What Drives the Liquidity of Eurozone Sovereign Bonds?

An Assessment of the New Rules on Bank Liquid Assets

Giovanni Petrella, Università Cattolica, Milan, *giovanni.petrella@unicatt.it*

Andrea Resti, Bocconi University, Milan, *andrea.resti@unibocconi.it*

This version: September 9, 2013

ABSTRACT - The new rules on bank liquidity set by the Basel Committee require banks to hold high-quality liquid assets (HQLAs) against future cash outflows in periods of market stress. Although the definition of HQLAs is still being fine-tuned, banks are allowed to use an unlimited amount of Treasuries issued by their own domestic governments, subject to no haircuts or concentration thresholds. To check the appropriateness of this rule, we investigate the liquidity of Eurozone government bonds in ordinary times and in periods of market turmoil (e.g., after the Lehman default and during the Eurozone crisis). We find that liquidity is driven by both market factors (as the quality spread between yields of BBB- and AAA-rated bonds) and bond-specific factors (e.g. duration, ratings and size), and that the effect of adverse market conditions strongly depends on each bond's characteristics. This evidence argues for rules on HQLAs that would constrain the eligibility of government bonds depending, e.g., on their duration and rating. Failing to recognize the important cross-sectional differences of government bonds' liquidity under adverse market conditions may lead to ineffective rules and unintended consequences.

Keywords: liquidity risk; Liquidity Coverage Ratio; High-Quality Liquid Assets (HQLAs); Basel 3; Basel Committee

JEL Codes: G18, G19, G29

1 Motivation and preview

The new liquidity rules recently agreed by the Basel Committee for Banking Supervision and the European Parliament require that banks hold a buffer of "high quality liquid assets" (henceforth, HQLAs) to withstand future liquidity shocks (the "liquidity buffer"). While improving the resilience of the banking sector, this requirement involves considerable adjustment costs for lenders[1] and might trigger a drop in credit supply to the real economy. It is therefore important that the new rules are carefully designed to effectively protect banks against systemic liquidity crises. Additionally, liquid assets must be defined in a way that mitigates the risk of market distortions, such as driving investment flows away from the banking sector.

The Basel Committee has designed a set of criteria to assess what financial securities will be eligible as HQLAs. These criteria include credit rating, issuer types[2], maximum price changes over a 30-day period. Most asset classes are also subject to concentration limits: e.g., high quality mortgage-based securities will not be allowed to exceed 15% of the total liquidity buffer.

Curiously enough, however, the eligibility requirements imposed on government bonds look rather loose. Banks will be allowed to include in their liquidity buffer an unlimited amount of Treasuries issued by their own domestic governments, or by foreign governments meeting a minimum rating threshold. No other binding criteria will be imposed, regarding e.g. the duration, age or issued amount of the bonds.

[1] See (Banking Stakeholder Group 2012).

[2] E.g., most bonds issued by banks are excluded, as they may prove illiquid during a financial crisis.

This choice is probably explained by the fact that in many countries banks play a key role in underwriting government debt, ensuring that public deficits are orderly financed. This implies that government bonds currently represent a considerable portion of bank assets and thus overly conservative rules on the definition of HQLAs may trigger uncontrolled sell-offs. In the European Union, the net exposures to domestic sovereign debt for a sample of banks accounted, on average, for 79.5% of core Tier 1 capital in 2010[3]. While this figure tends to be lower for very large banks (see Figure 1), the weighted average exposure still amounts to 49.2%, highlighting a strong link between banks and government debt.

Insert Figure 1 approximately here

One may wonder whether the decision to treat, for the purposes of liquidity risk regulation, all Treasury bonds as highly liquid – especially in times of market stress[4] – is appropriate (that is, supported by empirical evidence). This looks as a nontrivial research question, especially in the Eurozone where the national governments have handed over their monetary policy powers to the European Central Bank (ECB), and cannot use seignorage any more to fund public deficits and thus ensure that all their bonds will always be paid back. Consequently, confidence crises can occur (and have occurred) in the secondary market for Eurozone government bonds, where investors quickly dispose of the securities issued by one or more sovereign states, leading to sudden price drops and liquidity shortages.

The consequences of inaccurate eligibility criteria would be amplified by the lack of any concentration limits on government bonds. This means that, according to Basel 3 regulation,

---

[3] Data collected by the European Banking Authority as part of its latest stress test exercise. For details refer to http://www.eba.europa.eu/.

[4] The Basel Committee explicitly requires that, in order to qualify as HQLAs, the assets should be liquid during a period of market stress.

sovereigns can be used by banks to fill 100% of their liquidity buffers. It is therefore even more important that eligible government bonds can be trusted to be liquid under all circumstances, including a systemic shock.

This paper makes two contributions to the previous literature. First, we investigate the liquidity of Eurozone government bond markets in ordinary times as well as in periods of market turmoil. Our sample in fact includes both the 2008 liquidity crisis and the 2011 euro sovereign crisis. Second, differently from previous papers, we control for rating, duration and other factors when assessing government bond liquidity. Due to recent downgrades, credit ratings for Eurozone countries span a wide range of notches, including riskier ones. This provides an attractive empirical setting for testing the link between ratings and liquidity in the sovereign debt market.

The rest of the paper unfolds as follows. §2 briefly discusses the new rules on bank liquidity, with a focus on the eligibility criteria for liquid assets. §3 reviews relevant research papers on the liquidity of government bonds. §4 describes our data and methodology, introducing the liquidity measure and the indicators of market-wide stress used in our tests. §5 presents our empirical results. §6 concludes.

2 The new bank liquidity rules in a nutshell

The new post-crisis regulatory framework commonly known as Basel 3, agreed by the Basel Committee in 2010 and further refined in January 2013, introduces two liquidity coefficients that require financial institutions to hold a minimum amount of liquid assets and to issue more long-term debt.

The former – known as Liquidity Coverage Ratio (LCR) – is aimed at ensuring the short-term resilience of financial institutions. Banks will be required to hold a stock of liquid assets for an amount covering the net liquidity outflows which might be experienced, under stressed conditions, over the following 30 days[5]. Net cash outflows are to be computed based on a number of assumptions concerning run-off, roll-over and draw-down rates (Basel Committee on Banking Supervision 2010; Basel Committee on Banking Supervision 2013).

The latter – known as Net Stable Funding Ratio (NSFR) – requires that available stable funding (i.e., equity and liability financing expected to remain stable over a one-year time horizon) be at least equal to the matching assets (i.e., illiquid assets which cannot be easily turned into cash over the following 12 months).

In the European Union (EU), the two new ratios were enacted through a new Capital Requirements Directive (CRD4) and a Regulation (CRR) issued in June 2013.

Based on the Basel 3 documents, liquid assets in the LCR should mainly consist of

1. cash;
2. central bank reserves;
3. bonds issued or guaranteed by sovereigns with a rating at least equal to AA[6];
4. bonds issued or guaranteed by the bank's domestic country;
5. bonds issued by nonfinancial firms and covered bonds with a rating at least equal to AA[7], subject to a 15% haircut and a 40% concentration limit.

---

[5] The LCR requirement will be phased in gradually, starting with 60% in 2015 and reaching 100% in 2019, when banks will be finally expected to cover 100% of their potential cash outflows with a buffer of liquid assets.

[6] Government bonds with a rating at least equal to BBB- will also be accepted, but subject to a 15% haircut. Also, they will not be allowed to exceed 40% of the total liquidity buffer.

[7] Corporate bonds with a rating at least equal to BBB-, mortgage-backed securities (MBS) and blue chip stocks will also be eligible, but subject to a 50% haircut (25% for MBS). Also, jointly considered they will not be allowed to exceed 15% of the total liquidity buffer.

Liquid assets – in the Basel Committee intentions – must have a proven record as a reliable source of liquidity even during stressed market conditions.

The European Union, compared to the Basel Committee, has adopted a less prescriptive and more flexible approach. The definition of eligible liquid assets is not included in the CRD4 or in the CRR. Instead, the European regulation mandates the European Banking Authority (EBA) to test various eligibility criteria for HQLAs, providing input for level-two regulation to be issued by the European Commission[8]. This two-stage procedure leaves many details still open for calibration, impact assessment and review. Accordingly, article 509 of the CRR calls for EBA to propose appropriate definitions of liquid assets taking into account a number of different liquidity measures. Article 509, however, does not apply to cash and central bank reserves (items 1. and 2. above), nor to domestic government bonds (item 4.), for which *no further liquidity test is required*.

3 Literature review

While several studies have examined the liquidity of equity markets, relatively few have addressed the liquidity of government bonds. A possible explanation is that trading in these markets is mostly done over the counter, making data more difficult to access. Still, a number of papers have investigated the liquidity of government bond markets both in US and in Europe. Some of them are briefly reviewed below.

(Chakravarty and Sarkar 1999) is probably the first paper studying the liquidity of US Treasury bonds. Their analysis, based on a sample for 1995-1997, shows that the realized bid-ask spread decreases with the trading volume. (Fleming 2001) also looks at the liquidity of US government bonds based on a sample of bills and notes from December 30, 1996 to

[8] See articles 416, 460 and 509 of the CRR for further details.

March 31, 2000[9]. The data include the best bid and offer quotes, the associated quote sizes, the price and size of each trade, and whether the trade was a "take" (buyer-initiated) or a "hit" (seller-initiated). Fleming calculates a set of liquidity measures (trading volume, trading frequency, bid-ask spreads, quote sizes, trade sizes, price impact coefficients, and on-the-run/off-the-run yield spreads for the most active Treasury securities) and analyzes their behavior relative to one another and in time series. He finds that liquidity measures change substantially over time, that they are correlated, and that they correlate with episodes of market-wide instability (market crash in October 1997, 1998 Fall turmoil). Interestingly, correlations between trading volume and other liquidity measures are relatively weak and inconsistent, suggesting the former may not be a reliable indicator of market liquidity.

The effect of liquidity on returns, that has been the subject of several studies in the equity markets (see Amihud, Mendelson, and Pedersen 2006 for a survey), is investigated by (Goldreich, Hanke, and Nath 2005), who examine the liquidity of US Treasuries to assess the relationship between illiquidity and bond prices. More specifically, they look at how *future* liquidity affects bond prices, as theory suggests that investors require a compensation for illiquidity discounting the trading costs that will be incurred when opening and closing the position. They distinguish current liquidity from future liquidity by comparing the yields of on-the-run and off-the-run US Treasury notes. US Treasury securities, as any other bond issued on a regular basis, go through a predictable cycle of liquidity and illiquidity. The most recently issued bond ("on the run") attracts most of the liquidity; when another one is issued, the older bond goes "off the run" and becomes significantly less liquid: this is called the "on/off cycle". Because of this pattern, expected future liquidity is generally different from

---

[9] Data are from GovPX, a consolidated database contributed by all but one (eSpeed) of the major brokers in the interdealer government bond market.

current liquidity, and changes predictably over time. Goldreich et al. use GovPX data for two-year notes over the period January 1994 to December 2000 and find that the yield difference between the on-the-run note and the most recent off-the-run note is explained by the difference in the future liquidity of the two. This result shows that expected future liquidity is priced in the US Treasuries market, rather than just the current liquidity level.

The determinants of execution costs and the role of transparency are often investigated in market microstructure studies. (Dunne, Moore, and Portes 2006) look at the liquidity of government bond markets to investigate the effects of cross-country differences and inter-temporal changes in the level of transparency. They use a sample of US and European government bonds for selected months in 2003, 2004 and 2005. They find that countries that rely more on syndicate issuance and that impose secondary market obligations on primary dealers have higher percentages of turnover on the (transparent) MTS market. Dunne et al. estimate a number of liquidity measures (effective spread, steepness of the order book, trade size, liquidity available at the best bid and ask quotes, liquidity available at the three best quotes) and find that execution quality is closely related to the size of the issuer, the issuance techniques, and the obligations imposed on primary dealers. In markets where obligations on primary dealers are stronger, the steepness of the order book is larger and this implies that execution quality for large trades suffers in these markets. Dunne et al. also examine a 'transparency event' that occurred in June 2003 in the US Treasury market, when an increase in transparency on eSpeed brought an increase in effective spreads. They conclude that dealers prefer to operate on markets that are more opaque. Some degree of opacity seems necessary to induce dealers to supply both liquidity and pre-trade information. Greater transparency is associated with lower trade size and possibly involves higher spreads.

Recent studies look at liquidity conditions in times of market stress. (Beber, Brandt, and Kavajecz 2009) examine the behavior of order flow in the European government bond market and relate the sovereign yield spread (i.e., the difference between the sovereign bond yield and the swap yield) to differences in credit quality[10] and liquidity[11]. More specifically, they investigate the behavior of the order flow in times of market stress and try to disentangle flights-to-quality from flight-to-liquidity phenomena. They use intraday trades and quotes data on Euro-area government bonds from MTS markets. (Beber, Brandt, and Kavajecz 2009) find that investors demand both credit quality and liquidity, but they do so at different times and for different reasons: the bulk of sovereign yield spreads is explained by differences in credit quality, though liquidity plays a nontrivial role, especially for low credit risk countries and during periods of heightened market uncertainty[12]. They conclude that in times of market stress investors chase liquidity, not credit quality. Interestingly, and consistently with (Goldreich, Hanke, and Nath 2005), they also find – looking at the order flows in and out of the bond market – that investors price the transaction costs both when they enter and exit the bond market.

A related segment of research deals with the time series properties of equity and bond markets liquidity. (Chordia, Sarkar, and Subrahmanyam 2005) study cross-market liquidity dynamics in the stock and US Treasury bond markets using data from June 1991 to December 1998. They collect intraday data on Treasuries from GovPX and on stocks from TAQ to compute daily measures of liquidity for both markets. They find that liquidity and volatility in the equity and government bond markets are significantly correlated.

---

[10] Credity quality is proxied by the CDS premium.

[11] Liquidity is proxied by 4 different measures: effective spread, quoted depth at the best quotes, cumulative depth available at the first three levels of the limit order book, depth-to-spread ratio.

[12] (Favero, Pagano, and Von Thadden 2010; Darbha and Dufour 2013) provide related evidence on the liquidity component of the yield spread for Eurozone government bonds.

Interestingly, monetary policy expansions during crises are associated with increased market liquidity. This result highlights a link between "macro" liquidity (i.e., money in the financial system) and "micro" liquidity (i.e., trading costs). Based on a longer time span, (Goyenko and Ukhov 2009) also examine the joint dynamics of stock and Treasury bond illiquidity and find that liquidity conditions in the two markets affect each other. Additionally, they find that bond market illiquidity is immediately affected by monetary policy variables (i.e., federal funds rate and monetary aggregates), while stock market illiquidity reacts to monetary shocks with a lag. This result shows that bond illiquidity plays a role as a channel for transmitting monetary shocks into the equity market and confirms the link between macroeconomic variables and markets illiquidity.

None of the above-surveyed papers looks at the cross-sectional determinants of Eurozone government bond liquidity. (Li et al. 2009) and (Dufour and Nguyen 2012) investigate the effects of information risk on government bond returns, respectively, for the US Treasuries and for Eurozone sovereign bonds. However, they do not address the issue of liquidity variation across bonds. Additionally, their samples end in December 2002 for Li et al. and in September 2007 for Dufour and Nguyen; consequently their analyses do not fully incorporate the sub-prime mortgage crisis and completely miss the 2011 sovereign crisis.

Recently (Pelizzon et al. 2013) have looked at the impact of the Eurozone crisis on the liquidity of sovereign bonds using a new, sophisticated data set that tracks individual orders and their revisions throughout each trading day. Their analysis, however, differs from the one proposed in this paper because they focus on Italian bonds and on a "hectic" time window (June 2011- November 2012), hence do not compare their results with a "quiet", pre-crisis period.

4 Sample and methodology

4.1 Data

We use data from the MTS Time Series database. MTS is a major wholesale electronic market for fixed-income securities in Europe. We only consider bonds issued by governments and supranational institutions, excluding quasi-government bonds, corporate bonds, covered bonds, asset-backed securities. Our sample consists of 2,151 bonds and covers three full calendar years: 2006, 2008 and 2011[13]. These time windows allow us to study the behavior of the liquidity of the euro-area government bond markets both in ordinary times (2006) and in times of market stress (2008 and 2011).

For each bond, the data set includes daily trading volume, closing price, yield to maturity based on the midquote, as well as a number of control variables (modified duration, convexity, issuer name, bond type, trading venue, issue date, maturity date, coupon).

We supplement the MTS data with rating information. For bonds issued by governments, we collect the Standard & Poor's issuer rating, where available, from Datastream and Bloomberg. In case of missing information on the issuer rating, we recover issue-specific

---

[13] Since our liquidity indicators (see §4.2) are computed on a quarterly basis, data points in our analysis represent individual bonds observed in a given quarter. For the 10,150 data points where country codes are available, the main issuers are France (24%), Spain (16%), Italy (12%) and Germany (8%). Bonds issued by Eurozone countries account for 82% of the total data points with country codes available, remaining data points refer to bonds issued by the European Union, EU members not belonging to the Eurozone or countries participating to the European Exchange Rate Mechanism, which is a preparatory stage for countries that are going to adopt the euro currency. Out of the 9,354 data points where ratings are available, 46% are rated AAA, another 19% are rated AA, while grades below AA account for the remaining 26%. Finally, the 5,599 data points where the modified duration is available range from below one year (27%) to beyond seven years (26%).

ratings from S&P. For bonds issued by supranational entities (e.g., the European Stability Fund), we look at issue-specific ratings whenever available; this is because the bond's rating may significantly differ from the issuer's, depending e.g. on seniority.

4.2 Measures of liquidity and liquidity risk

Our key measure[14] of bond liquidity is the one originally proposed by Amihud (2002) and calculated as

$$ILLIQ_{id} = \frac{|r_{id}|}{TV_{id}} \qquad (1)$$

$ILLIQ_{id}$ (henceforth the "Amihud illiquidity" measure or simply the "Amihud" measure) captures the price impact of trading by relating the return r_{id} (that is, the change in price) for the *i*-th bond on day *d* to the traded volume TV_{id} for the same bond and day. Liquidity is high if a large volume can be traded with little or no impact on price, and vice versa. In other words, a more liquid bond has a lower price change (i.e., price impact) for a given traded volume, and vice versa. In our empirical analysis we first compute $ILLIQ_{id}$ on a daily basis, then average across all days in a given quarter to estimate the Amihud illiquidity for bond *i* in quarter *t* ($ILLIQ_{it}$) [15].

The Amihud was originally employed to analyze stocks' liquidity. However, it has increasingly been used also in the study of fixed income markets (see e.g. Lin, Wang, and

---

[14] Robustness checks based on different liquidity proxies will be shown in §5.4.

[15] Note that, since not all bonds are traded every day, quarterly Amihud measures are usually based on a number of daily observations which is less than the number of trading days for the quarter. On average, each bond has data for 25 days in a quarter. Bonds with less than 5 daily observations in a quarter were discarded.

Wu 2011; Friewald, Jankowitsch, and Subrahmanyam 2012; Dick-Nielsen, Feldhutter, and Lando 2012).

Another common measure of liquidity is the quoted bid-ask spread. The Amihud measure has two advantages over the quoted bid-ask spread. First, it is based on actual trades, whereas the bid-ask spread is only a measure of displayed (or potential) liquidity. Second, it measures the liquidity conditions for small as well as large trades. This is especially relevant in our case given that, as shown by (Dunne, Moore, and Portes 2006), for the MTS markets the quoting obligations imposed on primary dealers may actually lead to an “excess of transparency” which negatively affects execution quality, especially for large trades.

While the previous advantages are meaningful for any market, there is an additional reason leading us to avoid the use of the quoted bid-ask spread as a measure of liquidity in this paper that is specific to the MTS market. The daily average bid-ask spread computed by MTS is based only on observations below three basis point values (BPVs). MTS motivates this choice by stating that the quotes are non-representative when the bid-ask spread is higher than this threshold. Without entering into a discussion about this choice, we believe that the average bid-ask spread computed as previously described may underestimate the actual bid-ask spread and the underestimation may be particularly severe in times of market stress.

As a robustness check, we also use a modified Amihud measure (*IILLIQ**) as proposed by (Karolyi, Lee, and Van Dijk 2012):

$$ILLIQ^{*}_{id} = \log\left(1 + \frac{|r_{id}|}{TV_{id}}\right) \tag{2}$$

where the log is used to reduce the impact of outliers[16].

Illiquidity varies over time and this variation is a source of risk for investors. Consequently, we also consider liquidity risk in our analysis by computing the standard deviation[17] of the Amihud measure, $SIGMA_{it}$, using daily observations on a quarterly basis. A greater $SIGMA_{it}$ in quarter t suggests a higher uncertainty in future liquidity levels when holders of security i may need to sell their assets. $SIGMA^{*}_{id}$ denotes the standard deviation of the modified Amihud in (2).

The standard deviation measures total liquidity risk, as it does not disentangle the systematic component of liquidity from the idiosyncratic one. However, as originally pointed out by (Acharya and Pedersen 2005), a security that becomes illiquid in times of market-wide illiquidity is a source of special concern to investors. One should therefore focus on systematic liquidity risk only (Kamara, Lou, and Sadka 2008), that is, on the sensitivity of an asset's liquidity relative to changes in aggregate market liquidity.

The relationship between individual and market-wide liquidity can also be investigated from a different perspective: one can measure how much of a security's liquidity is driven by systematic factors (i.e., by aggregate market liquidity) and how much is firm-specific. We refer to this feature as "commonality" (or "synchronicity") in liquidity[18].

---

[16] Unlike (Karolyi, Lee, and Van Dijk 2012), we do not change sign to the log, as we want the modified Amihud to be similar, in interpretation, to the original one (that is, to increase when *illiquidity* goes up).

[17] The min-max range and the interquartile range are also computed as a robustness check.

[18] Some papers (see e.g. Acharya and Pedersen 2005; Brockman and Chung 2008) use the term "commonality in liquidity" to refer to what we call "systematic liquidity risk". Our notion of "commonality in liquidity" is consistent with (Karolyi, Lee, and Van Dijk 2012).

To measure systematic liquidity risk and commonality in liquidity, we estimate the following liquidity market model (LMM):

$$ILLIQ_{i,t} = \alpha + \beta_i ILLIQ_{mkt,t} + \varepsilon_{i,t} \tag{3}$$

where β_i measures the sensitivity of changes in asset i's liquidity to changes in aggregate liquidity (i.e., the systematic liquidity risk) and the R-square of the regression measures the proportion of individual liquidity explained by market liquidity (i.e., the commonality in liquidity). LMMs for individual bonds are estimated on a quarterly basis using daily observations (with input data winsorized at 1% and 99%)[19]. $BETA_{it}$ and RSQ_{it} denote the β and R-square of the LMM for bond i in quarter t. As a measure of aggregate illiquidity, we use the average Amihud for all bonds in our sample, weighted by the amount outstanding.

4.3 Market stress indicators

The liquidity of government bonds may fluctuate over time depending on overall market conditions. This is due to various effects. E.g., when risk aversion increases, investors may look for safe havens and refrain from investing in Treasury bonds issued by riskier countries. Additionally, when banks are under stress, the opportunity cost of their bond holdings may rise, leading to higher inventory costs and steeper liquidity-supply curves. Lastly, in times of financial turmoil investors may discount the risk that governments have to increase their debt to fund bank rescues, leading to a reduced willingness to trade Treasury bonds and thus to higher illiquidity.

Insert Figure 2 approximately here

[19] The LMM is not estimated unless at least five data points are available. Using higher thresholds, e.g. 12 or 20, would not affect our key results.

For these reasons, we need to test how bond liquidity actually responds to changes in general market conditions. We do this by considering several alternative indicators of market stress, all shown in Figure 2[20].

The first group includes various "quality spread" (QS) measures, all computed as the difference between the secondary market yields on BBB-rated and AAA-rated bonds. We consider three variants of the QS measure, based on the bonds' duration (5-7 years versus 7-10 years) or looking specifically at bonds issued by financial institutions. In times of financial stress, yields on BBB-rated issues tend to increase more significantly than for AAA-rated ones, so the gap between the two (i.e., the QS) widens. Previous studies have shown that the QS tends to rise during business cycle contractions and fall during expansions (Fama and French 1989; N.-F. Chen 1991) and is positively related to the volatility in stock market returns (Lindset and Westgaard 2007). This suggests that it is not only associated with an increase in the investor-perceived level of credit risk (triggering "flights to quality"), but also with a higher uncertainty in asset prices and company values[21]. Furthermore, according to (Mishkin 1991; Mishkin 1992), higher values of the QS can be viewed as the result of changes in the "lemon" discount on securities prices caused by asymmetric information, and signal an increase in informational opaqueness[22].

---

[20] White areas in Figure 2 indicate the periods investigated in our analysis.

[21] As shown by (L. Chen, Collin-Dufresne, and Goldstein 2009), the QS is also positively correlated to dividend yields (i.e., it increases when stock prices decrease more than dividends) and negatively correlated to various measures of leverage (e.g., debt over total assets) for Baa-rated companies (meaning that such companies can build up debt when the QS is low but must deleverage as the QS increases).

[22] See (Iannotta, Nocera, and Resti 2012) for further details.

The second group of indicators looks at the risk premiums required by investors to issue short term loans to banks. This includes the "TED spread" (computed as the difference between 3-month US dollar Libor rates and rates on 3-month US Treasury bills) and the "Euribor – OIS spread" (the gap between the rate on 3-month euro-denominated interbank deposits and the rate on overnight-indexed swaps in the same currency).

4.4 Estimated models

We estimate two models in our empirical analysis to explore the drivers of government bond liquidity in normal times as well as in times of systemic stress. The former ("the base model") explain bonds illiquidity and liquidity risk as follows:

$$y_{it} = \alpha + \beta_1 DUR_{it} + \beta_2 PD_{it} + \beta_3 DU\_OTR_{it} + \beta_4 LOG\_AMT_{it} + \beta_5 QS\_5\_7_t \tag{4}$$

where

- y_{it} denotes the dependent variable. We are going to test four different specifications for it, using $ILLIQ_{it}$ (illiquidity level), $SIGMA_{it}$ (total liquidity risk), $BETA_{it}$ (systematic liquidity risk) and RSQ_{it} (commonality in liquidity). Additional versions based on the modified Amihud shown in equation (2) ($ILLIQ^*_{it}$, $SIGMA^*_{it}$, etc.) will also be tested;
- DUR_{it} is the modified duration for bond *i* in quarter *t*;
- PD_{it} is the probability of default (PD) associated with bond *i*'s rating in quarter *t*. Ratings by Standard & Poor's were mapped to PDs based on long-term default rates[23];

---

[23] Issuer ratings were used for senior unsecured bonds, which represent the bulk of our data set; issue ratings were used, when available, for non-standard issues.

- DU_OTR_{it} is a dummy variable taking a value of one if bond *i* in quarter *t* has been issued by less than one year (and therefore can be considered an "on-the-run" issue);

- LOG_AMT_{it} is the natural log of the dollar-denominated outstanding amount for bond *i* in quarter *t*;

- $QS\_5\_7_t$ is the quality spread in quarter *t* for a sample of dollar-denominated corporate bonds with duration between five and seven years.

The base model, when applied to $ILLIQ_{it}$, tests whether one or more of the above variables explain the *average* liquidity level of government bonds. Consistent with the logic underlying the LCR, however, we also want to assess what factors affect liquidity *when the market is experiencing a system-wide stress*. We therefore introduce another model ("the interacted model") where the covariates are interacted with a dummy ("STRESS") taking a value of one whenever our stress indicator (QS_5_7) exceeds its 75-th percentile. Formally:

$$\begin{aligned} ILLIQ_{it} &= \alpha + \beta_1 DUR_{it} + \beta_2 PD_{it} + \beta_3 DU\_OTR_{it} + \beta_4 LOG\_AMT_{it} + \beta_5 QS\_5\_7_t + \\ &+ STRESS_t \cdot \left(\gamma_1 DUR_{it} + \gamma_2 PD_{it} + \gamma_3 DU_{OTRit} + \gamma_4 LOG\_AMT_{it} + \gamma_5 QS\_5\_7_t \right) \end{aligned} \qquad (5)$$

Based on equation (5), the effect of the *p*-th regressor on bond liquidity is β_p in normal times and $\beta_p+\gamma_p$ conditional on adverse market conditions. By performing a statistical test on γ_p, we can check whether a given liquidity driver becomes significantly more (less) powerful under a crisis scenario.

A final remark on our econometric approach. Although our data set may lend itself to panel data analysis, we estimate the previous models as a pooled OLS[24] and we are not going to introduce any fixed or random effect associated with individual bonds or quarters. In fact, although such effects would considerably increase the in-sample explanatory power of our

[24] Repeating our estimates using clustered standard errors as in (Petersen 2009) does not alter the results.

model, they would weaken the statistical significance of other variables (like duration, rating, quality spread) that can be used to identify securities and market conditions that – on an ex ante basis – are more prone to future liquidity shocks, getting important insight on how to calibrate the new rules on HQLAs.

5 Empirical findings

5.1 Liquidity level

Figure 3 shows the behavior over time of the Amihud illiquidity measure in our sample period[25]. In 2006 the Eurozone government bond market as a whole was highly liquid and individual bonds used to behave homogeneously, as shown by the width of the standard deviation bands. In 2008, however, liquidity started to deteriorate and briskly dropped after the collapse of Lehman Brothers in September. In 2011 market liquidity was disrupted again when the sovereign debt crisis hit large countries like Italy and Spain during the last half of the year: average illiquidity marked a considerable increase, with large differences across individual securities (as shown by the sharp rise in the width of the standard deviation bands).

Insert Figure 3 approximately here

Table 1 shows summary statistics for our main variables. For continuous ones, the last column of the table shows the linear correlation with the Amihud measure; for the two dummies (equal to one when bonds are, respectively, AAA-rated and zero coupon), the last column shows a t-test for the equality of the mean. Values significant at 1% and 0.1% are highlighted with one or two stars.

---

[25] The time series behavior of other liquidity measures, including *ILLIQ** and the bid ask spread, is qualitatively similar.

Insert Table 1 approximately here

Illiquidity, as expected, increases with duration (higher durations imply higher risks for market makers) and decreases with age (newly-issued, on-the-run bonds tend to be traded more frequently). Maturity at launch combines the two effects, as long-term issues either have a long duration or have become significantly off-the-run when the expiration date is closer, in both cases facing higher illiquidity (see correlations in Table 2). Better ratings, associated with lower PDs, enjoy better liquidity conditions (and AAA-rated securities are more liquid than other grades). Bonds with larger coupons are relatively more illiquid, although this may reflect the fact that zero coupons are mostly used for short maturities, and this implies lower duration. Trading activity is greater for larger issues, shorter maturity and younger bonds.

Insert Table 2 approximately here

Table 3 shows the results of our base model estimated for $y_{it} = ILLIQ_{it}$ and $ILLIQ^*_{it}$. Unadjusted Amihud illiquidity increases with duration and PD (i.e., for lower ratings), while on-the-run bonds (which we conventionally identify as those issued by less than one year) and larger issues show better liquidity conditions. Finally, shifts in the 5-7 year QS significantly affect illiquidity[26]. Moving from $ILLIQ_{it}$ to $ILLIQ^*_{it}$, all previous findings are confirmed and the adjusted R-square increases considerably.

Insert Table 3 approximately here

---

[26] Replacing the 5-7 year QS with the alternative market stress indicators discussed in §4.3 does not meaningfully change our results.

Table 3 also reports the standardized regression coefficients[27] in the right-end column to assess the relative importance of the explanatory variables. This analysis, also known as economic significance analysis, shows that modified duration and quality spread are by far the most powerful liquidity drivers, although PDs (and, to a lesser extent, the size of the issue) also play a significant role[28].

5.2 Total liquidity risk

The Amihud illiquidity measure estimates the transaction costs due to price impact allowing for the possibility of trading quantities larger than the depth displayed at the best quotes. The results in Table 3 therefore capture the *expected cost* of trading, conditional on several security and market characteristics. Expected costs are not, *per se*, a measure of risk, so further analyses are called for in order to investigate what drives liquidity risk in the market for Eurozone sovereign bonds.

We thus turn to quarterly standard deviations of Amihud ($SIGMA_{i,t}$) to investigate the *volatility* in liquidity costs. The results, shown in Table 4, are broadly similar to those shown for $ILLIQ_{it}$, with duration, market stress and PD playing the most significant roles. When moving from the unadjusted Amihud measure to the log-transformed one, the determinants of the quarterly standard deviations stay unchanged while the adjusted R-square increases to

---

[27] Standardized coefficients indicate by how many standard deviations the dependent variable would move following a one-standard deviation shift in the covariates.

[28] This result is consistent with the findings of (Friewald, Jankowitsch, and Subrahmanyam 2012) for the corporate bond market.

62%[29]. This evidence shows that total liquidity risk is driven by both market factors (as the quality spread) and bond-specific factors (as duration and PD).

Insert Table 4 approximately here

5.3 Systematic risk and commonality in liquidity

The standard deviation captures the overall volatility in illiquidity, including both idiosyncratic and systemic effects. However, idiosyncratic peaks in illiquidity can easily be averaged away by holding a well-diversified portfolio (something that banks can safely be assumed to do). Accordingly, we now focus on the systematic component of liquidity risk by looking at LMM betas. Once quarterly betas have been estimated[30], following the methodology described in §4.2, we use them as the dependent variable in the base model (setting $y_{it} = BETA_{it}$ or $BETA_{it}^{*}$ in equation (4)) to see how they are affected by our usual covariates. The results are shown in Table 5.

Insert Table 5 approximately here

Results for *BETA* and *BETA** are comparable. In both cases liquidity betas behave similarly to standard deviations in that they are mostly driven by PDs, quality spread and, to a larger extent, durations. The effect of the quality spread on liquidity betas, however, is different from the previous finding on total liquidity risk, as beta and quality spread move in opposite

---

[29] Results for alternative measures of volatility (max-min range and inter-quartile range) are qualitatively similar and available from the authors upon request.

[30] The LMM betas based on the unadjusted Amihud measure used for the regression in Table 5 have a mean value of 1.03 and a standard deviation of 1.96. The distribution is highly skewed to the right as the median is 0.25 and the skewness is 2.68. This is due to the existence of a small number of bond with large betas (the 90[th] percentile is 3.17 and the maximum is 10.43).

directions. This means that the average beta tends to decrease when the QS increases, which might initially sound as counterintuitive.

We propose two explanations for this result. First, a flight-to-quality phenomenon might be taking place, as in (Acharya, Amihud, and Bharath 2012). In fact we find that, when QS_5_7 increases above its third quartile, the share of bonds with negative betas rises from 21% to 23% (with the average beta falling from -0.22 to -0.28) as investors turn to high-quality securities[31]. All other things being equal, this effect drives down the average beta. Second, when QS_5_7 increases, some highly illiquid bonds may simply stop trading, so that their Amihud measure cannot be computed and the average beta increases less than it would if all bonds were always traded.

To check whether these two effects are enough to explain the negative sign found for QS_5_7, we make two changes to the models estimated in Table 5: first, we introduce a new variable ("QS_5_7_AA") where QS_5_7 is multiplied by a dummy variable equal to one if the bond's rating is AA or above. Second, we trim our sample by imposing that each bond be present for at least one quarter of low quality spread (STRESS = 0) and one quarter of high quality spread (STRESS =1) to reduce the "no-trading effect" mentioned above. The results are shown in Table 6: the coefficient for QS_5_7_AA is significantly negative, while the one for QS_5_7 is not statistically different from zero. This confirms that the drop in betas associated with higher quality spreads only occurs for high-quality bonds[32].

---

[31] Negative liquidity betas account for 32% of AAA-rated issues and 15% of non AAA-rated issues.

[32] Moving from Table 5 to Table 6 the sample change leads to a significant reduction in the variability of some covariates: the standard deviation drops from 10 basis points to 5 for PD (as several low-rated bonds stop trading in times of stress) and from 74% to 50% for LOG_AMT, while no significant change occurs in QS_5_7 and DUR. This drop in the range of variation affects the statistical significance of PD and LOG_AMT.

From the estimation of the LMM we also recover, in addition to the betas, the R-square of the regression, which is a measure of "commonality" or "synchronicity" in liquidity. This indicator measures a specific dimension of liquidity risk as it decomposes how much of the illiquidity is driven by systematic factors and how much is instead due to bond-specific causes. A larger portion of individual liquidity explained by market liquidity (i.e., a larger R-square) makes the liquidity of the asset more vulnerable to market-wide shocks. Table 7 presents the estimates of two regression models aimed at capturing the determinants of the commonality in liquidity as proxied by the R-square[33]. Results show that duration and DU_OTR are the only variables that significantly affect commonality in liquidity, while other covariates, including quality spread and PD, are not statistically significant.

Insert Table 7 approximately here

5.4 The impact of adverse market conditions on liquidity levels

The model in Table 3 captures the drivers of *expected liquidity costs*, while results in Table 4 and Table 5 show the determinants of liquidity risk (either total or systematic) and Table 7 investigates commonality in liquidity. None of them, however, addresses the specific issue of the selection of the appropriate assets that should count as HQLAs in the new liquidity rules.

HQLAs are supposed to shield banks against liquidity shocks, and to provide them with a buffer of securities that can be easily turned into cash under adverse market conditions. For HQLAs to achieve that goal, their liquidity must not decrease dramatically in an adverse

[33] To ensure that the dependent variable in Table 7 ranges from minus to plus infinity, we use the "odds ratio" of the R-square, that is log[RSQ/(1-RSQ)].

market environment. What really matters, consequently, is the *increase* in illiquidity *conditional on stressed market* conditions[34].

To measure this conditional illiquidity we estimate the interacted model (equation (5)), where our explanatory variables are multiplied by a "stress" dummy, equal to one when the stress indicator based on the 5-7 year QS exceeds the third quartile, zero otherwise. Table 8 shows the results.

Insert Table 8 approximately here

The estimates for the interacted model reported in Table 8 confirm the robustness of the coefficients estimated for the base model (both for *ILLIQ* and *ILLIQ**). Comparing the two regression specifications, the only major difference is the significant increase in the R-square (from 51.5% to 65.2% for *ILLIQ*, from 64.8% to 72% for *ILLIQ**).

As for the impact of adverse market conditions on liquidity, the effect of the modified duration increases significantly in times of market stress (almost tripling, from 0.038 to 0.038 + 0.074, for the unadjusted Amihud measure), while the impact of higher PDs increases roughly five-fold. On-the-run bonds enjoy better liquidity in times of crises, besides having a relative advantage in normal times. As in the base model shown in Table 3, larger issues continue to be more liquid, also during adverse market conditions.

*   *   *

---

[34] Although betas in Table 5 are clearly related to the effect of market-wide illiquidity and adverse market conditions, they only account for changes in the *steepness* of the relationship linking individual and systematic illiquidity. Accordingly, they cannot capture shifts in individual illiquidity that go beyond that relationship, e.g., changes in the *constant term* of the liquidity market model.

The Amihud index is a widely accepted measure of illiquidity, and its logarithmic transformation, *ILLIQ**, ensures that our findings are not biased by outliers. One might wonder, however, whether our results on conditional illiquidity are robust to a change in the illiquidity measure. We therefore repeat our test on a different illiquidity proxy.

As explained above, we prefer not to turn to the "plain vanilla" bid-ask spread, as – among other reasons – values above 3 BPVs are censored by MTS. Other liquidity proxies, e.g. traded volume or the Roll measure, also suffer from measure-specific biases or shortcomings. Hence, in line with (Dick-Nielsen, Feldhutter, and Lando 2012), we use principal components analysis to combine eight different liquidity proxies (m^k, see Table 9 for details)[35] and derive a robust illiquidity index ("ROIL") by taking the first principal component (PC1)[36], in order to preserve as much information as possible. Formally:

$$ROIL_{it} = \sum_{k=1}^{8} w_k \cdot m_{it}^k \tag{6}$$

where w_k are the factor loadings for PC1 (see the next-to-last column of Table 9).

Insert Table 9 approximately here

---

[35] We include the bid-ask spread among these eight liquidity-related variables. In fact, while it would be inappropriate to use it as a stand-alone liquidity indicator (due to data censoring), the bid-ask spread may still provide additional information when combined with other measures (e.g., by highlighting differences across bonds in "quiet" times). Since the standardized factor loading for the bid-ask spread only explains 17% of the total weight (see Table 9), censored spreads cannot be a major source of bias for ROIL.

[36] The first principal component explains 47.4% of the total variance. This value is in line with the evidence presented by (Dick-Nielsen, Feldhutter, and Lando 2012), whose first component accounts for 39% of the total variation in the liquidity variables.

Results for ROIL are shown in the last three columns of Table 8. Although they are based on a different liquidity metric, the sign and significance of the coefficients are broadly consistent with those found for *ILLIQ* and *ILLIQ**.

Overall, the findings in Table 8 show that the effect of a stressed market environment is significantly stronger for low rating, long-term bonds that are issued in relatively small amounts. Provisions allowing banks to use domestic sovereign bonds as HQLAs without setting any threshold or penalty based on these characteristics may therefore prove at odds with market evidence.

6 Final remarks

The new liquidity rules set in Basel 3 are expected to prompt a major shift in the business models of banks, tilting their asset mix towards low-risk, low-return assets and possibly constraining their ability to support growth through an adequate credit supply. Given this potential downside, it is important that these rules are calibrated in such a way to maximize effectiveness, while keeping undesirable effects in check.

This paper discusses the eligibility criteria for liquid assets (HQLAs) that banks will have to hold in a minimum amount to comply with the new Liquidity Coverage Ratio. The main focus of our study is on government bonds, which according to the current rules are eligible as HQLAs without any concentration limit or haircut based on duration, rating, issue size and age when issued by the banks' domestic country.

Our empirical analysis shows, by contrast, that these characteristics affect various liquidity measures, including its level, volatility and systematic risk. Additionally, the deterioration in liquidity levels under adverse market conditions strongly depends on a bond's modified duration, rating-implied probability of default and outstanding amount.

This evidence strongly argues in favor of rules on HQLAs that constrain the eligibility of government bonds based on their actual characteristics. Failing to address this issue may lead to regulatory innovations that exacerbate the vicious circle between banking crises, bailouts and reduced investors confidence in sovereign issuers, which has been so vividly witnessed in the Eurozone over the last three years.

7 Acknowledgements

Support from the European Commission's Joint Research Centre (JRC) and ARIME (Associazione per la ricerca su imprese intermediari e mercati) is gratefully acknowledged. We are thankful for comments by Claudia Curi, Andrea Enria, Mario Nava, Fabio Panetta and other participants to the presentations held at Bocconi University, the European Banking Authority, the CONSOB (Italian Supervisory Authority on Securities Markets) and the Financial Engineering and Banking Society 2013 conference.

8 References

Acharya, Viral V., Yakov Amihud, and Sreedhar Bharath. 2012. "Liquidity Risk of Corporate Bond Returns: A Conditional Approach." *Journal of Financial Economics* Forthcoming.

Acharya, Viral V., and Lasse Heje Pedersen. 2005. "Asset Pricing with Liquidity Risk." *Journal of Financial Economics* 77 (2) (August): 375–410. doi:10.1016/j.jfineco.2004.06.007.

Amihud, Yakov. 2002. "Illiquidity and Stock Returns: Cross-section and Time-series Effects." *Journal of Financial Markets* 5 (1): 31–56.

Amihud, Yakov, Haim Mendelson, and Lasse Heje Pedersen. 2006. *Liquidity and asset prices*. Boston: Now Publishing. http://public.eblib.com/EBLPublic/PublicView.do?ptiID=254564.

Banking Stakeholder Group. 2012. *New Bank Liquidity Rules: Dangers Ahead*. London: European Banking Authority.

Basel Committee on Banking Supervision. 2010. *Basel III: International Framework for Liquidity Risk Measurement, Standards and Monitoring*. Basel: Bank for International Settlements. http://www.bis.org/publ/bcbs188.htm.

———. 2013. *Basel III: The Liquidity Coverage Ratio and Liquidity Risk Monitoring Tools*. Basel: Bank for International Settlements. http://www.bis.org/publ/bcbs238.htm.

Beber, A., M. Brandt, and K. Kavajecz. 2009. "Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market." *Review of Financial Studies* 22 (3): 925–957.

Brockman, Paul, and Dennis Y. Chung. 2008. “Commonality Under Market Stress: Evidence from an Order-driven Market.” *International Review of Economics & Finance* 17 (2): 179–196.

Chakravarty, Sugato, and Asani Sarkar. 1999. *Liquidity in US Fixed Income Markets: A Comparison of the Bid-ask Spread in Corporate, Government and Municipal Bond Markets*. Federal Reserve Bank of New York. http://app.ny.frb.org/research/staff_reports/sr73.pdf.

Chen, Long, Pierre Collin-Dufresne, and Robert S. Goldstein. 2009. “On the Relation Between the Credit Spread Puzzle and the Equity Premium Puzzle.” *Review of Financial Studies* 22 (9): 3367–3409.

Chen, Nai-Fu. 1991. “Financial Investment Opportunities and the Macroeconomy.” *The Journal of Finance* 46 (2): 529–554. doi:10.1111/j.1540-6261.1991.tb02673.x.

Chordia, T., A. Sarkar, and A. Subrahmanyam. 2005. “An Empirical Analysis of Stock and Bond Market Liquidity.” *Review of Financial Studies* 18 (1): 85–129.

Darbha, Madhucchand, and Alfonso Dufour. 2013. “Measuring Euro Area Government Bond Market Liquidity and Its Asset Pricing Implications”. Working Paper. University of Reading. http://www.efmaefm.org/0EFMAMEETINGS/EFMA%20ANNUAL%20MEETINGS/2013-Reading/papers/Complete%20paper%20final.pdf.

Dick-Nielsen, Jens, Peter Feldhutter, and David Lando. 2012. “Corporate Bond Liquidity Before and After the Onset of the Subprime Crisis.” *Journal of Financial Economics* 103 (3) (March): 471–492. doi:10.1016/j.jfineco.2011.10.009.

Dufour, Alfonso, and Minh Nguyen. 2012. “Permanent Trading Impacts and Bond Yields.” *The European Journal of Finance* 18 (9) (October): 841–864. doi:10.1080/1351847X.2011.601639.

Dunne, Peter G., Michael Moore, and Richard Portes. 2006. *European Government Bond Markets: Transparency, Liquidity, Efficiency*. London: Centre for European Policy Research. http://qcite.qub.ac.uk/handle/123456789/12811.

Fama, E. F., and K. R. French. 1989. “Business Conditions and Expected Returns on Stocks and Bonds.” *Journal of Financial Economics* 25 (1): 23–49.

Favero, Carlo, Marco Pagano, and Ernst-Ludwig von Thadden. 2010. “How Does Liquidity Affect Government Bond Yields?” *Journal of Financial and Quantitative Analysis* 45 (01): 107–134. doi:10.1017/S0022109009990494.

Fleming, M. 2001. “Measuring Treasury Market Liquidity.” *FRB of New York Staff Report* (133). http://papers.ssrn.com/sol3/papers.cfm?abstract_id=276289.

Fong, Kingsley, Craig Holden, and Charles Trzcinka. 2011. “What Are The Best Liquidity Proxies For Global Research?” *Available at SSRN 1558447*. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1558447.

Friewald, Nils, Rainer Jankowitsch, and Marti Subrahmanyam. 2012. “Illiquidity or Credit Deterioration: A Study of Liquidity in the US Corporate Bond Market During Financial Crises.” *Journal of Financial Economics* 105 (1): 18–36. doi:10.1016/j.jfineco.2012.02.001.

Goldreich, D., B. Hanke, and P. Nath. 2005. “The Price of Future Liquidity: Time-varying Liquidity in the US Treasury Market.” *Review of Finance* 9 (1): 1–32.

Goyenko, R. Y., and A. D. Ukhov. 2009. “Stock and Bond Market Liquidity: A Long-run Empirical Analysis.” *Journal of Financial and Quantitative Analysis* 44 (01): 189–212.

Goyenko, R.Y., C.W. Holden, and C.A. Trzcinka. 2009. “Do Liquidity Measures Measure Liquidity?” *Journal of Financial Economics* 92 (2): 153–181.

Holden, Craig W. 2009. “New Low-frequency Spread Measures.” *Journal of Financial Markets* 12 (4): 778–813.
Kamara, A., X. Lou, and R. Sadka. 2008. “The Divergence of Liquidity Commonality in the Cross-section of Stocks.” *Journal of Financial Economics* 89 (3): 444–466.
Karolyi, George, Kuan-Hui Lee, and Mathijs Van Dijk. 2012. “Understanding Commonality in Liquidity Around the World.” *Journal of Financial Economics* 105 (1): 82–112. doi:10.1016/j.jfineco.2011.12.008.
Lesmond, David, Joseph Ogden, and Charles Trzcinka. 1999. “A New Estimate of Transaction Costs.” *Review of Financial Studies*. doi:10.1093/rfs/12.5.1113. http://dx.doi.org/10.1093/rfs/12.5.1113.
Li, Haitao, Junbo Wang, Chunchi Wu, and Yan He. 2009. “Are Liquidity and Information Risks Priced in the Treasury Bond Market?” *The Journal of Finance* 64 (1): 467–503.
Lin, Hai, Junbo Wang, and Chunchi Wu. 2011. “Liquidity Risk and Expected Corporate Bond Returns.” *Journal of Financial Economics* 99 (3) (March): 628–650. doi:10.1016/j.jfineco.2010.10.004.
Lindset, S., and S. Westgaard. 2007. “Determinants of Excess (Credit) Spreads: Evidence from the US Bond Market from 1919 to 2006.” *Available at SSRN 975241*. http://papers.ssrn.com/sol3/papers.cfm?abstract_id=975241.
Mishkin, F. S. 1991. *Asymmetric Information and Financial Crises: A Historical Perspective*. National Bureau of Economic Research. http://www.nber.org/papers/w3400.
———. 1992. *Anatomy of a Financial Crisis*. National Bureau of Economic Research. http://www.nber.org/papers/w3934.
Pelizzon, Loriana, Marti Subrahmanyam, Davide Tomio, and Jun Uno. 2013. “The Microstructure of the European Sovereign Bond Market: A Study of the Euro-zone Crisis”. Unpublished paper.
Petersen, Mitchell A. 2009. “Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches.” *Review of Financial Studies* 22 (1): 435–480.

Table 1 – Descriptive statistics and univariate tests

	Mean	Median	Max	Min	Std. Dev.	# obs.	ρ / t
ILLIQ	0.24	0.08	2.94	0.00	0.45	3,810	
ILLIQ*	0.15	0.07	1.08	0.00	0.20	3,810	95.8%**
LOG_AMT	15.35	16.01	18.00	-6.91	2.43	6,124	0.4%
DUR	4.78	3.35	46.83	0.00	4.96	5,599	57.9%**
AGE	10.41	3.75	108.45	0.00	24.05	10,150	-8.0%**
MATU	12.36	10.26	51.00	0.10	10.00	9,579	52.4%**
VOLUME	618	66	25372	0	1418	10,150	-25.4%**
PD	0.18%	0.03%	9.06%	0.02%	0.86%	9,354	34.9%**
COUPON	2.45	2.72	10.63	0.00	2.44	9,579	25.5%**
QS_5_7	1.76	1.66	3.83	0.63	0.98	10,150	30.0%**
DU_AAA	0.51	1.00	1.00	0.00	0.50	10,150	2.55*
DU_ZERO	0.41	0.00	1.00	0.00	0.49	10,150	14.40**

ILLIQ = Amihud measure; ILLIQ* = log-transformed Amihud - see eq.(2); LOG_AMT = natural log of the dollar-denominated outstanding amount; DUR = modified duration; AGE = time since launch (years); MATU = maturity at launch (years); VOLUME = traded volume; PD = probability of default associated with rating; COUPON = coupon rate (%); QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of 5-7 years); DU_AAA = dummy equal to one is rating is AAA; DU_ZERO = dummy equal to one for zero-coupon bonds. Values in the last column shows linear correlation coefficients with ILLIQ, except for DU_AAA and DU_ZERO, where it shows a t-test for the equality of the means. * and ** denote values significant at 1% and 0.1%

Table 2 – Pairwise correlations

	ILLIQ	LOG_ AMT	DUR	MATU	AGE	VOLUME	PD	COUPON	QS_5_7	DU_ AAA
ILLIQ*	95.8%									
LOG_AMT	0.4%	100.0%								
DUR	57.9%	14.5%	100.0%							
MATU	52.4%	-4.4%	86.9%	100.0%						
AGE	-8.0%	-16.0%	-16.7%	53.1%	100.0%					
VOLUME	-25.4%	23.3%	-12.8%	-21.4%	-8.7%	100.0%				
PD	34.9%	-7.0%	-0.8%	-5.8%	-3.8%	-5.2%	100.0%			
COUPON	25.5%	35.5%	26.6%	8.5%	18.2%	5.9%	9.7%	100.0%		
QS_5_7	30.0%	7.6%	1.5%	1.8%	-9.4%	-15.8%	10.2%	-5.5%	100.0%	
DU_AAA	-4.1%	0.5%	8.8%	20.4%	-21.5%	-21.0%	-19.8%	-19.2%	-3.1%	100.0%
DU_ZERO	-22.8%	-49.9%	-23.4%	1.9%	-20.0%	-13.9%	-6.9%	-88.2%	4.1%	21.7%

ILLIQ = Amihud measure; ILLIQ* = log-transformed Amihud - see eq.(2); LOG_AMT = natural log of the dollar-denominated outstanding amount; DUR = modified duration; AGE = time since launch (years); MATU = maturity at launch (years); VOLUME = traded volume; PD = probability of default associated with rating; COUPON = coupon rate (%);QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of 5-7 years); DU_AAA = dummy equal to one is rating is AAA; DU_ZERO = dummy equal to one for zero-coupon bonds.

Table 3 –Multivariate analysis of expected illiquidity

	Dependent variable: ILLIQ			Dependent variable: ILLIQ*		
Variable	Coefficient	P-value	Standardized coefficient	Coefficient	P-value	Standardized coefficient
Constant	1.223	0.0%		0.614	0.0%	
DUR	0.052	0.0%	0.56	0.028	0.0%	0.67
PD	112.487	0.0%	0.24	43.326	0.0%	0.20
DU_OTR	-0.057	0.0%	-0.06	-0.035	0.0%	-0.08
LOG_AMT	-0.095	0.0%	-0.15	-0.045	0.0%	-0.16
QS_5_7	0.183	0.0%	0.37	0.086	0.0%	0.38
Adjusted R-square	51.5%			64.8%		
Prob of F-statistic	0			0		
Number of observations	2,551			2,551		

ILLIQ = Amihud measure; ILLIQ* = log-transformed Amihud - see eq.(2); DUR = modified duration; PD = probability of default associated with rating; LOG_AMT = natural log of the dollar-denominated outstanding amount; DU_SHORT = dummy equal to one if time since launch is less than 1 year; DU_OTR = dummy equal to one if bond issued by less than one year ("on-the-run"); QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of 5-7 years). "Standardized coefficients" are obtained by an OLS regression on standardized variables.

Table 4 – Multivariate analysis of total liquidity risk

	Dependent variable: SIGMA			Dependent variable: SIGMA*		
Variable	Coefficient	P-value	Standardized coefficient	Coefficient	P-value	Standardized coefficient
Constant	0.974	0.0%		0.276	0.0%	
DUR	0.057	0.0%	0.783	0.021	0.0%	0.641
PD	128.396	0.0%	0.344	32.280	0.0%	0.188
DU_OTR	-0.054	0.5%	-0.070	-0.024	0.0%	-0.066
LOG_AMT	-0.082	0.0%	-0.168	-0.021	0.0%	-0.094
QS_5_7	0.227	0.0%	0.574	0.069	0.0%	0.380
Adjusted R-square	43.1%			61.9%		
Prob of F-statistic	0.00%			0.00%		
Number of observations	2,551			2,551		

SIGMA = quarterly standard deviation of the Amihud measure; SIGMA* = quarterly standard deviation of the log-transformed Amihud; DUR = modified duration; PD = probability of default associated with rating; LOG_AMT = natural log of the dollar-denominated outstanding amount; DU_SHORT = dummy equal to one if time since launch is less than 1 year; DU_OTR = dummy equal to one if bond issued by less than one year ("on-the-run"); QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of 5-7 years). "Standardized coefficients" are obtained by an OLS regression on standardized variables.

Table 5 – Multivariate analysis of systematic liquidity risk

	Dependent variable: BETA			Dependent variable: BETA*		
Variable	Coefficient	P-value	Standardized coefficient	Coefficient	P-value	Standardized coefficient
Constant	2.263	0.5%		-0.304	62.0%	
DUR	0.210	0.0%	0.529	0.162	0.0%	0.533
PD	422.479	0.0%	0.208	251.037	0.0%	0.161
DU_OTR	-0.043	55.0%	-0.010	-0.054	33.4%	-0.017
LOG_AMT	-0.150	0.2%	-0.056	0.028	45.2%	0.014
QS_5_7	-0.131	0.0%	-0.061	-0.156	0.0%	-0.095
Adjusted R-square	30.4%			30.6%		
Prob of F-statistic	0.00%			0.00%		
Number of observations	2,551			2,551		

BETA = quarterly liquidity beta based on the Amihud measure; BETA* = quarterly liquidity beta based on the log-transformed Amihud; DUR = modified duration; PD = probability of default associated with rating; LOG_AMT = natural log of the dollar-denominated outstanding amount; DU_SHORT = dummy equal to one if time since launch is less than 1 year; DU_OTR = dummy equal to one if bond issued by less than one year ("on-the-run"); QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of 5-7 years). "Standardized coefficients" are obtained by an OLS regression on standardized variables.

Table 6 - Systematic liquidity risk: additional checks

	Dependent variable: BETA			Dependent variable: BETA*		
Variable	Coefficient	P-value	Standardized coefficient	Coefficient	P-value	Standardized coefficient
Constant	0.527	75.1%		-0.990	42.6%	
DUR	0.189	0.0%	0.468	0.136	0.0%	0.448
PD	-130.473	50.1%	-0.029	-283.227	5.1%	-0.084
DU_OTR	-0.053	63.8%	-0.011	-0.040	63.4%	-0.011
LOG_AMT	-0.022	82.4%	-0.005	0.103	16.1%	0.033
QS_5_7	0.074	31.6%	0.034	-0.003	95.5%	-0.002
QS_5_7_AA	-0.310	0.0%	-0.169	-0.304	0.0%	-0.220
Adjusted R-square	22.9%			23.8%		
Prob of F-statistic	0.00%			0.00%		
Number of observations	1,431			1,431		

BETA = quarterly liquidity beta based on the Amihud measure; BETA* = quarterly liquidity beta based on the log-transformed Amihud; DUR = modified duration; PD = probability of default associated with rating; LOG_AMT = natural log of the dollar-denominated outstanding amount; DU_SHORT = dummy equal to one if time since launch is less than 1 year; DU_OTR = dummy equal to one if bond issued by less than one year ("on-the-run"); QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of 5-7 years); QS_5_7_AA = QS_5_7 if the bond is rated at least AA, 0 otherwise. "Standardized coefficients" are obtained by an OLS regression on standardized variables.

Table 7 – Multivariate analysis of commonality in liquidity

	Dependent variable: LOG_RSQ			Dependent variable: LOG_RSQ*		
Variable	Coefficient	P-value	Standardized coefficient	Coefficient	P-value	Standardized coefficient
Constant	-0.753	0.0%		-0.820	0.0%	
DUR	0.007	0.0%	0.206	0.006	0.0%	0.199
PD	2.646	41.4%	0.016	1.871	54.9%	0.012
DU_OTR	-0.018	0.9%	-0.053	-0.019	0.3%	-0.059
LOG_AMT	0.002	65.7%	0.010	0.007	12.7%	0.033
QS_5_7	0.003	44.4%	0.015	0.002	58.1%	0.011
Adjusted R-square	5.0%			5.2%		
Prob of F-statistic	0.00%			0.00%		
Number of observations	2,551			2,551		

LOG_RSQ = log of the R-square of the liquidity market model; LOG_RSQ* = log of the R-square of the liquidity market model based on ILLIQ*; DUR = modified duration; PD = probability of default associated with rating; LOG_AMT = natural log of the dollar-denominated outstanding amount; DU_SHORT = dummy equal to one if time since launch is less than 1 year; DU_OTR = dummy equal to one if bond issued by less than one year ("on-the-run"); QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of 5-7 years). "Standardized coefficients" are obtained by an OLS regression on standardized variables.

Table 8 – Multivariate analysis of expected illiquidity conditional on a stressed market environment

	Dependent variable: ILLIQ			Dependent variable: ILLIQ*			Dependent variable: ROIL		
Variable	Coefficient	P-value	Standardized coefficient	Coefficient	P-value	Standardized coefficient	Coefficient	P-value	Standardized coefficient
Constant	1.116	0.0%		0.589	0.0%		4.931	0.0%	
DUR	0.038	0.0%	0.42	0.024	0.0%	0.57	0.271	0.0%	0.61
PD	101.085	0.0%	0.21	39.342	0.0%	0.18	157.066	0.0%	0.07
DU_OTR	-0.039	0.3%	-0.04	-0.029	0.0%	-0.06	-0.591	0.0%	-0.13
LOG_AMT	-0.077	0.0%	-0.13	-0.040	0.0%	-0.14	-0.432	0.0%	-0.15
QS_5_7	0.072	0.0%	0.14	0.043	0.0%	0.19	0.679	0.0%	0.28
STRESS · DUR	0.074	0.0%	0.54	0.024	0.0%	0.38	0.207	0.0%	0.31
STRESS · PD	422.379	0.0%	0.30	140.354	0.0%	0.22	676.890	0.0%	0.10
STRESS · DU_OTR	-0.115	0.0%	-0.06	-0.036	0.4%	-0.04	-0.176	14.7%	-0.02
STRESS · LOG_AMT	-0.024	0.0%	-0.34	-0.007	0.0%	-0.20	-0.045	0.0%	-0.13
Adjusted R-square	65.2%			72.0%			76.0%		
Prob of F-statistic	0.00%			0.00%			0.00%		
Number of observations	2,551			2,551			2,548		

ILLIQ = Amihud measure; ILLIQ* = log-transformed Amihud - see eq.(2); ROIL = robust illiquidity index based on principal component analysis; DUR = modified duration; PD = probability of default associated with rating; LOG_AMT = natural log of the dollar-denominated outstanding amount; DU_SHORT = dummy equal to one if time since launch is less than 1 year; DU_OTR = dummy equal to one if bond issued by less than one year ("on-the-run"); QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of 5-7 years); STRESS = dummy equal to one if QS_5_7 is above the 3rd quartile. "Standardized coefficients" are obtained by an OLS regression on standardized variables.

Table 9 – Liquidity measures and weights used in the computation of the robust illiquidity indicator ("ROIL")

Measure (m^k)	Formula	Intuition	Factor loadings (w_k)	Normalised loadings ($\lvert w_k \rvert / \sum_k \lvert w_k \rvert$)
LOT-FHT (Fong, Holden, and Trzcinka 2011)	$2\ \sigma_r\ N^{-1}\left(\frac{1+z}{2}\right)$	The implied spread is derived from the actual distribution of observed returns (r) and zero returns (z)	0.48	0.18
Amihud (Amihud 2002)	$\frac{\lvert r_{id} \rvert}{TV_{id}}$	Price response associated with one monetary unit of trading volume	0.44	0.17
Bid-ask spread	$A_{i,\,d} - B_{i,\,d}$	Cost of a round-trip trade	0.44	0.17
Modified Roll (Holden 2009)	$2\sqrt{\frac{-Cov(\Delta P_d, \Delta P_{d-1})}{1-z}}$	To estimate the spread based on the breadth of price swings	0.43	0.16
Effective tick (Goyenko, Holden, and Trzcinka 2009; Holden 2009)	$\frac{\sum_{j=1}^{J} \hat{\gamma}_j tick_j}{\bar{P}}$	To derive the spread from the actual price ticks	0.28	0.11
Volume	$V_{id} \cdot P_{id} = TV_{id}$	An ex post measure of market activity is used as a liquidity proxy	-0.26	0.10
Zero (Lesmond, Ogden, and Trzcinka 1999)	$\frac{ZRD}{TD+NTD} = z$	A zero return occurs when the trading cost (spread) exceeds the change in value	0.21	0.08
Low spread days	$\frac{LSD}{TD+NTD}$	Days when the MTS bid-ask spread is below 3 bps over total trading days	-0.07	0. 03

σ_r = standard deviation of returns; N^{-1}(.) = inverse normal cumulative density function; r = price return; A = best ask price; B = best bid price; ΔP = absolute change in price from previous day; γ_j = weight associated to different price ticks, as defined in (Holden 2009); $tick_j$ = price tick (e.g., ¼, ½, etc.); V = traded volume (number of securities); ZRD = number of zero return days; TD = number of trade days; LSD = number of days when the bid-ask spread is below 3 basis point values. To make results more readable, the factor loadings w_k reported above refer to standardized liquidity measures.

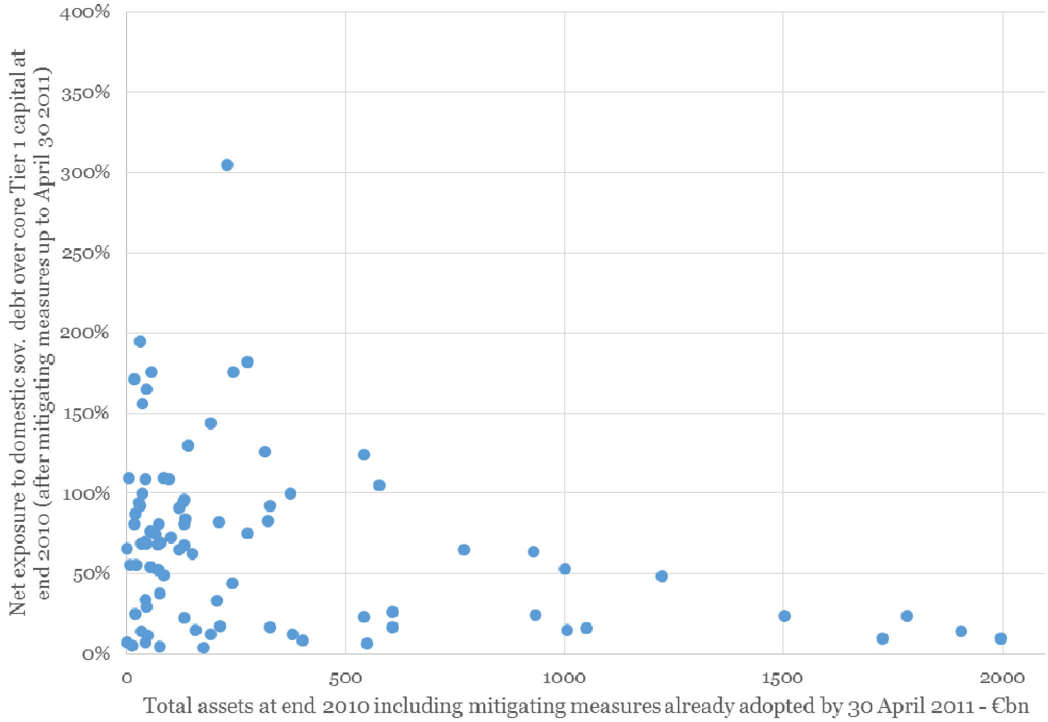

Figure 1 – Net exposure to sovereign debt for European banks participating in the 2011 stress test exercise

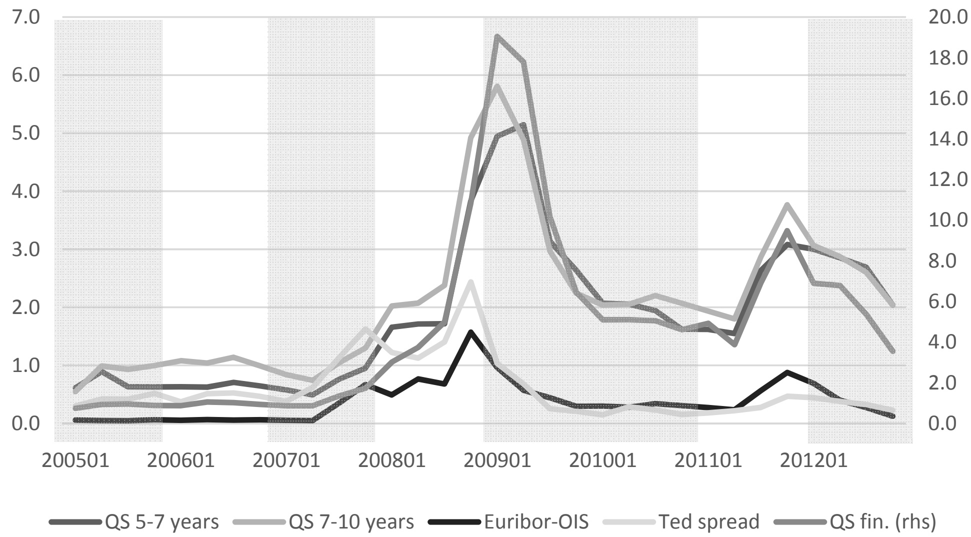

Figure 2 – Indicators of stress in debt and monetary markets

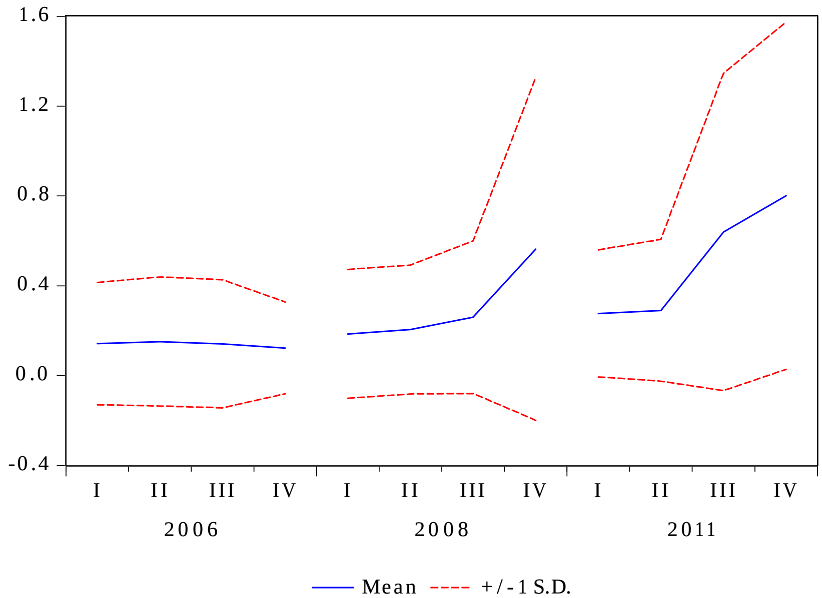

Figure 3 – Amihud illiquidity over time (mean +/– 1 standard deviation)