand and Tookes (2017)) to identify a causal relationship funding constraints and market illiquidity.

[4]For example, other studies that have attempted to explore the empirical implications of the relevant theoretical models (see for example Boudt, Paulus, and Rosenthal (2017), Dick-Nielsen and Gyntelberg (2013)) have only looked at either one side of the relationship between market and funding illiquidity or at both sides but separately. These approaches thus miss the crucial aspects of endogeneity and joint determination of both dimensions of liquidity that are key to uncovering liquidity spirals and their stabilizing/destabilizing dynamics

that the impact of market on funding liquidity can either be stabilizing or destabilizing depending on the equilibrium or on model's parameters. The dual reinforcing relationship between funding and market illiquidity that we document is at the core of the existence of potential illiquidity spirals.[5]

Second, after estimating the responses of market illiquidity to funding shocks for individual bonds in our sample, we find that these coefficients are on average positive, but with a different size across bonds. In other words, market illiquidity for individual bonds react differently to tightening funding constraints. This suggests that the role of intermediaries is on average destabilizing. We also find that the responses to funding illiquidity shocks are higher for long-term bonds, which are more capital intensive than short-term bonds. Interestingly, they decrease with the number of sovereign bonds issued by the country. By contrast, the responses of funding illiquidity to individual bonds' market illiquidity shocks are lower for bonds with higher haircuts, that are used less frequently as collaterals in repo transaction.

The rest of the paper is organized as follows. Section 2 presents the mechanisms highlighted in the theoretical literature to explain the interplay between funding and market liquidity. Section 3 describes our empirical framework and introduces the measures used to proxy for market and funding illiquidity. Section 4 describes the data used in this study, presents preliminary summary statistics and reports the results of the main estimations. Section 5 discusses the results of the cross-sectional analysis and a final section concludes.

2 Intermediary asset pricing

The idea that market illiquidity 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

[5]Our results have thus important implications for the new margin regulation for non-centrally cleared derivatives. In fact, shocks affecting initial and variation margins (hence impacting funding illiquidity) may not only have a first-order effect on trading capital, and overall credit risk, but also affect by a significant extent market illiquidity.

new. When investors need to trade and need immediacy, their demand would typically be absorbed by financial intermediaries. Various models suggest that these participants' wealth may be used directly to buy financial assets or as collateral to borrow cash or securities and engage into these activities.

On the one hand, market makers temporarily absorb imbalance by holding a possibly short term position in their inventory. Following the traditional inventory models (see Demsetz (1968), Stoll (1978), or Ho and Stoll (1981)), Weill (2007) formalizes the existence of the link between the cost faced by market makers to raise capital and liquidity provision.

On the other hand, other intermediaries such as mutual or hedge funds, may either be ready to absorb imbalance for a longer period, or to arbitrage prices. Even more capital is required for these activities, as participants need to hold positions for some time or across large baskets of securities. Constraints on the borrowing capacity may indeed create what Shleifer and Vishny (1997) name "limits to arbitrage". In particular, the authors 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 He and Krishnamurthy (2013)).

Brunnermeier and Pedersen (2009), and Gromb and Vayanos (2010) are among the first to elaborate on the two-sided nature of the relationship between funding illiquidity and market illiquidity, which is the main focus of our paper. When a trader buys a security that he can use as collateral to borrow a fraction of its value against it, or when the arbitrageurs face collateral-based financial constraints limiting their investment capacity, illiquidity assumes a dual perspective: two notions of funding and market illiquidity affect each other. Depending on the equilibrium or on the model's parameters, financial intermediaries may have a stabilizing or a destabilizing role, leading to cases of perverse illiquidity spirals.

3 The Empirical framework

In this section, we first introduce the empirical methodology adopted to identify the dynamic relationships between funding and market illiquidity based on the heteroskedasticity of illiquidity measures (Rigobon (2003) and Rigobon and Sack (2003)) and then discuss the main empirical proxies for market and funding illiquidity used in the empirical investigation.

3.1 Identification through heteroskedasticity

The framework adopted in our empirical investigation takes into account the fact that market and funding illiquidity are endogenously and jointly determined. Theories of financial intermediation suggest a direct dual causality between the two dimensions of illiquidity. Nonetheless, the empirical identification of this relationship is not a trivial task. In fact, as illiquidity 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 illiquidity causes changes in the other or whether both dimensions of illiquidity are endogenously determined.

We do not take a stand on a specific direction of causality and investigate the joint dynamic interaction between market and funding illiquidity by adopting the methodology proposed in Rigobon (2003) and Rigobon and Sack (2003). For the sake of exposition, we present below the simplest version of their model but in the empirical estimation we will consider the case where exogenous control variables are added to incorporate the potential effect of other factors affecting both market and funding illiquidity.

Let market and funding illiquidity follow the system of simultaneous equations:

$$m_t = \beta f_t + \epsilon_t \quad (1)$$

$$f_t = \alpha m_t + \eta_t, \quad (2)$$

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 parameters of interest in the model. We assume that the shocks affecting market and funding illiquidity in the model are uncorrelated, i.e. $E(\epsilon_t\eta_t) = 0$.[6]

Albeit very stylized, equations (1)-(2) have a straightforward interpretation in light of existing theoretical frameworks. In fact, the first equation of the system captures the finding whereby any asset's market illiquidity is a function of funding illiquidity affecting trading in that market.[7] The second equation is less rooted into these specific theoretical frameworks. In light of Brunnermeier and Pedersen (2009), the equation can be viewed as a simplified counterpart of the finding that the shadow cost of capital, used as proxy for a common funding illiquidity measure, is a function of market illiquidity and endogenous margins.[8] An alternative mechanism relates to market liquidity impacting capital gains on the arbitrageurs' existing positions but also their rebalancing decisions. On one hand, market illiquidity reduces the arbitrageurs' capital gain, which tightens their financial constraint. On the other hand, it reduces the maximum loss the position can experience in the subsequent period, which relaxes the financial constraint. In Gromb and Vayanos (2010), the mispricing wedge is a present value of future expected excess returns that are equalized across markets in equilibrium, and thus depends on sources of asset volatility. It is worth noticing that both Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2010) suggest that financial intermediaries may either play a stabilizing role ($\alpha < 0$) or a destabilizing role ($\alpha > 0$) depending on the equilibrium selected or on parameters' values.

Several studies have taken a specific stance and estimated a one-way causality relationship summarized by the parameter β usually found different from zero and statistically significant at conventional level. A few other studies have incidentally noted that α may also be different

[6] We will discuss the relaxation of this assumption later in the text below.

[7] See Proposition 1 in Brunnermeier and Pedersen (2009), p. 2211, or Proposition 1 in Gromb and Vayanos (2010), p. 462.

[8] See equation (14) and Propositions 2,3 in Brunnermeier and Pedersen (2009).

from zero. However, existing studies did not explicitly take into account the joint and contemporaneous relationship between the two dimensions of illiquidity and their natural endogeneity. 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 illiquidity and their covariance), but four parameters have to be estimated (namely α, β, and two variances).

Rigobon (2003) suggests that if the variance of the structural shocks is subject to regimes, then the identification problem can be solved.[9] This identification procedure can be intuitively explained in light of the simple model (1)-(2). Assume for simplicity that the variance of ϵ-shocks is constant while the variance of η-shocks is subject to two regimes, namely high or low. If the structural parameters α and β are stable across regimes, then the covariance matrix of the reduced form, as it is regime-specific, will provide six moments (three per regime) for six parameters to be estimated (namely α, β, and four variances), which solves the identification problem. The estimation of the two structural parameters assumes that the relative variances of market and funding illiquidity shocks change over time. Consider the second regime in which the variance of funding illiquidity shocks is high. 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. βf_t).[10] 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

[9]ITH is not the only solution to the identification problem highlighted above. In fact, the parameters 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 Chapter 14 in Kilian and Lütkepohl (2017) and the references therein.

[10]A quasi-natural experiment (such as Jylhä (2017)) would use an exogenous shock on funding constraints to identify the impact on market illiquidity; intuitively, our approach relies on *probabilistic* shocks rather than on a one-shot event.

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:

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

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 in the Internet Appendix 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:

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

In our empirical investigation we follow Rigobon and Sack (2003) and use an extended model that accounts for additional control variables that proxy for factors that may affect the dynamics of both dimensions of illiquidity, that is,

$$m_t = \beta f_t + \theta x_t + \epsilon_t, \qquad (4)$$

$$f_t = \alpha m_t + \phi x_t + \eta_t, \qquad (5)$$

where x_t is a vector of exogenous variables.[11]

The extended model relies on three key assumptions. First, ITH relies on a shift in the relative variances of the shocks across regimes. It thus requires any form of heteroskedasticity in the data, that may come for instance from economic events, policy shifts. ITH fails if the two covariance matrices are proportional, i.e. the relative variances are constant across

[11] See also Appendix 2 in the Internet Appendix for further details.

regimes. However, it is important to note that if the heteroskedasticity is misspecified in this model, the coefficients are still consistent (Rigobon (2003), Section IV). Furthemore, ITH does not require the volatility regimes to be identified optimally (e.g., by identifying structural breaks). It only requires sufficient heteroskedasticity to define at least two regimes in which the variances of the residuals are different.

Second, the parameters α and β are assumed to be time invariant as the volatility of shocks changes. As this is an important assumption for the validity of the model, we discuss it further in Section 5.2.

Third, the structural ϵ- and η-shocks are not correlated. However, this assumption is relaxed by including common unobservable heteroskedastic shocks in the model (Rigobon, 2003, Section III). The drawback of this amendment is that one cannot fully characterize the parameter α. Instead, we can only obtain a convolution comprising the parameter of interest α together with the coefficient on the (unobserved) common shock in the market illiquidity equation.[12]

3.2 Empirical proxies

It is worthwhile noting that the existing literature uses various measures to capture different aspects of market and funding illiquidity across markets, that we present below. We acknowledge that the various measures only proxy illiquidity along one dimension and cannot perfectly reflect its multifaceted nature. In our empirical investigation, we report and discuss our baseline results both in terms of single representative measures of market and funding illiquidity and, in the spirit of Korajczyk and Sadka (2008), the first principal components computed across the pool of all empirical proxies discussed in this Section. All our variables are observed or computed at the weekly frequency.

[12]Full details of this alternative estimation are discussed in Section 5.2.

3.2.1 Market illiquidity measures

We consider four alternative variables to measure market illiquidity. First, for each bond j in our sample, we use intraday quote data to compute the average daily relative quoted bid-ask spread defined 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 d indexes the day, 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.[13]

Second, we 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:

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

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. Both measures are then averaged at the weekly level as follows:

$$\begin{aligned} BAS_t^j &= \frac{1}{D(t)} \sum_{d=1}^{D(t)} BAS_d^j, \\ EBAS_t^j &= \frac{1}{D(t)} \sum_{d=1}^{D(t)} EBAS_d^j. \end{aligned}$$

where $D(t)$ is the number of trading days in week t. Effective spreads abstract from intraday patterns and successfully capture the (indirect) cost of an aggressive transaction, whatever its size, which indirectly accounts for market depth. Besides, they better capture the fact that traders strategically trade when spreads are low, which is particularly important in

[13]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).

markets where there are only few trades a day. We therefore use this variable $EBAS$ as our proxy for market illiquidity when focusing on single measures of illiquidity.

Third, while the spread measures matter for brokers and investors, they may not perfectly reflect the capacity of the market to absorb orders without moving prices. We therefore use a measure of the "price impact" of transactions, in the spirit of Kyle's lambda, measured as in Hasbrouck (1991) using the following Vector Autoregressive (VAR) for each bond j:

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

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. We use the intraday time series of transactions data over a one week period to estimate the coefficients on a weekly basis.[14]

Fourth, another conventional empirical proxy for market illiquidity used in asset pricing studies 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

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

can induce a large price change. The ILLIQ measure uses more aggregated information than the three measures defined above (namely, daily rather than intradaily) and may be less affected by microstructure noise.[15]

3.2.2 Funding illiquidity measures

We consider four alternative variables to capture funding illiquidity conditions in the European Treasury bond market. The first three are spreads between money market rates with the maturity of one week, using the Euro interbank offered rate (Euribor), the overnight index swap rate (OIS), the repo rate (Eurepo), and the main refinancing operation rate (MRO).

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. Our first proxy for funding illiquidity, the Euribor-OIS spread, thus reflects the state of credit and funding conditions in the interbank market. Recent findings suggest that liquidity conditions, not credit conditions, are the main drivers of short-term interbank spreads (Schwartz (2017)). We therefore use this variable as our proxy for funding illiquidity when focusing on single measures of illiquidity.

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

[15] Amihud (2002) uses daily data over a period of one year to calculate an ILLIQ measure for an asset in a given month. The existence of a small number of extremely large values may raise concerns (see Bali, Engle, and Murray (2016)). As a preliminary check, we first removed for all bonds any observations lying beyond two standard deviations from their mean before computing the ILLIQ measure. The correlation between the ILLIQ series with and without outliers over our sample period is equal to 0.91 and statistically significant.

collateral in the transaction. Our second proxy for funding illiquidity, the Euribor spread over the Eurepo, thus captures the state of funding conditions for *unsecured* relative to *secured* money market transactions in the euro area. This measure may complement the Euribor-OIS spread by accounting for changes in funding conditions independently of a higher risk aversion, a higher preference for cash or a greater uncertainty in the collateral value, which are associated with a higher repo spread (as indicated by Hördahl and King (2008)).[16]

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. 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). Using proprietary data on individual demands by financial institutions during the ECB auctions between June 2005 and October 2008, Drehman and Nikolaou (2013) 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. Our third measure of funding illiquidity is the difference between the average main refinancing operation (MRO) rate and the OIS rate.

Finally, the last funding illiquidity measure we considered is not directly obtained from money market spreads but has been associated with funding conditions in the US Treasury market, namely the noise measure introduced by Hu et al. (2013).[17] This measure is based on the assumption that the availability of capital allows traders to engage in arbitrage activities

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

[17] It is instructive to note that most of the existing literature aiming at measuring funding illiquidity relies on empirical proxies based on interest rates. A related strand of literature has extensively documented the role of interest rates, especially their variation due to monetary policy actions, on asset prices. As asset prices are a crucial channel through which illiquidity spirals develop, the use of these empirical proxies for funding illiquidity based on interest rates may generate an additional layer of endogeneity when trying to disentangle the dynamics relationship between funding and market illiquidity. Although we think this issue is important and deserve an adequate investigation, we leave it as an avenue to pursue in future research.

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.[18,19]

4 Data and institutional details

In this section, we first present the data and the descriptive statistics of the various illiquidity measures. Prior to estimating the reduced-form model and adopt the identification methodology discussed in Section 3.1, we formally test that time series of the variables of interest are indeed subject to heteroskedasticity and introduce our volatility regimes. We finally explore the dynamic relationship between funding and market illiquidity using this

[18]As Hu et al. (2013) show that their main results are not specific to a particular curve-fitting method employed, we chose to adopt a Nelson and Siegel (1987) methodology.

[19]In a previous draft of this study, we have included Fontaine and Garcia (2012)'s measure that is based on the interest rate differential between on-the-run / off-the-run bonds with similar maturities. However, since most Treasury agencies in Europe use re-openings to provide markets with a supply of off-the-run treasury securities, this measure may not be a suitable proxy for funding illiquidity in Europe. Nonetheless, the baseline results computed by including the Fontaine and Garcia (2012)'s measure are not very different from the baseline results reported in Section 5 and they are available from the authors upon request.

framework.

4.1 European government bond markets and the trading environment

Our study examines bonds issued by the 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.[20] Similarly to Beber, Brandt, and Kavajecz (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).[21]

The European Treasury bond markets combine electronic trading with dealer markets, where investment banks commit their own capital and provide liquidity to facilitate trading. This European government dealer bond market is reputed transparent *ex ante* (with dealers advertising the prices at which they are prepared to trade), but not *ex post*.[22] In particular, closing prices are available through data vendors but there is little to none information about trading volumes, even aggregated at a yearly frequency. The bond market data used in this study is from MTS Data, a product of MTS that is the most important electronic platform for euro-denominated government bonds. The MTS Data database has been analyzed in previous studies (see for instance Beber et al. (2009); Dufour and Nguyen (2012); Pelizzon et al. (2016)). Due to the lack of transparency on the OTC trades, it is however impossible to precisely quantify the market share of MTS relative to other dealer trading. Public reports available online suggest that roughly half of the trading would be electronic and half OTC

[20] 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. Those two countries are thus not part of our analysis.

[21] 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.

[22] 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.

over our sample period.[23]

Our data consists of local MTS and a centralized EuroMTS. Persaud (2006) reports that the MTS platforms jointly cover just over 70% of the overall electronic trading of European government bonds around the sample period used in the empirical investigation. Anecdotal evidence suggests that most of the trading in the electronic secondary market takes place in the local MTS while the amount of trading occurring on the centralized European MTS does not exceed 5% of the total trading.[24] MTS is an inter-dealer, fully-electronic and quote-driven market characterized by a high degree of transparency.[25]

Intermediation in the secondary Treasury market is still almost exclusively provided by traditional bank dealers, with little involvement of non-bank market-makers.[26] Local banks are key financial intermediaries in the European Treasury bond markets.[27] There are two types of market participants on the MTS platform: "market makers" and "market takers." Market makers with specific market-making obligations 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 limit order book according to price-time priority rules and MTS publishes the best five quotes on either side of the book. Some participants (e.g. hedge funds) do not meet the requirements to be "market makers" and hence can only be eligible for a market taking status. MTS requires market takers to

[23] 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) (source:
https://www.greenwich.com/blog/electronic-trading-bonds-growing-%E2%80%93-sort-of%E2%80%A6. According to the European Securities Markets Expert Group (ESME) report published in 2006, around 50% of trading in government bonds was conducted over the telephone.

[24] 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).

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

[26] This contrasts with the situation in the U.S. where inter-dealer platforms have granted more lenient access to non-bank players, including PTFs (Principal Trading Firms), according to a report from the BIS (2016).

[27] Brutti and Sauré (2015) report that over our sample period, the percentage of public debt holdings by local banks relative to total bank-held debt of issuing countries varies from 40% to 75% during the crisis period for GIIPS countries, and remains stable at approximately 35% for other Euro Area countries.

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 MTS is one million euros. Executed trades are immediately and automatically reported.

4.2 Data and summary statistics

We first collect the daily trading summaries of all European Treasury bonds denominated in euros and with a maturity longer than one year that are traded in the platform EuroMTS provided by MTS Data. It involves the closing bond prices, yield, time to maturity, duration, the total trading volume as well as the number of market makers during the day of 452 bonds, traded both in Local MTS and in EuroMTS. Our sample period spans from October 1st, 2004 to February 28th, 2011.[28] Next, we define our volatility regimes based on the vStoxx index, depending on whether the value of the index falls below its mean minus one standard deviation ("low vStoxx" regime), is above its mean plus one standard deviation ("high vStoxx" regime), or in-between the two (intermediate regime). We then focus on bonds that are traded at least fifteen days in each of the three volatility regimes.[29]

Table 1 reports the descriptive statistics of the government bonds. Panel (a) describes the statistics by country (averaging measures per bond then country). We first collect some of the characteristics of each bond as it first appears in the sample, namely its yield, time to maturity, duration, coupon's rate and number of registered market makers. Statistics on the number of trades and trade size are computed over the whole sample period. Overall, we have 149 unique securities across the ten countries.[30] Bonds of most countries have an average

[28]Note that our sample period includes the recent 2008-2009 financial crisis but not the downgrade of Spain and Italy that took place on October 7, 2011.

[29]In the Internet Appendix, we identify the volatility regimes directly from the time-series data as a robustness check, defining the various regimes from the reduced-form residuals by computing rolling-window variances of 20-week worth of observations for each variable. The advantage of defining volatility regimes exogenously is that the regimes are the same for all bonds in our sample, which enables us to check that these bonds are traded in each regime.

[30]Our main analysis focuses on a subsample of 149 bonds that are traded in the platform EuroMTS at least fifteen days in each of our three volatility regimes. This restriction enables us to compare estimates of α_j and β_j in Section 5.3 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 the Internet Appendix, we check the

duration between seven and nine years. German bonds exhibit the lowest yields while those from Greece record the highest. Italian Treasury bonds have the highest trading volume. This may not be surprising since Mercato dei Titoli di Stato (MTS), the first venue for electronic trading of Treasury bonds, was initially launched in 1988 by the Italian Treasury and the Bank of Italy, before EuroMST began its expansion across Europe in 1997. Bonds from Belgium, Finland, Greece, Italy and Portugal exhibit a higher activity than bonds from other countries, measured in number of trades as well as in the number of participants. These countries have either bonds with lower maturities or large amounts of debt outstanding.[31]

Panel (b) provides statistics on the cross-section of the 149 individual bonds (averaging measures per bond first). Bonds in our sample are characterized by a large heterogeneity, with a time to maturity spanning from 3.02 to 30.09 years, or a number of trades per week spanning from almost 3 to 97. To further investigate the sources of heterogeneity, we report additional descriptive statistics on the bonds' characteristics. Haircuts required when the bond is used as a collateral are available for February 2011; our measure *Haircut* is computed as the average haircut per bond across time during this month.[32] Haircuts are usually set as a function of the time to maturity, the coupon's structure and the credit quality of the issuer. The *Credit Default Swap* captures the Credit quality of the issuer.[33] Finally, we introduce a proxy for the capacity of the sovereign bond to be used as a safe asset in a Flight to Quality episode. To this end, we first run individual bond regressions of the bond's weekly yield change on first difference of the average spread across the 5-year CDS contracts of all European countries (using data from Bloomberg). Our variable *Flight To Quality* is

robustness of our results to the sample of bonds, by estimating our model using an extended sample of 452 bonds traded in EuroMTS over the sample period.

[31]ECB (2007) mentions 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.

[32]Since April 2010, the list of eligible assets and associated haircuts can be obtained from the European Central Bank website https://www.ecb.europa.eu/paym/coll/assets/html/index.en.html.

[33]CDS data is obtained for each country from Bloomberg covering the period from Oct 1, 2004 to Feb 28, 2011.

defined as the slope coefficient of the regression.[34] A positive coefficient is usually expected: when the average credit quality decreases (i.e., when the CDS spreads increase), the bond's price decreases (i.e., its yield increases). A negative coefficient thus reveals that the bond is seen by investors as a safe-haven investment when there is a Flight to Quality episode. Accordingly, the dummy D_{FtoQ} that takes value one if *Flight to Quality* is negative, and zero otherwise. We find evidence of heterogeneity in haircuts (with an average haircut of 3.44%), and credit quality (with an average CDS od 27.65). Interestingly, we find that the average coefficient of the Flight to Quality regressions in our sample of bonds is negative and equal to -0.06, which confirms that sovereign bonds are traditionally viewed as safe-haven investments. This heterogeneity across individual bonds in terms of activity and credit risk is one of the key advantages of our dataset on European Treasury markets. We will further exploit this heterogeneity in the subsequent Section 5.3.

In our empirical investigation, our main measure of market illiquidity, the effective bid-ask spread, as well as two alternative proxies, namely the bid-ask spread and the price impact measures, are computed using intraday data. [35] We then construct the weekly time series for each bond in the sample. Overall, the dataset provides us with more than 500 million quote and trade observations (intraday) and 62,176 bond-weeks. Our last proxy, Amihud's ILLIQ measure, is constructed on a weekly basis from daily data.

Table 2 reports summary statistics of the market illiquidity measures discussed in Section 3. In Panel (a), we report the mean and standard deviation (in parenthesis) across bonds by country. Both spread measures seem to be in line, but they do not rank countries in terms of market illiquidity similarly as Amihud's and the price impact measures. This suggests that various measures may capture different aspects of market illiquidity. Quite intuitively,

[34]We thank Markus Brunnermeier for useful suggestions on this issue.

[35]In fact, the MTS Data database 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.

the effective spread seems to be higher for countries in which bonds that are characterized by a higher average yield, a longer average time to maturity, or a lower number of trades per week. Interestingly, having more market makers does not seem to be linked to lower market illiquidity. Panel (b) reports the statistics of the distribution of the cross-section of bonds. In line with arguments suggesting strategic order submission from market participants, effective spread are on average lower than quoted spreads. Note that spreads are measured in basis points: an average effective spread of 3.74bp on an average transaction size of 7.23 million euros corresponds to a transaction cost of $2,704$ euros. The large heterogeneity across bonds' liquidity measures in our sample echoes the heterogeneity on their characteristics documented in Table 1. Panel (c) reports correlations between the various illiquidity measures. In line with existing studies, all measures are found to be highly correlated. Amihud's illiquidity measure is less correlated with the other measures than any other pair, with correlation coefficients with the three other measures ranging from 0.64 to 0.66. Nonetheless, the correlations reported are large and economically significant. This suggests that our results should be robust to the choice of the market illiquidity measure.

We compute the money market spreads using data on OIS, Euribor and Repo rates from Thomson Reuters' *Datastream*. We use our dataset containing all bonds traded in EuroMTS to compute the Noise measure. Funding illiquidity measures are reported in Table 3, Panel (a) but only the first two measures can be directly compared. The Euribor-Repo 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 denoting some potential misspecification due to the estimation process and the variability of market interest rates. Panel (b) reports the correlation among all funding illiquidity measures. All variables are significantly correlated at 1% level. The correlation between the noise measure and the Euribor-OIS spread is small, but it is highly correlated with the MRO, i.e., the central bank rate spread.[36]

4.3 Systematic components of market and funding illiquidity

In this section we discuss the construction of the systematic measures of funding and market illiquidity, $FILLIQ$ and $MILLIQ$ henceforth, computed as the first principal component of the relative menu of empirical proxies from both panels of illiquidity measures defined as in Section 3.

First, the results reported in Table 4, Panel (a) suggest that the first principal component of both panels of measures is sufficient to capture 81 and 57 percent of the cross-sectional variability of the market and funding illiquidity measures, respectively. This result echoes the one reported in Korajczyk and Sadka (2008) where a single factor can sufficiently explain the variability of the cross-section of market liquidity proxies computed for individual equities. Our finding also suggests that there are stronger and significant commonalities driving the time-series variation of funding and market illiquidity proxies in the European Treasury bond markets. In Panel (b), we notice that the factor loadings of all individual measures on their first principal component are positive and in the interval $[0.40, 0.59]$. The second component of funding illiquidity seems to be linked to the MRO and Noise measures, while the second component of market liquidity seems mainly correlated with Amihud's ILLIQ measure.[37] Besides, correlations with the standard illiquidity measures reported in Panel (c) all stand within an interval $[0.60, 0.96]$. The Repo measure seems to be the most correlated with the FILLIQ measure (i.e., with correlation coefficient of 0.88), while the effective spread seems to be the most correlated with the MILLIQ measure (i.e., with a correlation coefficient of

[36] The time series of all funding illiquidity proxies, not reported to save space, show that all measures increase at the end of 2009. This is in line with the timing of European sovereign bond crisis. See the next Section 4.3 for a discussion of the time-series dynamics of the systematic component of funding illiquidity.

[37] The NOISE measure requires a curve-fitting method to compute the equilibrium values of bond yields. However, this preliminary step may cause the empirical proxy for funding illiquidity to be imprecisely estimated. As a simple check, we have computed the first principal component of funding illiquidity proxies with and without the NOISE measure and found that the correlation between the two resulting FILLIQ measures is 0.95 and statistically significant.

0.96).

5 Empirical Results

5.1 Baseline estimations

Figure 1 plots the time series of the market illiquidity measure in Panel (a), and of the funding illiquidity measure in Panel (b). It is worth noting that the estimated proxies for the two dimensions of liquidity are significantly correlated over time. In fact, the contemporaneous correlation between the systematic component of market and funding illiquidity is equal to 0.71 and is statistically significant at 1 percent level.[38] 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 in this section.

Prior to estimating the reduced-form model, we first formally test that the time-series of the variables of interest exhibit heteroskedasticity. To this aim we use the White and the Breusch-Pagan tests that are routinely used to assess the null hypothesis of homoskedasticity. 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, whatever the measure of liquidity considered. This evidence allows us to confidently use the procedure discussed in Section 3.1.

Table 5, Panel (b) reports the variances and covariances of the market and funding illiquidity measures in the three regimes. The "low vStoxx" regime (12.31% of our observations) is characterized by a low volatility of both illiquidity measures. The "high vStoxx" regime (10.77% of our observations) is characterized by a high volatility of both illiquidity measures. The intermediate regime is characterized by a high volatility of funding illiquidity (namely 0.38, relative to 0.03 in the low vStoxx regime) but a relatively low volatility of market

[38]Similar calculations for the measures BAS, EBAS, IMP and ILLIQ against FILLIQ record correlations equal to 0.71, 0.70, 0.63, and 0.64, respectively. Conversely, correlation coefficients computed for the Euribor-OIS spread, the Euribor-Repo spread, the MRO-OIS spread, and the noise measure against MILLIQ are equal to 0.40, 0.47, 0.78, and 0.72 respectively.

illiquidity (namely 0.26 relative to 0.09 in the low vStoxx regime). The variances of the innovations when market and funding illiquidity are proxied by the effective spread and the Euribor-OIS spread respectively, reported in the three rows below, are qualitatively similar. The three regimes exhibit sufficient variation in volatilities that is required to identify our parameters of interest. Figure 1 also plots the time series of the residuals of the funding and market illiquidity measures in the three different regimes. While the "high vStoxx" regime mainly corresponds to the peak of the financial crisis, observations in the two other regimes do not correspond to a specific time period.

We finally estimate the reduced-form model described by equations (4)-(5) in Section 3.1. The first two exogenous variables used to proxy for common factors affecting illiquidity, namely mutual funds' net in flows to Treasury bond portfolios and the variations in M2 money supply in the Euro area, capture 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 flows by net inflows in billion USD in government bonds with intermediate and long maturities for the European countries, from EFPR reports.[39] We control for volatility, measured by changes in the implied volatility obtained from stock market option prices in the euro-area (i.e the vStoxx index) since many market microstructure models suggest that volatility negatively impacts market liquidity (e.g., either due to inventory management or to adverse selection costs).[40] Finally, we also include an end-of-the-month dummy to control for the discrete variation of European repo rates during the last trading day of each month. This choice is due to the empirical observation of European banks that are required to report their positions to the European Central Bank on the last trading day of each month. To complete the set of exogenous variables we also include the

[39]For further details on EPFR, see Jotikasthira, Lundblad, and Ramadorai (2012). As the time series is reported at the monthly frequency, we use a linear interpolation to convert the variables to the weekly frequency. The data on variations in money supply M2 is obtained from ECB's monetary statistics.

[40]Theoretical models of liquidity formation also predict that volatility is a state variable affecting market illiquidity.

lagged values of the systematic funding and market illiquidity variables. [41]

The results are reported in Table 6. The first two columns report the results of the estimation using the systematic measures MILLIQ and FILLIQ, and the last two columns report those using EBAS and Euribor-OIS as individual measures of market and funding illiquidity. Contemporaneous shocks to funding illiquidity are found to significantly affect the average market illiquidity across all local European Treasury bond markets, i.e., $\beta > 0$. The reverse causality link also applies as contemporaneous shocks to our proxy of market illiquidity significantly and positively affect funding illiquidity in the European Treasury markets, i.e., $\alpha > 0$. Both effects are sizable and economically significant whether one considers the principal components or the direct proxies for illiquidity. When MILLIQ and FILLIQ are used, one standard deviation shock to funding illiquidity (i.e. tightening of funding constraints) generates a contemporaneous increase in market illiquidity of 0.151 standard deviation across Treasury bond markets in Europe. One standard deviation shock to MILLIQ generates a contemporaneous change of 0.080 standard deviation in FILLIQ. Using individual measures for market and funding illiquidity leads to similar patterns, although the parameter estimates are slightly smaller. One standard deviation increase of the Euribor-OIS spread (that is, an increment of 9.92 basis points in our sample period) generates a contemporaneous increment of 0.35 bps in effective bid-ask spreads across Treasury bond markets in Europe, which correspond to a deterioration of 9% relative to the average effective spread. A one standard deviation increase in effective bid-ask spreads (2.92 bp in our sample) generates a contemporaneous increment of the Euribor-OIS spread of 0.32 bps, which corresponds to an improvement of 5.2% relative to the average Euribor-OIS spread. These results document that there are indeed feedback effects between market and funding illiquidity as theory would predict, and that the magnitude of these effects is relatively large. However, both Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2010) are agnostic on the sign of the

[41] We include up to three lags of the illiquidity variables are suggested by the results of conventional Information Criteria tests.

feedback effect, predicting a stabilizing role of financial intermediaries or illiquidity spirals depending on the equilibrium or the model's parameters. Our results document that both β and α are positive, signs that are consistent with a "bad" equilibrium in which illiquidity measures are reinforcing each other.

Mutual funds' net inflows and an increase in M2 money supply significantly reduce market illiquidity. Both signs are consistent with the prediction that lower "macroeconomic" illiquidity decreases market illiquidity. Their impact on funding illiquidity is however not significant. This finding may seem counter-intuitive; it is however in line with Chordia et al. (2005), who show that those variables are responsible for the commonalities in market illiquidity measures. Stock market volatility (vStoxx) is positively and significantly related to bond market illiquidity but not to funding illiquidity. Consistent with much anecdotal evidence, we find that 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 illiquidity increases.

5.2 Assessing ITH main assumptions

The first key assumption for ITH to work is that parameters α and β are constant over time, which need not to hold in our context. For example, the impact of funding on market illiquidity or its feedback effect would be different in quiet and turbulent times. To assess the validity of this assumption, we split our sample into two subsamples around Lehman Brother's bankruptcy in the fall of 2008, and we re-estimate the model on each of these subsamples.[42] Table 7 reports the results. We observe that the estimates of both parameters of interest (α and β) are quite similar both economically and statistically before and during the financial crisis, except for the market to funding coefficient (α) computed using the individual measures of market and funding illiquidity (namely the effective spread and the

[42]For brevity we report the details of the characteristics of these two subsamples and descriptive statistics on the liquidity measures or on volatility regimes by period in the Internet Appendix.

Euribor-OIS spread) that is not significant at the 10% level during the crisis. This difference may be due to the fact that the European Central Bank reacted to the worsening of conditions in financial markets and to the breakdown of the interbank market in September 2008 by providing enhanced credit support. In particular, the set of eligible collaterals accepted by the ECB which used to be limited to high-quality assets, such as government bonds, covered bonds and some asset-backed securities with some minimum rating, was extended. This in turn may have mitigated the impact of market illiquidity on financial institutions' funding constraints, which may explain our finding. This is in line with Aggarwal, Bai, and Laeven (2016) which documents that central bank purchases of low-quality bonds mitigated disruptions in short-term funding markets by reducing lending fees of these lower quality bonds during periods of market stress.[43]

Furthermore, we formally investigate the stability of the parameter estimates by using a test based on quintile regressions, as suggested in Rigobon (2016). The test is based on the idea that the instability of the parameters would generate non-linearity in the parameter estimates. In that case, the parameter estimates should be different across quintiles. Table 8 presents the test for stability across quintile in the relation between the market illiquidity of bond j and the funding illiquidity. p-values indicate that we cannot reject the equality of the median and respectively the 70%, 80% and 95% quintiles at the 10% level. Overall, the evidence reported in both Table 7 and Table 8 suggests that the parameters' stability should not be a major concern when interpreting our findings.[44]

The second key ITH assumption is that the structural shocks in the system of equation

[43] It is also worth noting that the impact of the variation in M2 money supply and of mutual fund flows on market illiquidity varies before and after the crisis: while the former significantly reduces illiquidity before the crisis but has no impact during the crisis, the latter reduces market illiquidity during the crisis but not before.

[44] As an additional robustness check, not reported to save space but available upon request, we have also run a battery of conventional structural stability tests on the residuals from the estimated model. These tests assess indirectly whether any structural instability in the parameters, not accounted for in the main model, is transferred to the model's residuals. In all cases, at conventional levels, we do not reject the null of parameter instability. This provides additional support for the validity of the assumption necessary to for the correct identification of the parameters of interest.

(4)-(5) are not correlated. We assess the relevance of this assumption by estimating an alternative model, based on Rigobon and Sack (2003), where an unobservable common shock is included. As highlighted in Rigobon (2003) this amendment is equivalent to relaxing the assumption on the correlation of the structural shocks. This however comes at a cost, as the extended model does not allow to identify α and β. 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 associated with the unobserved variable. Table 9 reports the estimates of this model, for both the subsample of 149 bonds and the full sample and for both approaches to measuring market and funding illiquidity. In all cases, the responses of funding to and from market illiquidity exhibit the same sign of those reported in the baseline estimations and they are statistically significant at conventional level.

5.3 Bond characteristics and illiquidity responses: a cross-sectional analysis

The results reported in Table 6 provide empirical evidence that, after controlling for endogeneity, funding illiquidity positively affects market illiquidity, and vice-versa. In this section, we take advantage of the existence of heterogeneity across maturities and across credit risk in our sample of bonds, as well as the heterogeneity across market participants in different countries, to analyze the main factors impacting the strength of the relationships between funding and market illiquidity and shed some light on the mechanism(s) governing them.

To this end, and for consistency with the results reported in Section 5.1, we define two measures of market illiquidity for each bond, namely a direct one, and a first principal component. We use the effective bid-ask spread $EBAS_{j,t}$ that we have computed for each individual bond j, and its mean $EBAS_j$. The first measure, $SEBAS_{j,t}$, is a time-series demeaned EBAS for each bond and defined as follows:[45]

$$SEBAS_{j,t} = EBAS_{j,t} - EBAS_j.$$

Hence, by construction it does not distinguish between the systematic and the idiosyncratic components of market illiquidity for each bond market. We construct another measure of individual bond market illiquidity based on $MILLIQ_t$ defined as in Section 4.3. More specifically, for each bond j, we compute $MILLIQ_{j,t}$ as the first principal component of the four proxies of market illiquidity, namely the bid-ask spread, the effective spread, the price impact and Amihud's illiquidity, measured at the individual bond level. The measure is then computed as:

$$IdioMILLIQ_{j,t} = MILLIQ_{j,t} - MILLIQ_t.$$

$IdioMILLIQ_{j,t}$ can be interpreted as the idiosyncratic market illiquidity component for each bond j as it is computed as the difference between an individual bond's measure of market illiquidity and its systematic, or market-wide, component.

We use the two variables to carry out the estimations in the reduced-form model used in Section 5.1. We estimate the same specification that includes lags of illiquidity variables and the set of control variables. This exercise provides us with a cross-sectional panel of contemporaneous coefficients (α_j, β_j). Table 10, Panel (a) reports statistics on the distribution of these coefficients. Using the $IdioMILLIQ_j$ idiosyncratic measure, the average of individual β_j's is much smaller than the estimate of β in Section 5.1. This result suggests that funding illiquidity mainly affects the systematic component of market illiquidity, $MILLIQ$, rather than the idiosyncratic illiquidity of each bond.[46]

The estimates of (α_j, β_j) are then used to identify their determinants in the cross section

[45] The demeaning is carried out for consistency with the construction of the second measure and to allow for a suitable comparison.

[46] Note also that we do not necessarily expect a significantly positive average α when considering the idiosyncratic component of market liquidity as we are mainly interested in the factors that can explain its cross-sectional variation.

of bonds. To this end, we run the following regression on the panel of bonds:

$$Y_j = a_0 + \Sigma_k a_k X_{k,j} + \varepsilon_j, \tag{6}$$

where $Y_j = (\alpha_j, \beta_j)$ and $X_{k,j}$ is a vector of individual bond's characteristics. We choose characteristics using the insights from the theoretical literature. According to Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2010), when funding constraints increase, traders become reluctant to take on positions, especially positions in assets which require high margins or more collateral. We therefore use haircuts in our regression (1). However, as described in Section 4.2, we only have data on haircuts data for February 2011 and only for the bonds that were not close to maturity during that month. Besides, since haircuts are determined based on the risk and maturity of assets, significantly correlated with other variables such as CDS (with a correlation coefficient of 0.6). In our regression (2) we therefore include as explanatory variable the credit risk of the issuer as a proxy for fundamental risk, measured by the *CDS* of the country, and we expect this variable to positively impact the parameter β_j. Gromb and Vayanos (2018) uncover another channel for long-term securities, for which asset returns are more sensitive to capital (i.e., they have a high "arbitrage-capital beta"). We thus include the time to maturity in our regression, and we also expect a positive coefficient. Besides, Gromb and Vayanos (2018) show that when markets are segmented, arbitrageurs cut their positions more in trades involving more risky assets, except when volatility concerns the hedgeable component. To capture this idea of segmentation, we compute the number of bonds that are available in each country in our sample: the higher the number of bonds, the less segmented is the market, and the better arbitrageurs may hedge. We expect the number of available bonds to negatively impact the sensitivity of funding on market illiquidity. Finally, Brunnermeier and Pedersen (2009) suggest that if investors anticipate that some risky high-margin securities would have more liquidity risk, the liquidity differential between high-volatility and low-volatility securities may increase in bad times. In our regression (3), we thus use the exposure of securities to Flight to Quality, $F-to-Q$, that is negative when the bond is perceived as safer by the investors. We expect the parameter estimate associated with the dummy variable to be positive.

The drivers of the responses of funding illiquidity to market illiquidity shocks, α_j are less easy to identify from the literature. We thus use the same explanatory variables as in the regressions of β_j. In the spirit of Brunnermeier and Pedersen (2009) or Gromb and Vayanos (2018), if the feedback effect from market to funding illiquidity is due to the use of securities as collaterals, it should be more severe for securities that do not use much capital, i.e., that have a low haircut, low risk or shorter maturity. We expect the parameters for the cross-section of α_j associated with haircut, time to maturity and CDS spreads to be all negative.

The results of the cross-sectional regressions are reported in Table 10, Panels (b) and (c). As expected, the impact of funding liquidity on market illiquidity β_j significantly increases with the bond's haircut, with credit risk, with time to maturity. Interestingly, it decreases significantly when the country issues more bonds or when bonds are perceived as safer assets. Overall, the market illiquidity of the bonds that are less liquid or perceived as such, or that have less substitutes, is more affected by variations in funding illiquidity, in line with theory.

By contrast, all our explanatory variables have an opposite effect, though not always significant, on the cross-section of α_j. In particular, we find that α's significantly decrease with haircut; our alphas computed using direct proxies also significantly decrease with time to maturity, and the issuer's credit risk. This is consistent with the fact that these bonds that have a higher haircut, longer time to maturity or credit risk are probably used less frequently as collateral, so that variations in market illiquidity for the latter impact less funding illiquidity. Interestingly, bonds that are viewed as safe in Flight To Quality episodes soften the magnitude of the effect of market illiquidity on funding illiquidity.[47]

[47]We have also carried out our estimations correcting the standard errors for the fact that the dependent variables in the cross-sectional regressions are estimated. The results, not reported to save space, are in line

6 Conclusions

This study explores the dynamics between market and funding illiquidity by taking into account the multifaceted nature of illiquidity and the natural endogeneity occurring between the two aspects of illiquidity. Using an identification technique based on the heteroskedasticity of illiquidity measures on data for the European Treasury bond market, we corroborate the existing evidence that shocks to funding constraints affect bond market illiquidity. However, we also document the existence of a positive and significant feedback effect between market and funding illiquidity shocks suggesting that market illiquidity shocks tighten funding constraints. We exploit the heterogeneity of our sample of bonds, characterized by different maturities and default risk, to investigate the determinants of the magnitude of these effects in the cross-section. We find that the market-to-funding illiquidity effect is stronger for short-term bonds and for bonds used as collaterals in repo transactions. Our results are robust to alternative definitions of the volatility regimes, alternative samples of bonds, and alternative model specifications.

Taken together, our findings suggests the presence of destabilizing liquidity spirals. As shown by Brunnermeier and Pedersen (2009), central banks can help mitigate market liquidity problems in such equilibria by boosting speculators' funding conditions during a liquidity crisis. In addition, our results have also important implications for the literature on the asset pricing effects of liquidity. In fact, in light of the evidence reported in our study, it is important to consider both market and funding illiquidity shocks when assessing the effects of liquidity shocks on asset pricing. Moreover, it is also plausible to hypothesize that funding illiquidity shocks may exert even stronger effects on asset prices than market illiquidity shocks.[48]

with the ones reported in Table 10.

[48]In a set of preliminary results for a companion research work, we find evidence of this pecking order when our illiquidity measures are used in an cross-sectional asset pricing exercise based on the same panel of government bond securities.

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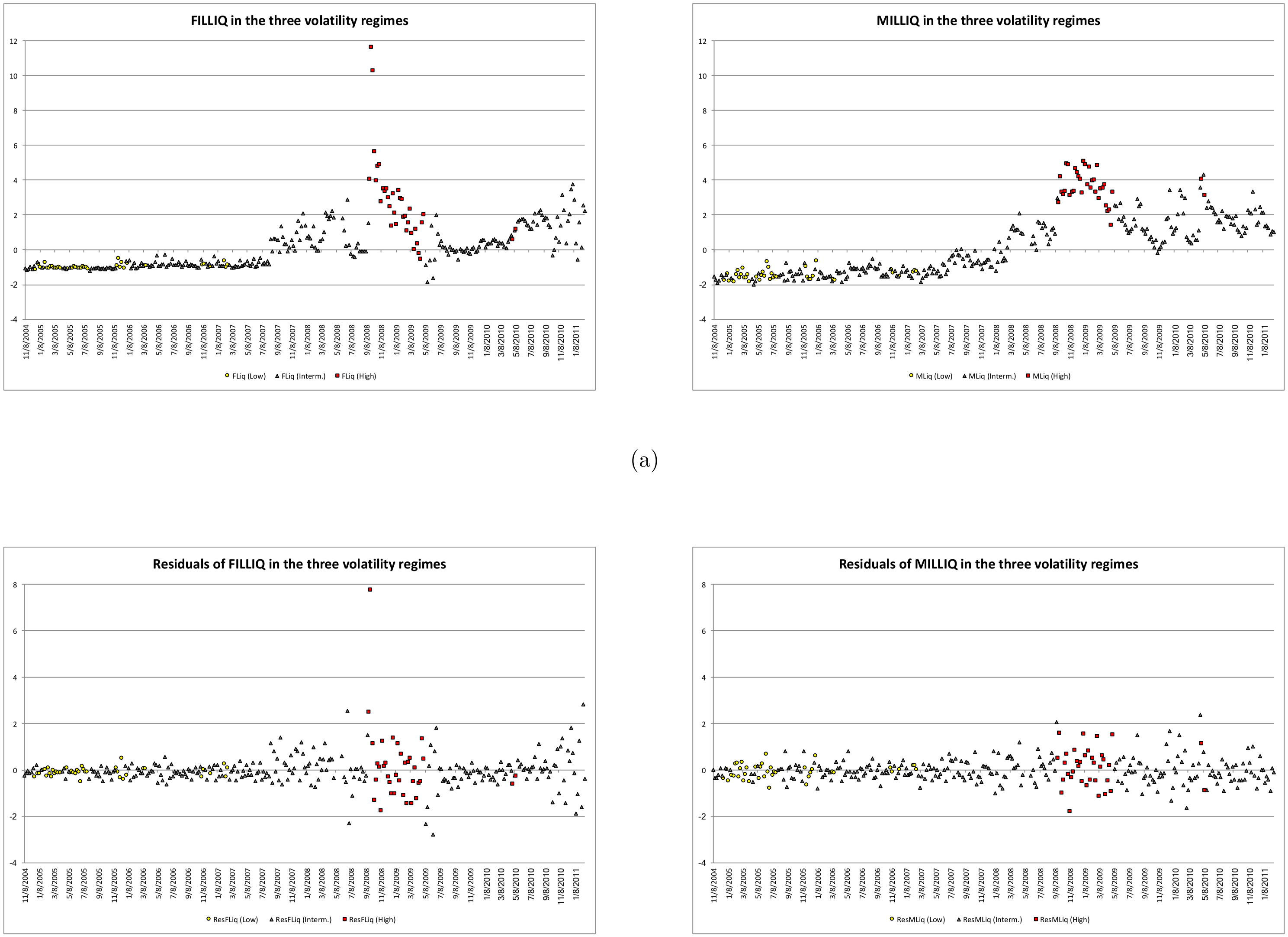

(b)

Figure 1: This Figure plots the time series of the market liquidity measure, MILLIQ and of the funding liquidity measure, FILLIQ, in Panel (a). Both measures are computed as the first principal component of a panel of liquidity proxies as defined in Section 3. Panel (b) corresponds to the times series of the residuals of FILLIQ and MILLIQ equations. Circles, triangles and squares respectively represent observations in the low, intermediate and high volatility regimes.

Table 1: **Descriptive statistics**

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 3 volatility regimes. Panel (a) reports the country average statistics, and Panel (b) reports statistics on the cross-section of bonds. In the tables, *No.* denotes the total number of bonds for each country, *Yield* is the end-of-day miquote bond yield (in percentage),*Mat.* is the time to maturity (in years), *Duration* is the bond duration (in years), *Coupon* is the coupon rate (in %), *No. MM* is the number of market makers 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 mio euros over the whole period. In Panel (b), we additionally report statistics on the bond's *Haircut*, the CDS of the bond, a proxy for *Flight to Quality* defined as the coefficient of the bond's yield change regressed on the first difference of the average spread across the 5-year CDS contracts across countries (from Bloomberg), and a dummy D_{FtoQ} that takes value one if Flight to Quality is negative, and zero otherwise.

Statistics by country

(a)

Country	**No.**	**Yield**	**Mat.**	**Duration**	**Coupon**	**No. MM**	**Trades**	**Size**
Austria	10	3.84	12.77	9.27	4.41	22	6	7.88
Belgium	12	3.71	13.11	9.12	4.61	29	16	8.00
Finland	5	3.42	8.80	7.23	4.70	29	14	9.43
France	28	3.54	12.60	8.70	4.63	20	8	7.01
Germany	23	3.45	10.86	7.88	4.20	20	9	6.91
Greece	14	4.11	9.98	7.49	4.91	27	17	7.57
Italy	29	3.96	13.88	8.91	2.35	40	55	5.21
Netherlands	11	3.55	11.86	8.50	4.59	25	7	8.49
Portugal	5	3.79	9.37	7.58	4.11	23	24	9.11
Spain	12	3.71	11.13	8.03	4.60	29	13	8.78

Cross-sectional statistics

(b)

	Mean	Median	Std	Min	Max
No.			149		
Yield	3.71	3.64	0.47	2.43	4.85
Mat.	11.98	10.13	6.76	3.02	30.09
Duration	8.41	8.14	2.98	2.74	16.92
Coupon	4.11	4.00	1.36	1.38	8.50
No. MM	27	24	15	8	76
Trades	20	11	21	3	97
Size	7.23	7.44	1.91	3.00	10.15
Haircut	3.44	3.00	2.22	0.50	10.50
CDS	27.65	21.12	18.11	4.82	89.67
Flight to quality	-0.06	-0.04	0.11	-1.11	0.04
D_{FtoQ}	0.93	1	0.26	0	1

Table 2: **Statistics of market illiquidity**

The table reports the summary statistics of market illiquidity variables across European Treasury 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. Market illiquidity variables include the the effective spread (EBAS, in bp), bid-ask spread (BAS, in bp), price-impact (IMP) and Amihud's ILLIQ measure. The definition of all measures is discussed in Section 3. The market illiquidity 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 illiquidity measures.

Descriptive statistics of market illiquidity variables by country

(a)

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

Cross-sectional statistics of market illiquidity variables

(b)

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

Correlations of market illiquidity measures

(c)

	Market Illiquidity Measure			
Variables	**EBAS**	**BAS**	**IMP**	**ILLIQ**
EBAS	1	0.92	0.85	0.66
BAS		1	0.75	0.64
IMP			1	0.63
ILLIQ				1

Table 3: **Statistics of funding illiquidity**

Panel (a) reports the summary statistics of European funding illiquidity variables from Oct 1, 2004 to Feb 28, 2011. Funding illiquidity variables include the spreads (in basis points) of the Euribor over the overnight-index-swap (OIS) rate (Euribor), of the Euribor over the General Collateral Repo (Repo), of the ECB's over Main-Refinancing Operation Rates over the OIS (MRO), and the Hu, Pan and Wang (2013) measure of noise. The definition of all measures is discussed in Section 3. The funding illiquidity 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 illiquidity measures.

Descriptive statistics on Funding Illiquidity measures

(a)

	Funding Liquidity Measure			
	Euribor	**Repo**	**MRO**	**Noise**
Mean	6.07	6.36	18.16	0.19
Median	2.80	3.20	2.15	0.03
Std Dev	9.92	9.34	26.00	0.22
Min	-17.00	-7.50	-8.50	0.03
Max	98.90	85.00	111.00	1.02
AC(1)	0.75	0.86	0.94	0.92

Correlations of funding illiquidity measures

(b)

	Funding Illiquidity Measures			
Variables	**Euribor**	**Repo**	**MRO**	**Noise**
Euribor	1	0.94	0.24	0.14
Repo		1	0.29	0.28
MRO			1	0.64
Noise				1

Table 4: **Principal Component Analysis**

Panel (a) reports the results from the principal component analysis of funding and market illiquidity variables. FILLIQ is the first principal component of the changes in the four funding illiquidity variables. MILLIQ denotes the first principal component of the changes in the four market illiquidity variables. Panel (b) reports the factor weights in the PCA decomposition. Panel (c) reports the correlations of the FILLIQ and MILLIQ measures with the standard illiquidity measures defined in Section 3.

Principal component analysis of funding and market illiquidity variables

(a)

	Funding Illiquidity Measures			**Market Illiquidity Measures**		
	Eigenvalue	Proportion	Cumulative	Eigenvalue	Proportion	Cumulative
PC1	2.28	0.57	0.57	3.25	0.81	0.81
PC2	1.30	0.33	0.90	0.44	0.11	0.92
PC3	0.36	0.09	0.99	0.26	0.06	0.99

Principal component analysis - Factor weights

(b)

	Funding Illiquidity Measures				**Market Illiquidity Measures**			
	Euribor	**Repo**	**MRO**	**Noise**	**EBAS**	**BAS**	**IMP**	**ILLIQ**
PC1	0.55	0.59	0.43	0.40	0.53	0.51	0.50	0.45
PC2	-0.46	-0.37	0.54	0.60	-0.28	-0.26	-0.22	0.89
PC3	-0.07	0.13	-0.72	0.68	-0.15	-0.60	0.79	-0.02

Contemporaneous Correlation Coefficients Across Illiquidity Measures

(c)

	Funding Illiquidity Measures				**Market Illiquidity Measures**			
Correlation	**Euribor**	**Repo**	**MRO**	**Noise**	**EBAS**	**BAS**	**IMP**	**ILLIQ**
FILLIQ	0.84	0.88	0.65	0.60				
MILLIQ					0.96	0.93	0.90	0.80

Table 5: **Volatility regimes**

Panel (a) reports the results from the White and the Breusch-Pagan heteroskedasticity test for funding and market illiquidity variables over the sample period from Oct 1, 2004 to Feb 28, 2011. The first two columns correspond to funding and market illiquidity defined as the principal component of a panel of empirical proxies. FILLIQ is the first principal component of the changes in the four funding illiquidity variables. MILLIQ denotes the first principal component of the changes in the four market illiquidity variables. The last two columns corresponds to measures of funding illiquidity and market illiquidity as respectively the Euribor-OIS spread and the effective bid-ask spread. From the vStoxx index, we classify three volatility regimes. Panel (b) reports the variances and covariances of the innovations in the market and funding illiquidity measures in the three regimes, for the systematic components and the single measures.

Tests for Heteroskedasticity

(a)

Variables	**FILLIQ**	**MILLIQ**	**Euribor**	**EBAS**
White Statistic	19.91	34.52	11.94	24.33
Breusch-Pagan Statistic	18.64	35.37	11.20	22.98

Variance-Covariance of the innovations under different regimes

(b)

Variables	**Low vStoxx**	**Interm. vStoxx**	**High vStoxx**
Variance of ϵ_{MILLIQ}	0.09	0.26	0.70
Variance of ϵ_{FILLIQ}	0.03	0.38	2.68
Covariance ϵ_{MILLIQ}, ϵ_{FILLIQ}	0.01	0.03	0.33
Variance of ϵ_{EBAS}	0.055	0.137	0.344
Variance of $\epsilon_{EURIBOR}$	0.028	0.311	2.104
Covariance ϵ_{EBAS}, $\epsilon_{EURIBOR}$	0.002	0.004	0.153
No. of obs.	40	250	35
Freq. of obs.	12.31%	76.92%	10.77%

Table 6: **Heteroskedasticity identification**

The table shows the coefficients and the t-values (in parentheses) of the parameters of the structural model based on Rigobon (2003). The first two columns correspond to funding and market illiquidity defined as the principal component of a panel of empirical proxies. FILLIQ is the first principal component of the changes in the four funding illiquidity variables. MILLIQ denotes the first principal component of the changes in the four market illiquidity variables. The last two columns corresponds to measures of funding illiquidity and market illiquidity as respectively the Euribor-OIS spread and the effective bid-ask spread. p-values are obtained from bootstrap with 1,000 replications. *** indicates that coefficients are significantly different from zero at the 1% level.

	First Principal Components		**Direct proxies**	
	MILLIQ	**FILLIQ**	**EBAS**	**Euribor**
β (funding to market)	0.151***		0.120***	
	(57.12)		(53.90)	
α (market to funding)		0.080***		0.033***
		(28.47)		(16.88)
Implied volatility (vStoxx)	0.016***	0.008	0.009***	−0.002
	(4.14)	(0.13)	(4.33)	(−0.46)
Variation in M2 money supply	−0.220***	−0.013	−0.131***	0.018
	(−4.06)	(−0.28)	(−4.06)	(0.34)
Mutual funds' flows	−0.380***	0.081	−0.012*	0.005
	(−2.55)	(0.29)	(−1.86)	(0.36)
End-of-month dummy	−0.023	0.250***	0.05	0.22***
	(-0.37)	(2.38)	(1.06)	(2.44)
market_{t-1}	0.574***	0.135*	0.518***	0.140
	(10.22)	(1.68)	(9.22)	(1.42)
market_{t-2}	0.197***	0.176*	0.182***	0.067
	(3.05)	(1.91)	(2.93)	(0.61)
market_{t-3}	−0.046	−0.230*	0.174***	−0.136
	(−0.71)	(-2.47)	(2.81)	(-1.24)
funding_{t-1}	0.061	0.810***	−0.009	0.634***
	(1.51)	(14.13)	(−0.29)	(11.23)
funding_{t-2}	−0.069	−0.243***	0.027	−0.008
	(−1.35)	(−3.33)	(0.71)	(−0.12)
funding_{t-3}	−0.043	0.181**	−0.036	0.136**
	(−0.83)	(2.46)	(−0.93)	(1.98)

Table 7: **Estimation before / during the financial crisis**

The table shows the coefficients and the t-values (in parentheses) of the parameters of the structural model based on Rigobon (2003). Panel (a) reports the results on the non-crisis period (from Oct 1, 2004 to Sept 30, 2008), while Panel (b) reports the results on the crisis period (from Oct 1, 2008 to Feb 28, 2011). The first two columns correspond to funding and market illiquidity defined as the principal component of a panel of empirical proxies. FILLIQ is the first principal component of the changes in the four funding illiquidity variables. MILLIQ denotes the first principal component of the changes in the four market illiquidity variables. The last two columns corresponds to measures of funding illiquidity and market illiquidity as respectively the Euribor-OIS spread and the effective bid-ask spread. p-values are obtained from bootstrap with 1,000 replications. *** indicates that coefficients are significantly different from zero at the 1% level.

Before the financial crisis (from Oct 1, 2004 to Sept 30, 2008)

(a)

	First Principal Components		**Direct proxies**	
	MILLIQ	**FILLIQ**	**EBAS**	**Euribor**
β (funding to market)	0.15***		0.056***	
	(27.66)		(28.21)	
α (market to funding)		0.10***		0.030***
		(35.61)		(8.63)
Implied volatility (vStoxx)	0.02***	0.01	0.008***	0.014***
	(3.06)	(0.11)	(2.18)	(2.32)
Variation in M2 money supply	−0.18***	−0.06	−0.083***	0.064
	(−2.61)	(−0.82)	(−2.21)	(−1.10)
Mutual funds' flows	−0.00	0.00	−0.002	0.003
	(−0.86)	(1.12)	(−0.33)	(1.22)
End-of-month dummy	−0.04	0.24***	0.022	0.054
	(-0.53)	(2.76)	(0.56)	(0.88)

During the financial crisis (from Oct 1, 2008 to Feb 28, 2011)

(b)

	First Principal Components		**Direct proxies**	
	MILLIQ	**FILLIQ**	**EBAS**	**Euribor**
β (funding to market)	0.16***		0.067***	
	(39.68)		(11.32)	
α (market to funding)		0.08***		0.020
		(13.48)		(1.62)
Implied volatility (vStoxx)	0.02***	0.01	0.010***	−0.009
	(2.93)	(1.99)	(1.98)	(−1.34)
Variation in M2 money supply	0.14	−0.57***	−0.006	0.199
	(0.63)	(−2.38)	(−0.03)	(0.85)
Mutual funds' flows	−0.01***	0.00	−0.007***	0.001
	(−2.38)	(0.12)	(−2.03)	(0.82)
End-of-month dummy	−0.00	0.27***	0.110	0.354***
	(0.02)	(1.76)	(0.88)	(2.17)

Table 8: **Parameter stability and quantile regressions**

The table reports the p-values of the null-hypothesis $H_0 : \phi_m = \phi_q$ computed by estimating quantile regressions. $\phi = \alpha, \beta$ as in equations (1) and (2) of the main text and m, q are the median and q-percentile, respectively.

H_0:	$\phi_m = \phi_{0.7}$	$\phi_m = \phi_{0.8}$	$\phi_m = \phi_{0.95}$
First principal components			
funding to market (β)	0.60	0.12	0.88
market to funding (α)	0.99	0.93	0.75
Direct measures			
funding to market (β)	0.85	0.14	0.46
market to funding (α)	0.58	0.97	0.54

Table 9: **Rigobon and Sack (2003)'s identification**

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 characterization of the alpha parameter. Instead, we obtain theta = (1+alpha*gamma)/(beta+gamma). Values in parenthesis denote the t-values obtained by bootstrapping with 1,000 replications. *** indicates that coefficients are significantly different from zero at the 1% level.

Variables	**MILLIQ**		**FILLIQ**	
First Principal components				
beta	0.164***	(19.70)		
theta			0.223***	(14.89)
Direct proxies				
beta	0.182***	(14.70)		
theta			0.167***	(15.64)

Table 10: **Bond-by-bond estimations**

The table reports the coefficients (and t-statistics in brackets) of the analysis at the individual bond level. We estimate α and β in the Reduced-form model (3). In each panel, the first columns correspond to estimates α^{FPC} and β^{FPC} defining funding and market illiquidity as the principal components of a panel of empirical proxies. FILLIQ is the first principal component of the changes in the four funding illiquidity variables. The idiosyncratic market illiquidity measure $IdioMILLIQ_j$ is defined as the difference between the individual market illiquidity measure $MILLIQ_j$ computed as the first principal component across market illiquidity measures for bond j, and the systematic market illiquidity measure $MILLIQ$ defined in Section 3. The last columns corresponds to estimates α^{IND} and β^{IND} defining funding illiquidity and market illiquidity as individual measures, that is respectively the Euribor-OIS spread and the effective bid-ask spread. The idiosyncratic market illiquidity measure $SEBAS_j$ is defined as the difference between the individual market illiquidity measure $EBAS_{j,t}$, and its average $EBAS_j$. Panel (a) reports the cross-sectional statistics of the estimates of α_j and β_j. Panels (b) and (c) report the estimates of the cross-sectional regression (1): $Y_j = a_0 + \Sigma_k a_k X_{k,j} + \varepsilon_j$, where $X_{k,j}$ are bond-specific Haircuts, CDS, Years-to-maturity, the number of bonds traded in the Country, and Flight-to-Quality is defined in Section 4.2. *** (resp. **, *) indicates that coefficients are significantly different from zero at the 1% level (resp. 5% level, 10% level.)

Bond-by-bond estimations

(a)

	β^{FPC}	α^{FPC}	β^{IND}	α^{IND}
No Bonds		149		
Mean	0.08	0.03	0.15	0.02
Std	0.19	0.16	0.38	0.53
Min	−0.41	−0.66	−0.75	−1.47
Max	0.59	0.42	0.99	1.52

Explaining exposure to funding illiquidity (β) in the cross-section of bonds

(b)

	First Principal Comp. β^{FPC}					Direct proxies β^{IND}				
	(1)	**(2a)**	**(2b)**	**(2c)**	**(3)**	**(1)**	**(2a)**	**(2b)**	**(2c)**	**(3)**
Intercept	−0.051*	0.029	−0.068*	−0.003	0.109***	−0.124**	−0.125***	−0.251***	−0.257***	0.214***
	(−1.82)	(1.26)	(−1.96)	(−0.07)	(6.43)	(−2.37)	(−3.32)	(−4.34)	(−3.13)	(6.19)
Haircut	0.037***					0.083***				
	(5.37)					(6.50)				
CDS		0.002***	0.001***	0.001***			0.005***	0.005***	0.005***	
		(2.78)	(3.11)	(2.70)			(9.67)	(10.05)	(9.84)	
Maturity			0.008***	0.008***				0.010***	0.010***	
			(3.63)	(3.86)				(2.82)	(2.78)	
Nb. bonds				−0.003*					0.000	
				(−1.87)					(0.12)	
F-to-Q					0.496***					1.003***
					(3.75)					(3.71)
Adj RSQ	0.1833	0.0436	0.1169	0.1316	0.0810	0.2497	0.3847	0.4126	0.4086	0.0796
Nb obs.	125	149	149	149	149	125	149	149	149	149

Table 10: (c'ed)

Explaining exposure to funding illiquidity (α) in the cross-section of bonds

(c)

	First Principal Comp. α^{FPC}					**Direct proxies α^{IND}**				
	(1)	**(2a)**	**(2b)**	**(2c)**	**(3)**	**(1)**	**(2a)**	**(2b)**	**(2c)**	**(3)**
Intercept	-0.095^{***}	0.024	0.060^{*}	0.059	0.017	0.362^{***}	0.296^{***}	0.435^{***}	0.342^{**}	-0.010
	(3.98)	(1.18)	(1.93)	(1.33)	(1.12)	(4.46)	(4.89)	(4.62)	(2.56)	(-0.19)
Haircut	-0.015^{**}					-0.098^{***}				
	(-2.59)					(-4.92)				
CDS		0.000	0.000	0.000			-0.005^{***}	-0.005^{***}	-0.005^{***}	
		(0.29)	(0.20)	(0.20)			(-5.91)	(-6.07)	(-5.75)	
Maturity			-0.003	-0.003				-0.011^{*}	-0.011^{**}	
			(-1.52)	(-1.51)				(-1.91)	(-2.01)	
Nb. bonds				0.000					0.005	
				(0.02)					(0.98)	
F-to-Q					-0.180					-0.551
					(-1.55)					(-1.41)
Adj RSQ	0.0438	-0.0062	0.0026	-0.0042	0.0094	0.1579	0.1867	0.2012	0.2009	0.0065
Nb obs.	125	149	149	149	149	125	149	149	149	149

Appendix to: Funding Constraints and Market Illiquidity in the European Treasury Bond Market

Sophie Moinas * **Minh Nguyen** † **Giorgio Valente**‡

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**Corresponding author*: Toulouse School of Economics (University of Toulouse 1 Capitole, TSM and CEPR.) Toulouse, France. E-mail: sophie.moinas@ut-capitole.fr

†Newcastle University Business School, Newcastle upon Tyne, United Kingdom. Email: minh.nguyen@newcastle.ac.uk

‡Hong Kong Institute for Monetary Research, Hong Kong Monetary Authority, Central District, Hong Kong. E-mail: gvalente@hkma.gov.hk

1 Appendix 1: Identification strategy

The appendix follows the identification strategy in the Section Identification through heteroskedasticity of Moinas, Nguyen and Valente (2018).

$$\begin{aligned} m_t &= \beta f_t + \epsilon_t & (1) \\ f_t &= \alpha m_t + \eta_t, & (2) \end{aligned}$$

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

$$\begin{aligned} \Omega_i &\equiv \begin{bmatrix} \varpi_{11,i} & \varpi_{12,i} \\ . & \varpi_{22,i} \end{bmatrix} & (3) \\ &= \frac{1}{(1-\alpha\beta)^2} \begin{bmatrix} \beta^2\sigma^2_{\eta,i} + \sigma^2_{\epsilon,i} & \beta^2\sigma^2_{\eta,i} + \alpha\sigma^2_{\epsilon,i} \\ . & \sigma^2_{\eta,i} + \alpha^2\sigma^2_{\epsilon,i} \end{bmatrix}, & (4) \end{aligned}$$

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:

$$\begin{aligned} \beta^2\sigma^2_{\eta,i} + \sigma^2_{\epsilon,i} &= (1-\alpha\beta)^2 \varpi_{11,i} & (5) \\ \beta^2\sigma^2_{\eta,i} + \alpha\sigma^2_{\epsilon,i} &= (1-\alpha\beta)^2 \varpi_{12,i} & (6) \\ \sigma^2_{\eta,i} + \alpha^2\sigma^2_{\epsilon,i} &= (1-\alpha\beta)^2 \varpi_{22,i} & (7) \end{aligned}$$

Solving these equations leads to the following moment condition:

$$\frac{\varpi_{12,i} - \beta\varpi_{22,i}}{\varpi_{11,i} - \beta\varpi_{12,i}} - \alpha = 0, \quad (8)$$

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:

$$\frac{\varpi_{12,1} - \beta\varpi_{22,1}}{\varpi_{11,1} - \beta\varpi_{12,1}} = \frac{\varpi_{12,2} - \beta\varpi_{22,2}}{\varpi_{11,2} - \beta\varpi_{12,2}}, \tag{9}$$

After some algebra, β solves the quadratic equation[1]:

$$a\beta^2 - b\beta + c = 0, \tag{10}$$

where

$$a = \varpi_{22,1} \times \varpi_{12,2} - \varpi_{22,2} \times \varpi_{12,1} \tag{11}$$

$$b = \varpi_{22,1} \times \varpi_{11,2} - \varpi_{22,2} \times \varpi_{11,1} \tag{12}$$

$$c = \varpi_{12,1} \times \varpi_{11,2} - \varpi_{12,2} \times \varpi_{11,1} \tag{13}$$

When the number of 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.

[1] 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 $\beta^* = 1/\alpha$.

2 Appendix 2: Model with exogenous variables

This appendix discusses an extension of the reduced-form model presented in Section 3.3 of the main text by including exogenous variables. As Rigobon (2003) and Rigobon and Sack (2003) we start from the observation that market and funding liquidity are determined simultaneously and we model their time-series dynamics by using the following system:

$$m_t = \beta f_t + \theta x_t + \gamma z_t + \epsilon_t, \tag{14}$$

$$f_t = \alpha m_t + \phi x_t + z_t + \eta_t, \tag{15}$$

where m_t is the systematic component of market illiquidity, f_t is the systematic component of funding illiquidity, x_t is a vector of exogenous variables, z_t is a latent variable, ϵ_t and η_t are shocks in each equation. The variable z_t is included to capture the influence of other determinants of illiquidity that we do not observe, unlike x_t that are instead observable. For identification purposes, as in Rigobon and Sack (2003, p. 643) the parameter of the common shock z_t is normalized to one in the second equation while β, α, θ, ϕ are the free parameters of 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:

$$\nu_t^m = \frac{1}{1-\alpha\beta}\left[\left(\beta+\gamma\right)z_t + \beta\eta_t + \epsilon_t\right], \tag{16}$$

$$\nu_t^f = \frac{1}{1-\alpha\beta}\left[\left(1+\alpha\gamma\right)z_t + \eta_t + \alpha\epsilon_t\right] \tag{17}$$

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

$$\Omega = \frac{1}{(1-\alpha\beta)^2}\left[\begin{array}{cc} (\beta+\gamma)^2\sigma_z^2+\beta^2\sigma_\eta^2+\sigma_\epsilon^2 & (1+\alpha\gamma)(\beta+\gamma)\sigma_z^2+\beta^2\sigma_\eta^2+\alpha\sigma_\epsilon^2 \\ . & (1+\alpha\gamma)^2\sigma_z^2+\sigma_\eta^2+\alpha^2\sigma_\epsilon^2 \end{array}\right], \quad (18)$$

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) suggest the following moment conditions with regime i $(i \neq 1)$:

$$\frac{\Delta\Omega_{i1,12} - \beta\Delta\Omega_{i1,22}}{\Delta\Omega_{i1,11} - \beta\Delta\Omega_{i1,12}} - \theta = 0, \quad (19)$$

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

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

where

$$a = \Delta\Omega_{31,22}\Delta\Omega_{21,12} - \Delta\Omega_{21,22}\Delta\Omega_{31,12} \quad (20)$$

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

$$c = \Delta\Omega_{31,12}\Delta\Omega_{21,11} - \Delta\Omega_{21,12}\Delta\Omega_{31,11} \quad (22)$$

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 (19) moment conditions in the GMM estimation. We establish the distributions of the estimated coefficients and perform significance tests in 1000 replications.

3 Appendix 3: Additional results

We perform a number of additional tests to complement our baseline results. More specifically, we investigate the role played by the sample of bonds used in the empirical exercise, a different volatility-regime classification. We also provide and estimate an alternative parametrization of the reduced-form model. In all cases, we document that the baseline results reported in the previous section are robust to alternative choices.

3.1 Sample of bonds

Our main 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 results to the sample of bonds, by estimating the reduced-form model using an extended sample of 452 bonds traded in EuroMTS over the sample period.

Table 1, Panel (a) reports some descriptive statistics on the full sample, by country. In comparison with Table 1 of the main text, we find 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 time 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 estimate the model for the direct proxies of market and funding illiquidity, and for the measures defined as the first principal components. We construct systematic components $FILLIQ$ and $MILLIQ$ from both panels of funding and market illiquidity 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 captures 57 and 75 percent of the cross-sectional variability of the funding and market illiquidity measures, respectively. Besides, the heteroskedasticity tests also reject the null hypothesis of homoskedasticity for both FILLIQ and MILLIQ at the 1% level.

Table 1, Panel (b) reports the estimates of the reduced-form model similar to the one discussed in Section 5 of the main text. The results are perfectly in line with those reported in Table 6, although slightly less economically significant. In particular, both effects of funding to and from market illiquidity are positive and significant, with coefficients of $0.06-0.07$ for β and 0.05 for α, respectively.

As an final 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. This however comes at a cost, as the extended model does not allow to identify α and β. 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 associated with the unobserved variable. Table 2 reports the estimates of this model for the full sample and for both approaches to measuring market and funding illiquidity. In all cases, the responses of funding to and from market illiquidity are positive, significant, and close to those reported previously.

3.2 Different Volatility-regime Classification

As an additional robustness check we identify the volatility regimes directly from the time-series data. More specifically, we define the various regimes from the reduced-form residuals by computing rolling-window variances of N-week worth of observations for each variable. As in Rigobon and Sack (2003), 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 $c = 0.5$.[2]

Table 3 reports the results of the estimation of the reduced-form model defined in (**??**) on the sample of 149 bonds and on the full sample, for the direct measures of illiquidity and the first principal components. Again, both effects of funding to and from market illiquidity are positive and significant. The coefficients of 0.150 for β and 0.067 for α for the subsample that we obtain when using principal component measures, and of 0.132 for β and 0.04 for α for the full sample, are very close from the values obtained with the alternative definition of volatility regimes.

[2]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.

Table 1: **Full sample of bonds**

Panel (a) reports the country average statistics for the full sample of the ten Euro-area government bond markets. We consider all 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. *No.* denotes the total number of bonds for each country, *Yield* is the end-of-day miquote bond yield (in percentage), *Mat* is the time to maturity (in years), *Duration* is the bond duration (in years), *Coupon* is the coupon rate (in percentage), *No. MM* is the number of market makers, *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 t-values (in parentheses) of the parameters of the structural model based on Rigobon (2003), estimated on the full sample of bonds. The first two columns correspond to funding and market illiquidity defined as the principal component of a panel of empirical proxies. FILLIQ is the first principal component of the changes in the four funding illiquidity variables. MILLIQ denotes the first principal component of the changes in the four market illiquidity variables. The last two columns corresponds to measures of funding illiquidity and market illiquidity as respectively the Euribor-OIS spread and the effective bid-ask spread. 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**	**Mat.**	**Duration**	**Coupon**	**No. MM**	**Trades**	**Size**
Austria	19	3.65	10.83	7.84	4.63	28	61	4.46
Belgium	34	3.46	8.47	6.42	5.01	35	226	5.02
Finland	13	3.27	7.69	6.30	4.37	35	79	4.76
France	70	3.32	7.94	5.96	4.70	24	256	4.39
Germany	104	3.16	6.68	5.06	4.26	27	256	4.39
Greece	35	3.84	7.80	5.87	5.02	35	212	4.27
Italy	86	3.62	8.53	5.96	2.36	51	2,476	3.28
Netherlands	31	3.29	8.25	6.22	4.35	28	105	5.78
Portugal	21	3.65	9.20	7.02	4.50	37	215	4.89
Spain	39	3.56	8.70	6.40	4.65	37	187	4.88

Heteroskedasticity identification on the full sample of bonds

(b)

	First Principal Components		**Direct proxies**	
	MILLIQ	**FILLIQ**	**EBAS**	**Euribor**
β (funding to market)	0.063***		0.070***	
	(5.18)		(20.83)	
α (market to funding)		0.052***		0.055***
		(32.64)		(3.16)
Implied volatility (vStoxx)	0.021***	0.008	0.033***	0.064
	(3.99)	(1.17)	(5.25)	(1.16)
Variation in M2 money supply	−0.050***	−0.130	−0.151***	0.070
	(−1.86)	(−1.92)	(−3.69)	(0.18)
Mutual funds' flows	−0.160***	−0.023	−0.440*	−0.465
	(−2.02)	(−0.08)	(−1.86)	(−0.19)
End-of-month dummy	0.038	0.220***	1.270	1.840***
	(0.64)	(2.09)	(1.52)	(2.39)

Table 2: **Rigobon and Sack (2003)'s identification**

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 parenthesis denote the t-values obtained by bootstrapping with 1,000 replications. *** indicates that coefficients are significantly different from zero at the 1% level.

	Full sample			
Variables	**MILLIQ**		**FILLIQ**	
First Principal components				
beta	0.141***	(28.31)		
theta			0.280***	(8.45)
Direct proxies				
beta	0.104***	(16.70)		
theta			0.446***	(9.92)

Table 3: **Volatility regimes defined based on rolling-window variances**

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 (**??**), on the subsample of 149 bonds as well as on the full sample. Values in parenthesis denote the t-values obtained by bootstrapping with 1,000 replications. *** indicates that coefficients are significantly different from zero at the 1% level.

	Subsample of 149 bonds				**Full sample**			
Variables	**MILLIQ**		**FILLIQ**		**MILLIQ**		**FILLIQ**	
First Principal components								
beta	0.150***	(78.10)			0.132***	(32.91)		
alpha			0.067***	(25.06)			0.04***	(11.25)
Direct proxies								
beta	0.039***	(6.12)			0.132***	(23.41)		
alpha			0.052***	(2.09)			0.107***	(19.35)