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An empirical analysis of Eurozone government bonds liquidity: Determinants, predictability and implications for the new bank prudential rules°

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Abstract

Based on a large and representative data set we investigate the liquidity of Eurozone government bonds in ordinary times as well as in periods of market turmoil looking at the behavior of several liquidity indicators from 2005 to 2012. We find that the effect of adverse market conditions on liquidity strongly depends on individual bond's characteristics.

We then analyze the relative performance of different liquidity metrics. This allows us to discuss the appropriateness of the inclusion criteria for liquid assets used by the Basel Committee and the European Union. Our evidence argues for rules on HQLAs that should constrain the eligibility of government bonds depending on their characteristics (primarily, duration and rating).

We also study the persistence of liquidity measures over time to assess which indicators might be used to anticipate future bond liquidity, especially ahead of market-wide crises. Based on rank correlation analysis we find that a wide array of liquidity metrics can provide stable indications over time.

Keywords: Liquidity risk; liquidity coverage ratio; high-quality liquid assets (HQLAs); Basel 3; Basel Committee

JEL Codes: G18, G19, G29

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1 Introduction

The liquidity rules agreed by the Basel Committee for Banking Supervision (2013) and the European Parliament (2013a, 2013b) as part of a large regulatory reform known as Basel 3 require that banks hold a buffer of "high-quality liquid assets" (HQLAs) to withstand future liquidity shocks (the "liquidity buffer")[1]. While improving the resilience of the banking sector, this requirement involves considerable adjustment costs for lenders (Banking Stakeholder Group 2012) 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 while minimizing the risk of negative side effects. For this reason, 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 or introducing regulatory-driven segmentations in secondary markets.

The Basel Committee has designed a set of criteria to assess which financial securities will be eligible as HQLAs. These criteria include credit rating, issuer type,[2] and maximum price changes over a 30-day period. Most asset classes are also subject to concentration limits[3]. Curiously enough, however, the eligibility requirements imposed on government bonds look rather loose. Namely, foreign Treasuries meeting a minimum rating threshold are subject to no further eligibility criteria (regarding, e.g., the duration, age, or issued amounts) and, most strikingly, domestic government bonds are subject to *no eligibility requirements at all*. Additionally, while some concentration limits exist for HQLAs, they do not apply to domestic government bonds. In fact, according to Basel 3 regulation, domestic Treasuries can represent up to 100% of a bank's liquidity buffer.[4] This provision reinforces the importance of investigating the liquidity of government bond in times of market turmoil.

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[1] Banks might also get secured funding from the central bank by pledging eligible securities as collateral in repo deals. However, this option would not alter the actual liquidity of bank assets.

[2] For example, most bonds issued by banks are excluded.

[3] For example, high quality mortgage-based securities will not be allowed to exceed 15% of the total liquidity buffer.

[4] Paragraph 44 in of the Basel Committee on Banking Supervision (2013) states, "The stock of HQLA should be well diversified within the asset classes themselves (except for sovereign debt of the bank's home jurisdiction or from the jurisdiction in which the bank operates; central bank reserves; central bank debt

The motivation for our paper is therefore the following: we intend to examine the soundness of the decision to treat all domestic Treasury bonds (and foreign bonds meeting a minimum rating threshold) as highly liquid, even in times of market stress,[5] for the purposes of liquidity risk regulation. This seems a nontrivial issue, especially in the Eurozone, where the national governments have handed over their monetary policy powers to the European Central Bank (ECB) and can no longer use seigniorage 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. In such cases investors quickly dispose of the securities issued by one or more sovereign states, leading to sudden price drops and liquidity shortages.

To assess whether government bonds can be trusted to be reasonably liquid in a stressed market environment, including a systemic shock, we investigate the liquidity of European government bond markets in ordinary times, as well as in periods of market turmoil[6]. Our sample period spans from 2005 to 2012, covering both the Lehman Brothers collapse and the Eurozone sovereign crisis. Our data set includes European government bonds traded in the MTS market, an electronic wholesale trading platform.

We first examine the cross-sectional relation between liquidity and a number of bond characteristics, controlling for market conditions. In doing so, we use the Amihud liquidity measure and look at different dimensions of liquidity (liquidity level, total liquidity risk, systematic liquidity risk, and liquidity commonality); we also employ a robust illiquidity measure computed, using principal component analysis, as a combination of eight liquidity proxies. We find that liquidity is driven by both market factors (as the quality spread between

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securities; and cash).” Banks are therefore allowed to include in their liquidity buffer an unlimited amount of Treasuries issued by their own domestic governments.

[5] The Basel Committee explicitly requires that, in order to qualify as an HQLA, the asset should be liquid during a period of market stress (see paragraph 23 in Basel Committee on Banking Supervision, 2013).

[6] Our research design follows (Dick-Nielsen, Feldhutter, and Lando 2012) who study the liquidity of the US corporate bond market before and after the onset of the US subprime crisis. Our paper differs from theirs for both the sample and the methodology: as for the sample, we look at Eurozone government bonds and, as for the methodology, we study the determinants of liquidity measures, whereas they investigate the liquidity component of the yield spread (i.e., the liquidity premium).

BBB- and AAA-rated bond yields) and bond-specific factors (as duration, ratings, and size), and that the effect of adverse market conditions strongly depends on each bond's characteristics.

In the last part of this paper, we look at alternative liquidity measures (including the bid-ask spread, the Modified Roll measure, LOT-FHT, Effective tick, traded volume, Zeroes and Low-spread days) to see which one proves most reliable in signaling the illiquidity of individual securities *ahead of* market-wide crisis episodes. We therefore compute serial correlations between adjacent quarters to check whether the liquidity levels computed, e.g., in the second quarter of 2008 could be used to assess what bonds would prove most illiquid in the subsequent three months, when markets were disrupted by the Lehman Brothers collapse. We find that some measures – mostly "trade-based" ones[7] – prove highly volatile and provide liquidity rankings that fluctuate considerably over time. On the other hand, "quote-based" liquidity metrics are more stable over time, although they may be more loosely connected with the actual market's ability to absorb an imbalance in the order flow.

The paper contributes to the existing literature in four ways. First, we provide a timely assessment of an important piece of bank regulation that addresses one of the most painful lessons learned at global level during the financial crisis (i.e., the need for detailed liquidity rules). Second, recent papers look at market liquidity during recent financial crises in the corporate bond (Dick-Nielsen, Feldhutter, and Lando 2012; Friewald, Jankowitsch, and Subrahmanyam 2012) and equity markets (Rösch and Kaserer 2013). This paper fills the gap with respect to the government bond market[8]. Third, unlike previous papers[9], we control for rating, duration, and other factors when assessing government bond liquidity. Due to a wave of downgrades, the credit ratings for Eurozone countries span a wide range of levels. This provides an attractive empirical setting for testing the link between ratings and liquidity in the sovereign debt market. Our findings indicate that significant cross-sectional differences across bonds are in fact explained by the rating level of the issuing government. This is a

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[7] See Section 4.3 for a discussion of "trade-based" and "quote-based" liquidity measures.

[8] (Beber, Brandt, and Kavajecz 2009) also study the liquidity of government bonds; however, they do not consider recent financial crises as their sample covers the time span April 2003-December 2004.

[9] (Dufour and Nguyen 2012) control for different factors in their empirical analysis; however, they study the information content of government bond trades while we study overall transaction costs.

novel empirical result as it shows the importance of rating also for government bonds liquidity, complementing the well-known result on corporate bonds (Acharya, Amihud, and Bharath 2013; Friewald, Jankowitsch, and Subrahmanyam 2012). Fourth, we compare different liquidity measures for sovereign bonds based on a novel perspective: their ability to assess individual bonds ahead of market-wide crises.

The rest of the paper unfolds as follows. Section 2 briefly discusses the new rules on bank liquidity, with a focus on the eligibility criteria for liquid assets. Section 3 reviews relevant papers on the liquidity of government bonds. Section 4 describes our data and methodology, introducing the liquidity measures and indicators of market-wide stress used in our tests. Section 5 presents our results on what drives the liquidity of individual Treasury bonds, while Section 6 looks at a set of alternative liquidity measures to see which one can better anticipate individual liquidity levels in a disrupted market environment. Section 7 concludes the paper.

2 The new bank liquidity rules in a nutshell

The new post-crisis regulatory framework commonly known as Basel 3, set by the Basel Committee in 2010 (Basel Committee on Banking Supervision 2010) and further refined in January 2013 (Basel Committee on Banking Supervision 2013), introduces two liquidity coefficients that require financial institutions to, respectively, hold a minimum amount of liquid assets and issue more long-term debt. In this Section we briefly review the two liquidity coefficients.[10]

The former coefficient, known as the 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 in an amount covering the net liquidity outflows that might be experienced, under stressed conditions, over the following 30 days.[11] Net cash outflows are to be computed based on a number of assumptions concerning run-off, roll-over, and draw-down rates (Basel

[10] For the sake of brevity, we do not provide a general description of the Basel 3 liquidity rules and focus on the regulatory topics that are relevant to our paper. The interested reader may refer to the Basel Committee on Banking Supervision's website at http://www.bis.org/bcbs/basel3.htm for a full set of documents on Basel 3.

[11] 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.

Committee on Banking Supervision, 2010, 2013). The latter, known as the 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 that cannot be easily turned into cash over the following 12 months).

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

1. Cash (with no concentration limit);
2. Central bank reserves and debt securities (with no concentration limit);
3. Bonds issued or guaranteed by the bank's domestic country (with no concentration limit);
4. Bonds issued or guaranteed by sovereigns with a rating equal to at least AA;
5. Bonds issued or guaranteed by sovereigns with a rating equal to at least BBB-;
6. Bonds issued by nonfinancial firms and covered bonds with a rating equal to at least AA-;
7. Bonds issued by nonfinancial firms with a rating equal to at least BBB-, mortgage-backed securities (MBSs), and blue chip stocks.

Securities listed in items 1 to 4 are known as Level 1 assets and are not subject to any haircut for the purpose of calculating the LCR. Securities listed in items 5 and 6 are known as Level 2A assets and are subject to a 15% haircut. Securities listed in item 7 are known as Level 2B assets are subject to a 25% (MBSs) or 50% (corporate bonds and equities) haircut. Level 2 assets (i.e., Levels 2A and 2B assets) should not account for more than 40% of HQLAs and Level 2B alone should not account for more than 15% of HQLAs.

In the EU, the two new ratios were enacted through a new capital requirements directive (CRD4) and capital requirements regulation (CRR) issued in June 2013. The European rules, compared to those of the Basel Committee, follow a less prescriptive and more flexible approach.[12] 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, the

[12] Additionally, regarding the implementation timetable, the European regulation requires that an LCR of at least 100% be achieved in 2018, one year earlier than the Basel Committee's full phase-in (i.e., 2019).

authority responsible for regulating and supervising banks in the EU), to test various eligibility criteria for HQLAs, providing input for implementing regulation to be issued by the European Commission. Accordingly, article 509 of the CRR calls for the EBA to propose appropriate definitions of liquid assets, taking into account a number of different liquidity measures. [13] On October 10, 2014 the European Commission issued the implementing regulation ruling the liquidity coverage requirement in the European Union. The implementing regulation considers bonds issued by any EU member state as Level 1 ('extremely high liquidity and credit quality' in the wording of the CRR) assets.[14] Consequently, banks are actually allowed to use government bonds issued by any EU member state without limitations.

3 Literature review

While a large number of 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 has investigated the liquidity of government bond markets in both the United States and in Europe. Although earlier studies in this area can be traced back to the seventies, we focus our literature review on more recent papers.

Chakravarty and Sarkar (1999) study the liquidity of government bonds based on a sample of US Treasury bonds from 1995 to 1997 and show 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 Treasury bills and notes from December 30, 1996, to March 31, 2000.[15]

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[13] On December 20, 2013, the EBA published a report in fulfillment of the mandate set forth by article 509 (EBA, 2013). However, the EBA report only looks at the *average* relationship between the characteristics of several asset classes (including government bonds) and their liquidity, without investigating the effect of adverse market conditions. This contrasts with the definition of liquid assets provided by the Basel Committee (which must have "a proven record as a reliable source of liquidity even during stressed market conditions", see paragraph 50(c) of (Basel Committee on Banking Supervision 2013)). See also footnote 36 for further differences between the EBA report and our paper.

[14] For details, see http://ec.europa.eu/internal_market/bank/docs/regcapital/acts/delegated/141010_delegated-act-liquidity-coverage_en.pdf.

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

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 buyer- or 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. The author 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 determinants of execution costs and the role of transparency are investigated by (Dunne, Moore, and Portes 2006), who look at the liquidity of government bond markets to study 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. (2006) 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 greater and this implies that execution quality for large trades suffers in these markets. Dunne et al. (2006) also examine a “transparency event” that occurred in June 2003 in the US Treasury market, when an increase in transparency on eSpeed led to an increase in effective spreads. The authors conclude that dealers prefer to operate in 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.

More recent studies look at liquidity conditions in times of market stress. Beber et al. (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[16] and liquidity.[17] More specifically, they investigate the behavior of the order flow in times of market stress and try to disentangle flight-to-quality from flight-to-liquidity phenomena. Using intraday trades and quotes data on Euro-area government bonds from MTS markets, the authors 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, although liquidity plays a nontrivial role, especially for low credit risk countries and during periods of heightened market uncertainty.[18] Beber et al. (2009) conclude that in times of market stress, investors chase liquidity, not credit quality.

None of the above-mentioned 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 for, respectively, US Treasuries and Eurozone sovereign bonds. However, they do not address the issue of liquidity variation across bonds. Additionally, the 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 Eurozone sovereign crisis.

Lastly, Pelizzon et al. (2013) look 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 that proposed in this paper because they focus on Italian bonds and on a “hectic” time window (June 2011 to November 2012) and hence do not compare their results with a “quiet,” pre-crisis period.

4 Sample and methodology

4.1 Data

Our data are from the MTS Time Series database. MTS is a major wholesale electronic market for fixed-income securities in Europe. We base our analysis on a eight-year time

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[16] Credit quality is proxied by the CDS premium.

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

[18] Favero et al. (2010) and Darbha and Dufour (2013) provide related evidence on the liquidity component of the yield spread for Eurozone government bonds.

window, spanning from 2005 to 2012. This allows us to study the liquidity of European government bond markets both in ordinary times and in times of market stress (the Lehman collapse in 2008 and the escalation of the Eurozone crisis in 2011-2012). We consider bonds issued by the EU or by individual EU members. We focus on governments and supranational institutions, excluding quasi-government bonds, corporate bonds, covered bonds, and asset-backed securities. There are 3,102 bonds traded in the MTS market during our sample period that satisfy our initial conditions; since some of them are not available for all 32 quarters in our time span, the total number of bond/quarter combinations is 27,547 (see Table 1).

Insert Table 1 approximately here

For each bond, the data set includes daily trading volume, closing price, and yield to maturity based on the midquote, as well as a number of additional variables (issuer name, issue date and maturity date). We add data on modified duration and rating information from Datastream, Bloomberg, and Standard & Poor's and convert the ratings into probabilities of default (PDs) based on the empirical long-term default rates published by Standard & Poor's. As ratings and modified durations are not available for all bonds in our original sample, this leaves us with 20,637 bond/quarter combinations.

We then calculate the Amihud indicator (our main liquidity measure, see Section 4.2) on a quarterly basis,[19] and discard quarters when fewer than five daily values are available. This produces a final sample of 6,741 bond/quarter combinations with 1,506 bonds (see again Table 1); this will be the reference data set for the regression analyses described below in §5.

As documented in Table 1, the main issuers are France, Spain, Italy and Germany. While most data points pertain to AAA-rated issues, more than one-quarter have a rating of a single

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[19] We calculate quarterly liquidity indicators mainly for three reasons. First, most bonds do not trade every day. On average, each bond has Amihud indices available for 25 days in a quarter (which is approximately made by 62 trading days). To deal with this issue, we used quarterly averages after discarding bond/quarter combinations with less than five daily observations. The second reason why we use quarterly data is that in Section 5.3 we use as a dependent variable the bonds' liquidity betas, which require a sample of at least five observations to be estimated for each bond and quarter. Third, many of the liquidity proxies described in Section 4.3 require a time series of daily observations to be estimated (e.g., LOT-FHT by (Lesmond, Ogden, and Trzcinka 1999) and (Fong, Holden, and Trzcinka 2011); Modified Roll by (Holden 2009); Effective Tick by (Goyenko, Holden, and Trzcinka 2009; Holden 2009); Zero by (Lesmond, Ogden, and Trzcinka 1999); Low spread days).

A or below. All years contribute significantly to our sample, which also shows adequate diversification across durations.

4.2 *Measures of liquidity and liquidity risk: the Amihud index*

Our key measure[20] of bond liquidity is that originally proposed by Amihud (2002) and calculated as

$$ILLIQ_{id} = \frac{|r_{id}|}{TV_{id}} \tag{1}$$

$ILLIQ_{id}$ (henceforth the Amihud illiquidity measure or simply the Amihud measure) captures the price impact of trading by relating the return r_{id} (i.e., change in price) for the ith bond on day d to the traded volume in monetary value 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 and then average it across all days in a given quarter to estimate the Amihud illiquidity for bond i in quarter t ($ILLIQ_{it}$).

The Amihud measure was originally employed to analyze stock liquidity. However, it has also been increasingly used in the study of fixed income markets (e.g., Lin et al., 2011; Dick-Nielsen et al., 2012; Friewald et al., 2012).

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 et al. (2006), for the MTS markets the quoting obligations imposed on primary dealers can actually lead to an excess of transparency that negatively affects execution quality, especially for large trades.

[20] The Amihud illiquidity index has been expressly quoted by the Basel Committee on Banking Supervision (2014) as a tool to assist in the definition of HQLAs and was used by the EBA in its report on eligible HQLAs to the European Commission (EBA, 2013). Additional liquidity proxies and a combined liquidity indicator based on a principal component analysis are also considered in this paper; see Section 4.3 for details.

While the previous advantages are meaningful for any market, there is an additional reason, specific to the MTS market, to avoid the use of the quoted bid–ask spread as the main liquidity measure in this paper. The daily average bid–ask spread computed by MTS is based only on observations below three basis point values (or BPVs)[21]. The MTS company 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**) proposed by Karolyi et al. (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.[22]

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[23] 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. The term $SIGMA^{*}_{id}$ denotes the standard deviation of the modified Amihud measure in (2).

The standard deviation measures total liquidity risk, since 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 also look at

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[21] No such censoring applies to floating-rate securities.

[22] Unlike Karolyi et al. (2012), we do not change sign for the log, since we want the modified Amihud to be similar, in interpretation, to the original one (i.e., to increase when *illiquidity* goes up).

[23] As a robustness check, we also compute the min–max range and the interquartile range.

systematic liquidity risk (Kamara et al., 2008), that is, 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.[24]

To measure systematic liquidity risk and commonality in liquidity, we estimate the following liquidity market model (LMM)[25]:

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

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-squared of the regression measures the proportion of individual liquidity explained by market liquidity (i.e., the commonality in liquidity). The LMMs for individual bonds are estimated on a quarterly basis using daily observations (with input data winsorized at 1% and 99%).[26] $BETA_{it}$ and RSQ_{it} denote the β and R-squared of the LMM for bond i in quarter t. As a measure of aggregate illiquidity, we use the average Amihud measure for all bonds in our sample, weighted by the amount outstanding.

4.3 Additional liquidity measures

The Amihud index is a widely accepted measure of illiquidity and its logarithmic transformation, *ILLIQ**, ensures that our findings are not biased by outliers. However, in the last part of this paper we will be considering a number of alternative liquidity measures. Our aim is twofold. On one hand, we wish to check that our key results (especially on how

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[24] Some papers (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 that of Karolyi et al. (2012).

[25] The first paper estimating a liquidity market model is probably (Chordia, Roll, and Subrahmanyam 2000). Subsequent papers using it are (Acharya, Amihud, and Bharath 2013; Acharya and Pedersen 2005; Brockman and Chung 2008; Coughenour and Saad 2004; Dick-Nielsen, Feldhutter, and Lando 2012).

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

individual liquidity measures react to adverse market condition) are robust to the choice of a different indicator. On the other hand, we want to compare several widespread liquidity proxies to see which ones perform best in assessing individual securities ahead of a market-wide downturn.

Table 2 shows a full list of the liquidity indicators (including the Amihud index) used in this paper. The list includes trade-based measures, order-based measures and order-based proxies.

Trade-based measures include trading value, trading volume, the number of trades (frequency) and the turnover ratio. These measures are simple to calculate using readily available data. However, they are ex post rather than ex ante measures. In this sense, they indicate what people have traded in the past, and can be driven by contingent market conditions. Importantly, they do not consider the costs associated with trading as well as the actual possibility of trading immediately, which is the essence of liquidity.

Order-based measures are based on limit order book data and, as such, they provide information about the possibility and the costs of trading immediately. The majority of these measures are constructed around the bid-ask spread, which represents an estimate of the cost that an investor must incur in order to trade immediately. However, this estimate of transaction cost is only valid for small trades. A more complete measure of liquidity must also consider the market impact costs of trading large orders. For this reason, measures of quoted depth (i.e., the quantity of shares available for trading at each quote level in the limit order book) should also be computed to analyze jointly the price and quantity dimensions of the limit order book and, consequently, to get a better estimate of the market liquidity.

Order-based proxies aim at estimating the bid-ask spread; however, they are not based on quote data but on price data (and, consequently, they are proxies rather than measures).

Besides the Amihud index (a trade-based measure that was extensively discussed above), we consider the following measures and proxies:

- the trading volume (a trade-based measure), that is, the total euro value of the trades executed during the day;

- the bid-ask spread (an order-based measure), that is, the difference between the best (i.e., the lowest) ask quote and the best bid (i.e., the highest) quote available in the limit order book[27];
- the estimator of the effective bid-ask spread derived by Roll (1984) on the basis of the serial covariance of price changes (i.e., returns). This is an order-based proxy, as the effective spread is inferred from a time series of traded prices. The basic intuition is that the presence of the bid-ask spread results in transitory price movements ("bid-ask bounce") that are serially negatively correlated and the strength of this autocorrelation is a proxy for the size of the bid-ask spread. Roll's model considers only fixed trading costs (i.e., transitory costs) and assumes that (i.) the market is informationally efficient, (ii.) the information is symmetrically distributed (i.e., adverse selection costs are ignored), (iii.) the distribution of price changes is stationary, and (iv.) the idiosyncratic component of the return is independent of buy/sell trades sequence. We will be using the Extended Roll measure as refined by Holden (2009), where the systematic component of the return is removed;
- the Effective Tick measure proposed by (Holden, 2009) and (Goyenko, Holden and Trzcinka, 2009), where a weighted-average percent effective spread is derived, based on actual trade prices (and consequently belonging to the order-based proxies category) and observed ticks[28]. This measure is based on the intuition that observed price clustering depends both on the tick size and the width of the bid-ask spread;
- the percentage of days with zero returns, which is used as a proxy for liquidity by (Lesmond, Ogden and Trzcinka, 1999), based on the idea that the return is zero when the market is inactive (i.e., there is no trading activity). This measure consequently falls in the trade-based category. Its theoretical underpinning is that an investor will trade only when the cost of trading is lower than the profit from trading. Thus, we observe zero returns whenever the trading cost (i.e., the bid-ask spread) exceeds the change in value that is expected by the trader. If the expected change in value is

[27] As explained in Section 4.2, in our data set bid-ask spread observations above three basis point values are censored by MTS.

[28] Tick is the minimum price increment for quotes and prices.

lower than the bid-ask spread a trader will abstain from trading as the expected trading profits would be negative;

- the LOT measure, also due to (Lesmond, Ogden and Trzcinka, 1999). This is an estimate of the bid-ask spread based on the actual distribution of observed returns (including zero returns). The idea underlying LOT estimator is that the observed return is the realization of an underlying (unobservable, potential or true) return process. As previously mentioned, securities with larger bid-ask spread pose a larger hurdle for potential traders and, consequently, a larger portion of true non-zero returns are incorporated into the observed zero returns. We will be using the LOT measure as simplified by (Fong, Holden and Trzcinka, 2001), where it is assumed that transaction costs are symmetric and that the unobservable true securities return process is normally distributed with mean zero;
- the share of trading days in a quarter where the bid ask spread was below three times the basis point value ("low spread days").

Since each one of these measures (m^k) has its own strengths and weaknesses, we combine them into a single indicator. Namely, in line with Dick-Nielsen et al. (2012), we use principal components analysis to merge them into a robust illiquidity index (ROIL) by taking the first principal component (PC1),[29] to preserve as much information as possible. Formally,

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

where the w_k are the factor loadings for PC1 (reported in the next-to-last column of Table 2).

Insert Table 2 approximately here

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

4.4 Alternative liquidity channels

According to the Basel rules (Basel Committee on Banking Supervision 2013, para. 25), liquid assets are of "high quality" if "their liquidity-generating capacity is assumed to remain intact even in periods of severe idiosyncratic and market stress". In principle, a security can generate liquidity through three different channels: i) an outright sale on the secondary market (the "cash channel"); ii) a repo with a private counterparty (the "private repo channel"); iii) a refinancing operation with the central bank (the "central bank channel").

To assess the viability of the first channel, a number of market liquidity measures can be used: in this paper, we focus on the Amihud indicator (a widely used liquidity measure that was presented in detail in Section 4.2) and we also provide evidence based on a combination of different measures.

As concerns the second channel, a security used as underlying asset in a repo clearly needs not to be sold on the secondary market. Nevertheless, market liquidity still plays a crucial role in determining whether a private counterparty is willing to perform a repurchase transaction on that asset. Significant liquidity drops may make a security simply not eligible for repurchase agreements, as potential lenders anticipate that it could prove hard to sell if necessary. At the very least, illiquid securities will be subjected to higher haircuts, reducing their liquidity-generating potential. In this regard, it should be noticed that the Basel rules also define HQLAs as "assets that are more likely to generate funds without incurring large discounts in sale *or repurchase agreement (repo) markets*" (Basel Committee on Banking Supervision 2013, para. 24). For these reasons, we believe that secondary market liquidity (i.e., liquidity in the "cash channel") also affects the ability of an asset to generate liquidity via the private repo channel.

The third channel is somewhat different, as central banks are free to accept highly illiquid assets in refinancing operations, and sometimes do (e.g., when unconventional policy measures are used to deal with severe market downturns). Accordingly, one may argue that – although market liquidity measures are relevant for the cash channel and the private repo channel – they should not affect an asset's eligibility as HQLA, since the "central bank channel" is prepared to provide liquidity under any circumstances.

However, the Basel rules explicitly state that, although central bank eligibility may "provide additional confidence that banks are holding assets that could be used in events of severe stress, […] *central bank eligibility does not by itself constitute the basis for the categorisation of an asset as HQLA*" (Basel Committee on Banking Supervision 2013, paras 26–27). In other words, access to the "central bank channel" is not enough, by itself, to secure the status of high-quality liquid asset. This is due to the fact that, while central banks may indeed be willing to broaden eligibility criteria in times of stress for financial stability reasons (on an *ex post* basis), they cannot preemptively commit to do so in the future (on an *ex ante* basis). Should they do so, this would lead to moral hazard behavior by banks, which would heavily invest in illiquid assets to gain the illiquidity premium (overlooking their liquidity equilibrium in exchange for short-term profits). This is even more true in the Eurozone, where the ECB enjoys an independent and supranational status that makes it not accountable to national parliaments and therefore less prone to political pressures. Accordingly, banks cannot blindly rely on the "central bank channel" and assume that securities experiencing severe liquidity disruptions will always qualify for central bank funding; this explains why such channel is explicitly ruled out by the Basel Committee. This reinforces the policy relevance of our study, suggesting that market liquidity should always be taken into account when assessing whether a security should qualify as HQLA.

4.5 Market stress indicators

The liquidity of government bonds may fluctuate over time, depending on overall market conditions. This is due to various effects; for example, when risk aversion increases, investors may look for safe havens and refrain from investing in Treasury bonds issued by riskier countries. Additionally, when banks acting as market makers 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 might increase their debt to fund bank rescues, leading to a reduced willingness to trade Treasury bonds and thus to higher illiquidity.

Insert Figure 1 approximately here

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 1.[30]

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 European

[30] The white areas in Figure 1 indicate the periods investigated in our analysis.

corporate bonds[31]. We consider three variants of the QS measure, based on the bonds' duration (five to seven years versus seven to ten 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 (Chen, 1991; Fama and French, 1989) and is positively related to the volatility in stock market returns (Lindset and Westgaard, 2007). This suggests that the QS is not only associated with an increase in the investor-perceived level of credit risk (triggering flights to quality), but also with higher uncertainty in asset prices and company values,[32] which may lead to increased liquidity risk. Furthermore, according to Mishkin (1991, 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 (Iannotta et al. 2013).

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 the three-month US dollar Libor rate and the rate on three-month US Treasury bills) and the Euribor–OIS spread (the gap between the rate on three-month euro-denominated interbank deposits and the rate on overnight-indexed swaps in the same currency).

4.6 Econometric specifications

In Section 5 we will estimate two models to explore the drivers of government bond liquidity in normal times, as well as in times of systemic stress. The former model (the base model) explains bond illiquidity and liquidity risk as follows:

$$y_{it} = \alpha + \beta_1 DUR_{it} + \beta_2 PD_{it} + \beta_3 DU\_OTR_{it} + \beta_4 LOG\_AMT_{it} + \beta_5 QS\_5\_7_{it} + \eta_{it} \quad (4)$$

where

[31] We employ Bank of America Merrill Lynch bond indices, also available on FRED database maintained by St. Louis Fed.

[32] As shown by Chen et al. (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).

- y_{it} denotes the dependent variable. We 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 measure shown in equation (2) ($ILLIQ^{*}_{it}$, $SIGMA^{*}_{it}$, etc.) are also tested;
- DUR_{it} is the modified duration for bond *i* in quarter *t*;
- PD_{it} is the probability of default associated with bond *i*'s rating in quarter *t*;
- DU_OTR_{it} is a dummy variable that takes 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 system-wide stress*. We therefore introduce another model (the interacted model) where the covariates are interacted with a dummy (STRESS) that takes a value of one whenever our stress indicator (QS_5_7) exceeds its 75th percentile. Formally,

$$ILLIQ_{it} = \alpha + \beta_1 DUR_{it} + \beta_2 PD_{it} + \beta_3 DU\_OTR_{it} + \beta_4 LOG\_AMT_{it} + \beta_5 QS\_5\_7_{it} + STRESS \cdot (\gamma_1 DUR_{it} + \gamma_2 PD_{it} + \gamma_3 DU\_OTR_{it} + \gamma_4 LOG\_AMT_{it} + \gamma_5 QS\_5\_7_{it}) + \omega_{it} \qquad (5)$$

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.

Although our data set may lend itself to panel data analysis, we estimate the previous models as a pooled OLS[33] and we do not introduce any fixed or random effect associated with individual bonds or quarters. In fact, although such effects would considerably increase our model's in-sample explanatory power, they would weaken the statistical significance of other variables (e.g., size, duration, rating, quality spread) that can be used to identify security characteristics and market conditions that – on an ex ante basis – are more prone to future liquidity shocks, getting important insight on how to design effective rules on HQLAs[34]. However, we will control for a set of country dummies to check whether the bond/market characteristics included in equations (5) and (6) are still significant once national segmentations are accounted for.

Finally, in Section 6 we will not be using an econometric model, but will rather rely on simple descriptive measures (serial correlations) to check how persistent are the liquidity scores assigned to individual securities by the various indicators reported in Table 2.

5 Empirical findings

5.1 Liquidity level

Figure 2 shows the behavior over time of the Amihud illiquidity measure in our sample period. In 2005-2007, 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 2010, market liquidity was disrupted again by the sovereign debt crisis in the Eurozone: the situation evolved unfavorably as large countries, such as Italy and Spain, were hit during the last half of 2011. Average illiquidity increased considerably, with large differences across individual securities (as shown by the

[33] Performing our estimates using clustered standard errors as in Petersen (2009), to control for heteroskedasticity and correlation in the residuals, does not alter the results.

[34] The size of the issue, for example, does not change over time and might be not statistically significant in a fixed effect panel. By contrast, the size of the issue is a factor that is clearly related the liquidity of a bond, is easily observable and, consequently, might be used to identify liquid bonds for regulatory purposes.

sharp rise in the width of the standard deviation bands)[35]. Liquidity conditions eased partially in the last part of 2012, although the heterogeneity across bonds was still high.

Insert Figure 2 approximately here

Table 3 shows summary statistics for the main variables used in this Section. For continuous variables, 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.

Insert Table 3 approximately here

Illiquidity, as expected, increases with duration (longer durations imply higher risks for market makers) and age (newly-issued on-the-run bonds tend to be traded more frequently). Maturity at launch combines the two effects, since long-term issues either have a long duration or become significantly off-the-run as the expiration date is closer, in both cases facing higher illiquidity (see the correlations in Table 4). 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, which implies a shorter duration. Trading activity is greater for larger issues, shorter maturity, and younger bonds.

Insert Table 4 approximately here

Table 5 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 enjoy better liquidity conditions.[36] Finally, the five- to seven-year QS

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[35] The correlation between Amihud illiquidity measures (both *ILLIQ* and *ILLIQ**) and trading volume is negative (respectively -0.26 with *ILLIQ* and -0.33 with *ILLIQ**) and statistically significant. Accordingly, when the Amihud measure increases traded volume dries up and banks should anticipate difficulties in selling bonds on the market.

[36] These results are consistent with those of EBA (2013), which focuses on expected illiquidity levels and does not address liquidity risk (see Sections 5.2 and 5.4) and liquidity conditional on adverse market conditions (Section 5.4).

significantly affects illiquidity.[37] Moving from $ILLIQ_{it}$ to $ILLIQ^*_{it}$, all previous findings are confirmed and the adjusted R-squared increases considerably[38]. Panel B shows that all the above results also hold for the model with country dummies.[39]

Insert Table 5 approximately here

Table 5 also reports the standardized regression coefficients[40] in the rightmost 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. This result is consistent with the findings of Friewald et al. (2012) for the corporate bond market.

5.2 Total liquidity risk

The Amihud illiquidity measure estimates the transaction costs due to price impact allowing for the possibility of trading quantities greater than the depth displayed at the best quotes. The results in Table 5 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 to investigate what drives liquidity risk in the market for Eurozone sovereign bonds.

We thus turn to quarterly standard deviations of the Amihud measure ($SIGMA_{i,t}$) to investigate the *volatility* in liquidity costs. The results, shown in Table 6, 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

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[37] Replacing the five- to seven-year QS with the alternative market stress indicators discussed in Section 4.3 does not meaningfully change our results.

[38] Results are also robust to further alternative specifications, like using the natural log of ILLIQ as the dependent variable (to ensure that it can take any value between minus and plus infinity) or replacing PD by rating dummies.

[39] For brevity's sake, the tables in the remainder of the paper do not report coefficient estimates for the model with country dummies, since our results are always robust to their inclusion.

[40] The standardized coefficients indicate by how many standard deviations the dependent variable would move following a one standard deviation shift in the covariates.

determinants of the quarterly standard deviations remain unchanged while the adjusted R-squared increases to 57%.[41] This evidence shows that total liquidity risk is driven by both market factors (as the quality spread) and bond-specific factors (as the duration and the probability of default).

Insert Table 6 approximately here

5.3 Systematic risk and commonality in liquidity

The standard deviation captures the overall volatility in illiquidity, including both idiosyncratic and systematic 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 the LMM betas. Once the quarterly betas are estimated,[42] following the methodology described in Section 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 7.

Insert Table 7 approximately here

The results for *BETA* and *BETA** are comparable. In both cases liquidity betas behave similarly to standard deviations, in that they are mostly driven by the PD, the QS, and, to a larger extent, duration. The effect of the QS on liquidity betas, however, is different from that previously found for total liquidity risk, since beta and QS move in opposite directions. This means that the average beta tends to decrease as the QS increases, which might initially sound counterintuitive.

We propose two explanations for this result. First, a flight-to-quality behavior might be taking place, as in Acharya et al. (2013). We find that, when QS_5_7 increases above its

[41] Results for alternative measures of volatility (max-min range and inter-quartile range) are qualitatively similar.

[42] The LMM betas based on the unadjusted Amihud measure used for the regression in Table 7 have a mean value of 1.04 and a standard deviation of 3.42. The distribution is highly skewed to the right, since the median is 0.20 and the skewness is 28.17. This is due to the existence of a small number of bonds with large betas (the 90th percentile is 3.00 and the maximum is 193.00).

third quartile, the share of bonds with negative betas rises from 22.5% to 23.9% (with average beta falling from -0.30 to -0.42) showing that investors turn to high-quality securities.[43] 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.

From the estimation of the LMM, we also recover, in addition to the betas, the R-squared of the regression, which is a measure of commonality in liquidity. This indicator measures a specific dimension of liquidity risk, since 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-squared) makes the liquidity of the asset more vulnerable to market-wide shocks. Table 8 presents the estimates of two regression models aimed at capturing the determinants of the commonality in liquidity as proxied by R-squared.[44] The results show that commonality is stronger for small, low-quality, short-duration, on-the-run issues, while the quality spread apparently has no clear effect.

Insert Table 8 approximately here

5.4 The impact of adverse market conditions on liquidity levels

The model in Table 5 captures the drivers of *expected liquidity costs*, while the results in Table 6 and Table 7 show the determinants of liquidity risk (either total or systematic) and Table 8 investigates commonality in liquidity. None of the previous analyses, 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

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

[44] To ensure that the dependent variable in Table 8 ranges from minus to plus infinity, we use the odds ratio of R-squared, that is, log[RSQ/(1-RSQ)].

market environment. What really matters, consequently, is the *increase* in illiquidity *conditional on stressed market* conditions.[45]

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 five- to seven-year QS exceeds the third quartile and zero otherwise. Table 9 shows the results[46].

Insert Table 9 approximately here

The estimates for the interacted model reported in Table 9 confirm the robustness of the coefficients estimated for the base model (for both *ILLIQ* and *ILLIQ**). Comparing the two regression specifications, the only major difference is the significant increase in the R-squared (from 44.1% to 48.2% for *ILLIQ* and from 58.8% to 60.7% 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 (doubling, from 0.040 to 0.040 + 0.040, for the unadjusted Amihud measure), while the impact of higher PDs roughly triples. The high significance of the duration and PDs is consistent with theoretical models and empirical evidence showing that liquidity level is directly affected by the costs and risks of liquidity provision (e.g., (Hasbrouck 2006; Foucault, Pagano, and Röell 2013)). On-the-run bonds enjoy better liquidity in times of crises, besides having a relative advantage in normal times. This result complements (Pasquariello and Vega 2009). As in the base model shown in Table 5, larger issues continue to be more liquid also under adverse market conditions.

One might wonder whether our results on conditional illiquidity are robust to changes in the illiquidity measure. We therefore repeat our test on a different illiquidity proxy, ROIL, the robust illiquidity measure described in §4.3. The results for are shown in the last three columns of Table 9. Although they are based on a different liquidity metric, the sign and

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[45] Although the betas in Table 7 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, such as changes in the *constant term* of the LMM.

[46] We also estimated model (5) after including the stress dummy as an additive dummy without interactions, and excluding QS_5_7. The results (not reported for brevity) are unaffected.

significance of the coefficients are broadly consistent with those found for *ILLIQ* and *ILLIQ**.

5.5 Discussion of the results

Overall our findings show that the effect of a stressed market environment is significantly stronger for low-rated, 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.

The policymakers' choice to impose such mild constraints on government bonds is probably explained by the fact that banks play a key role in underwriting government debt in many countries, ensuring that public deficits are financed in an orderly fashion. In the European Union (EU), net exposure to domestic sovereign debt for a sample of banks accounted for, on average, 79.5% of core Tier 1 capital in 2010.[47] While this figure tends to be lower for very large banks (see Figure 3), the weighted average exposure still amounts to 49.2%, highlighting a strong link between banks and government debt. The fact that sovereign debt currently represents a considerable portion of bank assets implies that overly conservative rules on the definition of HQLAs might trigger uncontrolled sell-offs.

Insert Figure 3 approximately here

6 Which liquidity measures can anticipate individual liquidity in market-wide crises?

6.1 Descriptive statistics and pairwise correlations

We now turn to the last part of our analysis and look at which liquidity measures, among those listed in Table 2 and discussed in §4, can be considered more reliable in screening illiquid bonds ahead of market crises.

Table 10 provides descriptive statistics for the various liquidity metrics. Since each indicator can only be computed for some bonds and quarters in our sample, such descriptive statistics are provided twice: the top part of the table reports values based on different samples for

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[47] Data collected by the European Banking Authority (EBA) as part of the 2011 stress test exercise. For details, see http://www.eba.europa.eu.

each measure, while the bottom part shows results derived from a (smaller) common sample where all measures are jointly available.

Insert Table 10 approximately here

Table 11 shows pairwise correlations among our liquidity measures. While correlations tend to be high for most indicators, lower values are found for the traded volume, the share of days with zero returns ("Zeroes") and for low-spread days (the incidence of days where the bid ask spread does not exceed three basis point values). Since some metrics are associated with *increasing liquidity* (rather than *illiquidity*), their correlations with the remaining indicators are – unsurprisingly – negative: this is the case for the traded volume, Zeroesand low-spread days.

Insert Table 11 approximately here

Correlations are further confirmed by Figure 4, where we depict the behavior of our key liquidity measures over time: most measures show a drop in liquidity (or a spike in illiquidity) in 2008-2009 (Lehman Brothers collapse) and 2011-2012 (widening of the Eurozone crisis).

Insert Figure 4 approximately here

6.2 An analysis of serial correlations

We now turn to an analysis of serial correlations to assess what liquidity measures can better *anticipate* individual liquidity levels ahead of market-wide crises.

Figure 5 provides an example by comparing the behavior of two widely-accepted liquidity metrics – the bid-ask spread and the Amihud index ("ILLIQ") upon the occurrence of the Lehman Brothers collapse. The x-axes report data for the third quarter of 2008, whose average liquidity indicators are still largely unaffected by the post-Lehman market environment (which only accounts for 10 trading days); the y-axes refer to the fourth quarter of 2008, when market-wide was consistently and severely disrupted.

Insert Figure 5 approximately here

One can see that, as we move from the third to the fourth quarter, both illiquidity indicators experience an increase (the red line interpolating the dots has a slope above 45 degrees, especially for the Amihud index). However, while individual bid ask spreads behave consistently across the two quarters, the post-Lehman Amihud values are somewhat unrelated to those reported for the previous quarter. This can be summarized by looking at serial correlations (that is, correlations between the values of a given liquidity measure in a specific quarter and those in the previous one): the result for the bid-ask spread (92.1%) is considerably higher than the one for the Amihud index (72.0%).

Figure 6 generalizes this example by extending it to all quarters in our sample and all relevant metrics. Different line patterns indicate the behavior of the various liquidity measures described in Section 4, while the shaded area in the background shows the quality spread, our preferred indicator of market-wide distress.

Insert Figure 6 approximately here

The figure leads to the following remarks:

- most liquidity indicators tend to be rather stable in "normal" times with serial correlations generally above 80% (the exception being the Effective Tick, where individual values look very volatile over time);
- correlations drop in times of market distress, and the decrease looks especially severe for the Roll measure;
- the behavior of low-spread days looks interestingly dichotomous, depending on whether one looks at the Lehman crisis (where its predictive ability looks very low) or at the 2011-2012 Eurozone turmoil (where serial correlations drop, but remain higher than for most other liquidity indicators): this could depend on MTS modifying quoting obligations over time, although we have no clear evidence of such a behavior;
- the robust illiquidity measure ("ROIL") generated through principal component analysis, while suffering several drops in serial correlations over time, mostly remains above 80%, witnessing no dramatic plunge upon the occurrence of market-wide liquidity crises;
- the highest serial correlations are observed for the bid-ask spread and the Zeroes measure. This could be interpreted as a sign that market participants should use those indicators if they want to rely on liquidity metrics that keep stable over time. However, it should be emphasized that both indicators may be affected by the specific microstructure of the MTS market. On one hand MTS is based on market makers who commit to post quotes within a predefined maximum bid ask spread, but it is unclear whether such "best" quotes can absorb a significant volume of trades

without being significantly revised. Additionally, the bid-ask spread observations are recorded by MTS only if they are below the 3 BPV threshold: consequently, any spike in this metric might actually not appear in the data. On the other hand, Zeroes could be easily manipulated by market participants if it were used as a liquidity measure for, say, regulatory purposes (since it would be enough to trade a security in small amounts to improve its reported liquidity);

- leaving aside Zeroes, one could say that "trade-based" measures prove more volatile and provide liquidity assessments that fluctuate considerably over time. On the other hand, "quote-based" liquidity indices are more stable over time, although they may be more loosely connected with the market's actual ability to absorb an increase in traded volumes.

Correlations can be biased by outliers; this could be especially true in times of market distress. We therefore repeat our analysis by looking at rank correlations, which are not affected by large individual values and only reflect the agreement between rankings in two adjacent quarters. The result is shown in Figure 7. While most results from the previous analysis are confirmed (including generalized drops in correlation following market-wide distress, and the disappointing performance of Effective tick and Roll), it is worth noting that the differences among the best performing measures tend to become smaller. This suggests that liquidity rankings across bonds appear rather persistent and, if one is interested in liquidity rankings – rather than in liquidity levels – there is a wide array of liquidity metrics providing stable indications over time.

Insert Figure 7 approximately here

7 Conclusions

The new liquidity rules introduced by Basel 3 regulatory framework 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 as a minimum to comply with the new Liquidity Coverage Ratio requirement. 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, or age when issued by the bank’s 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. However, the implementing measures recently enacted in the EU do not impose any constraint and all sovereigns issued by EU member states may be included in the liquidity buffer without limitations. Based on our empirical evidence, we believe that this provision might actually exacerbate the vicious circle between sovereign debt, banking crises and bailouts, as it has been so vividly witnessed in the Eurozone over the last years.

The introduction of new rules should always involve an accurate cost/benefit analysis. This would ensure that no additional regulatory burdens are imposed onto market participants (that are ultimately paid for by the users of financial services) unless they provide material advantages. In the case of rules limiting the eligibility of domestic government bonds for LCR purposes, we feel confident that such a test would be passed. In terms of advantages, our findings show that variables such as duration and credit ratings would help identify resilient bonds under stressed market conditions. In terms of costs, duration, age, outstanding amount and credit ratings are readily available characteristics and can be easily obtained without having to implement any dedicated risk management system. Accordingly, we do not anticipate that limiting the eligibility of domestic sovereign bonds as HQLA (or imposing haircuts) with reference to such characteristics would impose a material operational burden on banks.

As part of our empirical analysis we have also computed a number of alternative liquidity measures and assessed which ones can be considered more reliable in assessing individual liquidity ahead of a market downturn. We highlighted that – while the bid-ask spread provides values that keep considerably consistent over time – this could be due to market microstructure features, and therefore must be evaluated with care. On the other hand, the robust illiquidity indicator that we derived through principal component analysis looks reasonably equipped to provide a liquidity assessment that is both robust to market-specific features and reasonably stable over time.

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Table 1. Sample composition

	Whole sample *Observations*	*(%)*	*Sub-sample with Amihud index* *Observations*	*(%)*
(a) by issuing country				
France	6,561	24%	1,166	23%
Spain	4,425	16%	515	10%
Italy	3,372	12%	2,214	44%
Germany	2,340	8%	849	17%
Belgium	2,021	7%	467	9%
The Netherlands	1,068	4%	407	8%
Others	7,760	28%	1,123	22%
Total	27,547		5,060	
(b) by rating grade				
AAA	12,042	44%	2,958	44%
AA	5,395	20%	1,639	24%
A and below	7,349	27%	2,144	32%
(missing)	2,761	10%	0	0%
Total	27,547		6,741	
(c) by duration				
Below 1 year	12,324	45%	1,532	23%
1-3 years	2,867	10%	1,332	20%
3-5 years	2,261	8%	814	12%
5-7 years	1,697	6%	742	11%
Beyond 7 years	3,847	14%	2,321	34%
(missing)	4,551	17%	0	0%
Total	27,547		6,741	
(d) by year				
2005	3,164	11%	1,078	16%
2006	3,033	11%	1,084	16%
2007	2,956	11%	995	15%
2008	3,084	11%	758	11%
2009	3,337	12%	677	10%
2010	3,722	14%	651	10%
2011	4,033	15%	709	11%
2012	4,218	15%	789	12%
Total	27,547		6,741	

Table 2. Liquidity measures and weights used in the computation of the robust illiquidity indicator (ROIL)

Measure (m^k)	Formula	Intuition	Factor loadings (w_k)	Normalized loadings ($\lvert w_k\rvert / \sum_k \lvert w_k\rvert$)
Amihud measure (Amihud, 2002)	$\frac{\lvert r_{id}\rvert}{TV_{id}}$	Price response associated with one monetary unit of trading volume.	0.44	0.17
LOT-FHT (Lesmond et al. 1999; Fong et al., 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).	0.45	0.17
Bid–ask spread	$A_{i,\,d} - B_{i,\,d}$	Cost of a round-trip trade.	0.42	0.16
Extended 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.	0.48	0.18
Effective tick (Goyenko et al., 2009; Holden, 2009)	$\frac{\sum_{j=1}^{J}\hat{\gamma}_j tick_j}{\overline{P}}$	To derive the spread from the actual price ticks.	0.27	0.10
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
Zeroes (Lesmond et al., 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 BPV over total trading days.	-0.08	0. 03

In this table, 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 the previous day; γ_j = weight associated with different price ticks, as defined by Holden (2009); $tick_j$ = price tick (e.g., ¼, ½); V = traded volume (number of securities); ZRD = number of zero-return days; TD = number of trade days; and LSD = number of days when the bid–ask spread is below three basis point values. To make the results more readable, the factor loadings w_k reported above refer to standardized liquidity measures.

Table 3. Descriptive statistics and univariate tests

	Mean	Median	Max	Min	Std. Dev.	# obs.	ρ / t
ILLIQ	0.27	0.10	3.29	0.00	0.46	6,741	
ILLIQ*	0.17	0.09	1.13	0.00	0.21	6,741	95.1%**
LOG_AMT	16.49	16.65	17.67	-6.91	0.82	6,741	5.5%**
DUR	5.51	4.26	29.11	0.00	5.08	6,741	49.8%**
MATU	11.58	10.28	51.00	0.08	9.76	6,741	52.5%**
AGE	3.46	2.30	20.48	0.00	3.52	6,741	13.9%**
VOLUME	1570	817	25900	0.00	2120	6,741	-25.9%**
PD	0.09%	0.04%	2.29%	0.03%	0.11%	6,741	30.1%**
COUPON	3.46	3.80	10.50	0.00	1.93	6,741	21.8%**
QS_5_7	1.66	1.62	5.14	0.49	1.17	6,741	28.7%**
DU_AAA	0.44	0.00	1.00	0.00	0.50	6,741	3.05*
DU_ZERO	0.15	0.00	1.00	0.00	0.36	6,741	12.0**

ILLIQ = Amihud measure; ILLIQ* = log-transformed Amihud - see eq.; 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 4. Pairwise correlations

	ILLIQ	ILLIQ*	LOG_ AMT	DUR	MATU	AGE	VOLUME	PD	COUPON	QS_5_7	DU_ AAA
ILLIQ*	95.1%										
LOG_AMT	5.5%	10.1%									
DUR	49.8%	62.9%	28.6%								
MATU	52.5%	64.4%	24.0%	89.2%							
AGE	13.9%	18.3%	10.2%	14.3%	49.1%						
VOLUME	-25.9%	-33.2%	10.9%	-16.8%	-23.2%	-21.7%					
PD	30.1%	26.4%	-1.5%	-9.5%	-6.6%	-4.1%	3.8%				
COUPON	21.8%	29.8%	20.2%	39.2%	57.4%	64.9%	-14.4%	0.5%			
QS_5_7	28.7%	32.5%	16.9%	11.4%	10.4%	2.4%	-19.0%	13.0%	-4.9%		
DU_AAA	-7.0%	-3.5%	0.9%	13.7%	9.4%	4.4%	-30.1%	-47.0%	2.7%	-15.6%	
DU_ZERO	-22.2%	-30.4%	-35.9%	-41.5%	-46.0%	-38.3%	9.7%	3.5%	-75.5%	-3.4%	-12.5%

ILLIQ = Amihud measure; ILLIQ* = log-transformed Amihud - see eq.; 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 5. Multivariate analysis of expected illiquidity

	Dependent variable: ILLIQ			Dependent variable: ILLIQ*		
Variable	Coefficient	P-value	Standardized coefficient	Coefficient	P-value	Standardized coefficient
(a) Model without country dummies						
Constant	1.137	0.00%		0.511	0.00%	
DUR	0.048	0.00%	0.53	0.026	0.00%	0.65
PD	130.453	0.00%	0.32	52.974	0.00%	0.29
DU_OTR	-0.092	0.00%	-0.09	-0.048	0.00%	-0.11
LOG_AMT	-0.082	0.00%	-0.15	-0.036	0.00%	-0.14
QS_5_7	0.083	0.00%	0.21	0.042	0.00%	0.24
Adjusted R-square	42.65%			57.01%		
Prob of F-statistic	0			0		
Number of observations	6,741			6,741		
(b) Model with country dummies						
Constant	1.231	0.00%		0.501	0.00%	
DUR	0.047	0.00%	0.52	0.026	0.00%	0.64
PD	137.232	0.00%	0.34	57.751	0.00%	0.32
DU_OTR	-0.100	0.00%	-0.10	-0.048	0.00%	-0.11
LOG_AMT	-0.089	0.00%	-0.16	-0.035	0.00%	-0.14
QS_5_7	0.086	0.00%	0.22	0.044	0.00%	0.25
DU_BE	-0.056	0.40%	-0.03	-0.035	0.00%	-0.04
DU_DE	0.122	0.00%	0.09	0.047	0.00%	0.08
DU_ES	0.118	0.00%	0.07	0.036	0.00%	0.05
DU_FR	0.030	5.84%	0.02	0.004	51.74%	0.01
DU_IT	-0.015	28.02%	-0.02	-0.030	0.00%	-0.07
DU_NL	-0.030	14.96%	-0.02	-0.026	0.11%	-0.03
Adjusted R-square	44.10%			58.81%		
Prob of F-statistic	0			0		
Number of observations	6,741			6,741		

ILLIQ = Amihud measure. eq- (1); ILLIQ* = log-transformed Amihud – (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 6. Multivariate analysis of total liquidity risk

	Dependent variable: SIGMA			Dependent variable: SIGMA*		
Variable	Coefficient	P-value	Standardized coefficient	Coefficient	P-value	Standardized coefficient
Constant	0.966	0.00%		0.257	0.00%	
DUR	0.054	0.00%	0.50	0.021	0.00%	0.65
PD	151.539	0.00%	0.31	41.154	0.00%	0.28
DU_OTR	-0.097	0.00%	-0.08	-0.035	0.00%	-0.10
LOG_AMT	-0.073	0.00%	-0.11	-0.018	0.00%	-0.09
QS_5_7	0.098	0.00%	0.21	0.034	0.00%	0.24
Adjusted R-square	39.28%			57.23%		
Prob of F-statistic	0			0		
Number of observations	6,741			6,741		

In this table, SIGMA = quarterly standard deviation of the Amihud measure; SIGMA* = quarterly standard deviation of the log-transformed Amihud measure; 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 the time since the launch is less than one year; DU_OTR = dummy equal to one if the bond was issued by less than one year (“on the run”); and QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of five to seven years). Standardized coefficients are obtained by an OLS regression on standardized variables.

Table 7. Multivariate analysis of systematic liquidity risk

	Dependent variable: BETA			Dependent variable: BETA*		
Variable	Coefficient	P-value	Standardized coefficient	Coefficient	P-value	Standardized coefficient
Constant	5.100	0.00%		0.867	0.87%	
DUR	0.232	0.00%	0.58	0.160	0.00%	0.54
PD	907.174	0.00%	0.51	202.593	0.00%	0.15
DU_OTR	-0.244	0.35%	-0.06	-0.160	0.00%	-0.05
LOG_AMT	-0.345	0.00%	-0.14	-0.044	3.03%	-0.02
QS_5_7	-0.214	0.00%	-0.12	-0.119	0.00%	-0.09
Adjusted R-square	18.05%			29.29%		
Prob of F-statistic	0			0		
Number of observations	6,741			6,741		

In this table, BETA = quarterly liquidity beta based on the Amihud measure; BETA* = quarterly liquidity beta based on the log-transformed Amihud measure; 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 the time since the launch is less than one year; DU_OTR = dummy equal to one if the bond was issued by less than one year ("on the run"); and QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of five to seven years). Standardized coefficients are obtained by an OLS regression on standardized variables.

Table 8. 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	0.000	0.00%		0.000	0.00%	
DUR	-0.725	0.00%	0.00	-0.784	0.00%	0.00
PD	0.007	0.00%	0.22	0.007	0.00%	0.23
DU_OTR	3.768	2.60%	0.03	4.731	0.34%	0.04
LOG_AMT	-0.019	0.00%	-0.05	-0.020	0.00%	-0.06
QS_5_7	0.000	97.22%	0.00	0.004	7.04%	0.02
Adjusted R-square	5.41%			6.61%		
Prob of F-statistic	77.08461			95.26571		
Number of observations	6,741			6,741		

In this table, BETA = quarterly liquidity beta based on the Amihud measure; BETA* = quarterly liquidity beta based on the log-transformed Amihud measure; 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 the time since the launch is less than one year; DU_OTR = dummy equal to one if the bond was issued by less than one year ("on the run"); and QS_5_7 = quality spread (difference between yields on Baa-rated and Aaa-rated corporate bonds with a duration of five to seven years). Standardized coefficients are obtained by an OLS regression on standardized variables.

Table 9. Multivariate analysis of expected illiquidity conditional on a stressed market environment

	Dependent variable: ILLIQ			Dependent variable: ILLIQ*			Dependent variable: ROIL*		
Variable	Coefficient	P-value	Standard-ized coefficient	Coefficient	P-value	Standard-ized coefficient	Coefficient	P-value	Standard-ized coefficient
Constant	1.219	0.00%		0.551	0.00%		4.261	0.00%	
DUR	0.040	0.00%	0.45	0.024	0.00%	0.59	0.281	0.00%	0.64
PD	91.764	0.00%	0.23	37.449	0.00%	0.21	242.017	0.00%	0.12
DU_OTR	-0.058	0.00%	-0.06	-0.033	0.00%	-0.08	-0.626	0.00%	-0.13
LOG_AMT	-0.084	0.00%	-0.15	-0.037	0.00%	-0.15	-0.385	0.00%	-0.14
QS_5_7	0.073	0.00%	0.19	0.037	0.00%	0.21	0.577	0.00%	0.30
STRESS · DUR	0.040	0.00%	0.29	0.013	0.00%	0.20	0.121	0.00%	0.18
STRESS · PD	142.449	0.00%	0.24	55.457	0.00%	0.21	494.775	0.00%	0.17
STRESS · DU_OTR	-0.131	0.00%	-0.07	-0.059	0.00%	-0.07	-0.507	0.00%	-0.05
STRESS · LOG_AMT	-0.017	0.00%	-0.24	-0.005	0.00%	-0.16	-0.056	0.00%	-0.17
Adjusted R-square	48.24%			60.69%			66.95%		
Prob of F-statistic	0			0			0		
Number of observations	6,741			6,741			6,741		

In this table, ILLIQ = Amihud measure (equation (1)); ILLIQ* = log-transformed Amihud measure (equation (2)); ROIL = robust illiquidity index based on principal component analysis (equation (6)); 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 the time since the launch is less than one year; DU_OTR = dummy equal to one if the bond was 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 five to seven years); and STRESS = dummy equal to one if QS_5_7 is above the third quartile. Standardized coefficients are obtained by an OLS regression on standardized variables.

Table 10. Descriptive statistics for alternative liquidity measures

	Mean	Median	Max	Min	Std. Dev.	# obs.
1) Individual samples						
Bid-ask spread	0.10	0.05	0.57	0.00	0.11	13,000
ILLIQ (Amihud)	0.23	0.07	3.29	0.00	0.47	10,276
Modified Roll	0.23	0.15	1.49	0.00	0.27	11,153
LOT-FHT	0.00	0.00	0.02	0.00	0.00	10,552
Effective tick	0.02	0.02	0.17	0.00	0.03	14,807
Volume	611	63	25900	0	1400	27,547
Zeroes	74.9%	88.9%	100.0%	0.0%	30.3%	27,547
Low-spread days	40.5%	11.1%	100.0%	0.0%	44.3%	27,547
ROIL	37.8%	6.0%	1196.5%	-449.6%	193.9%	13,601
2) Common sample						
Bid-ask spread	0.08	0.04	0.57	0.00	0.11	8,225
ILLIQ (Amihud)	0.18	0.07	3.29	0.00	0.31	8,225
Modified Roll	0.23	0.16	1.49	0.00	0.27	8,225
LOT-FHT	0.00	0.00	0.02	0.00	0.00	8,225
Effective tick	0.02	0.02	0.17	0.00	0.02	8,225
Volume	1660	970	25900	0	2040	8,225
Zeroes	40.8%	43.1%	100.0%	14.1%	22.8%	8,225
Low-spread days	88.3%	97.0%	100.0%	15.9%	18.5%	8,225
ROIL	0.0%	-44.7%	1196.5%	-449.6%	191.6%	8,225

Table 11. Correlations among alternative liquidity measures (sample sizes are reported in italics)

	Bid-ask spread	Amihud	Modified Roll	LOT-FHT	Effective tick	Volume	Zeroes	Low-spread days	ROIL
Bid-ask spread	100% *13000*								
Amihud	66% *9155*	100% *10276*							
Modified Roll	71% *11091*	61% *8281*	100% *11153*						
LOT-FHT	77% *9407*	83% *10223*	76% *8472*	100% *10552*					
Effective tick	36% *11878*	42% *10276*	32% *10595*	41% *10552*	100% *14807*				
Volume	-24% *13000*	-25% *10276*	-17% *11153*	-29% *10552*	-19% *14807*	100% *29674*			
Zeroes	18% *13000*	23% *10276*	7% *11153*	23% *10552*	24% *14807*	-72% *27547*	100% *27547*		
Low-spread days	-7% *13000*	-29% *10276*	10% *11153*	-26% *10552*	-12% *14807*	45% *27547*	68% *27547*	100% *27547*	
ROIL	82% *12418*	85% *10276*	77% *11135*	91% *10552*	56% *13061*	-48% *13601*	-40% *13601*	-27% *13601*	100% *13601*

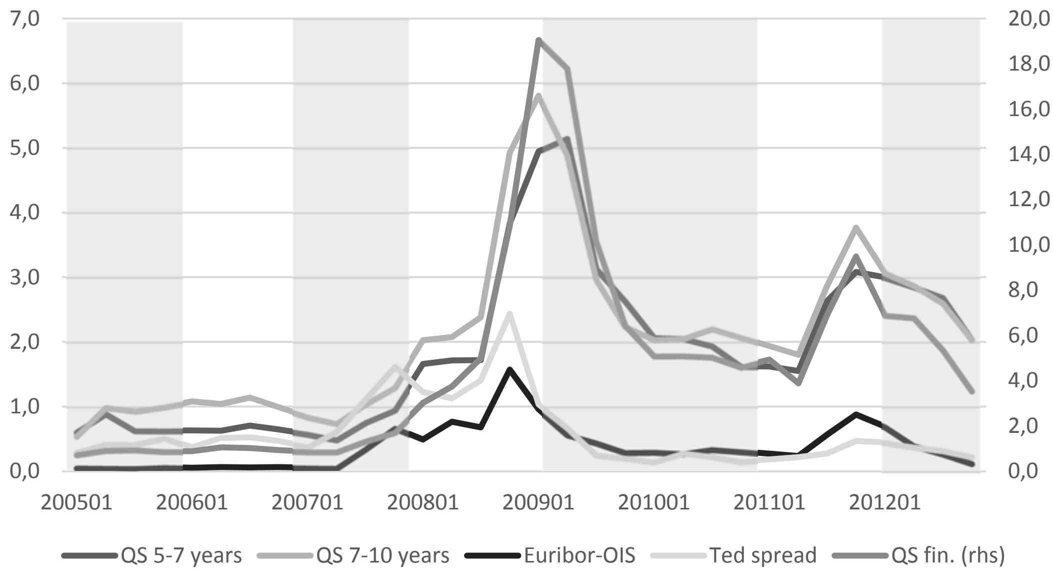

Figure 1. Indicators of stress in debt and monetary markets

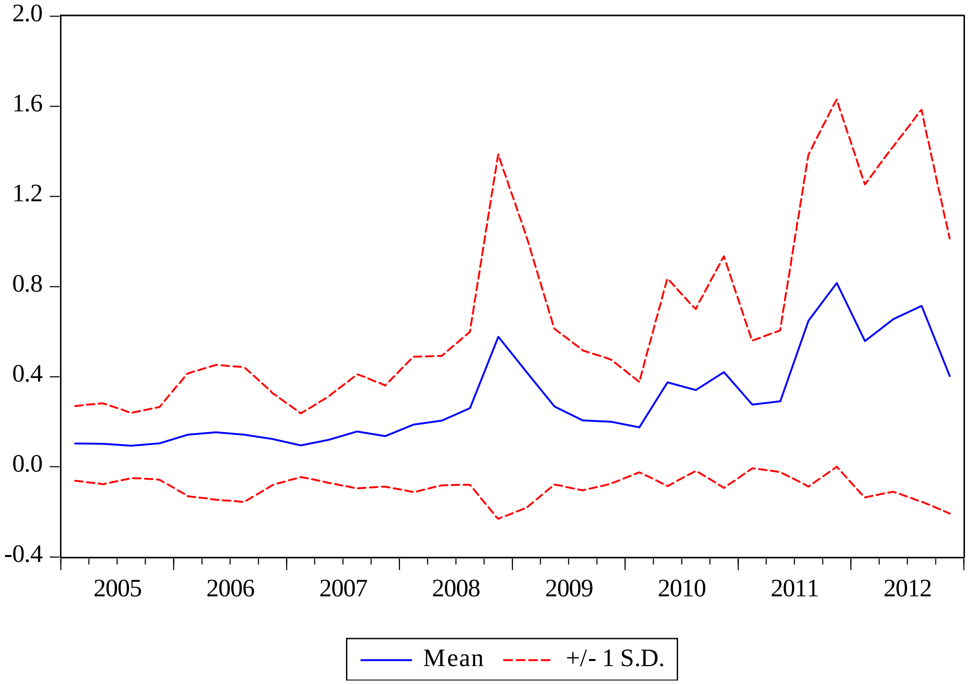

Figure 2. Amihud illiquidity over time (mean +/– 1 standard deviation)

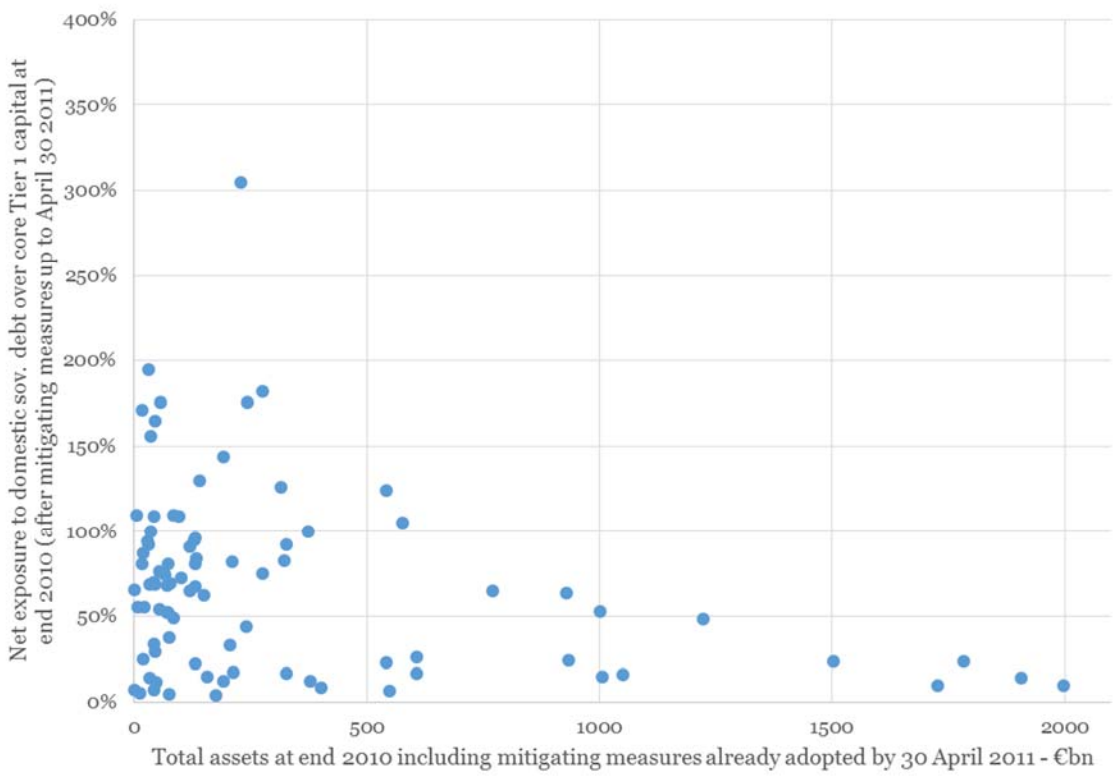

Figure 3. Net exposure to sovereign debt for European banks participating in the 2011 stress test exercise

Figure 4 - Different liquidity measures over time (mean +/– 1 standard deviation, open samples)

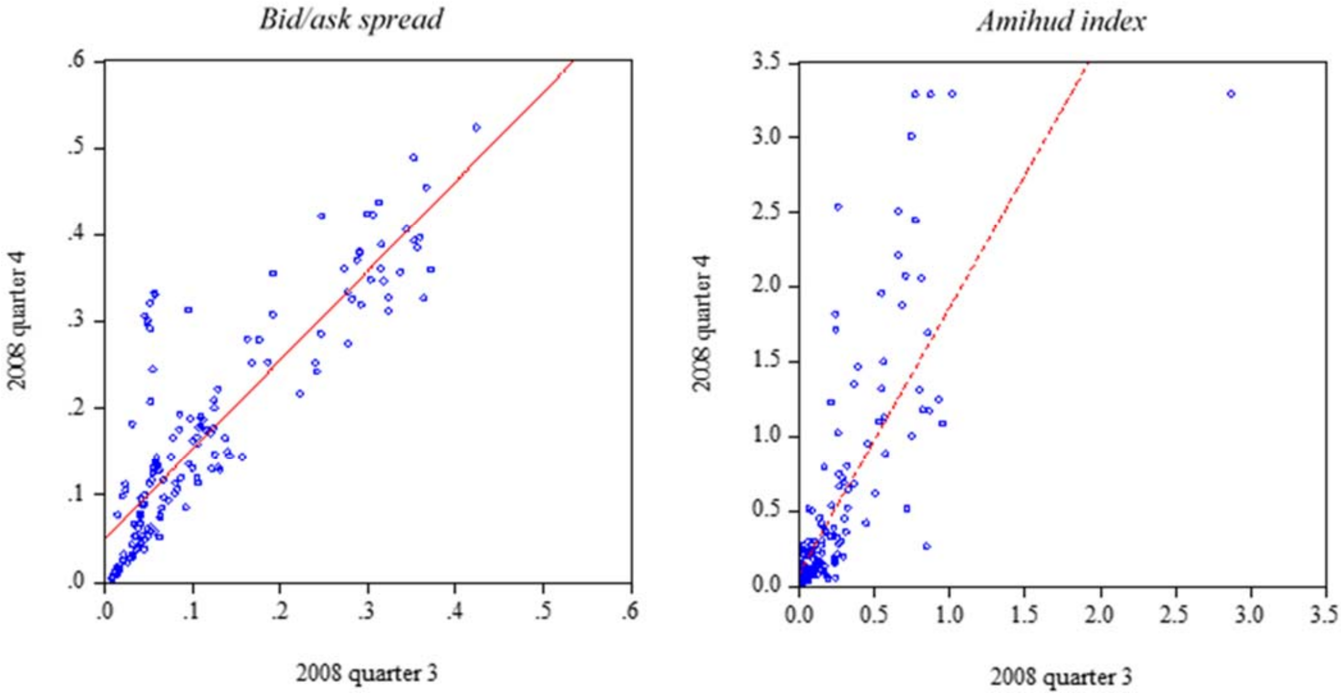

Figure 5 . A comparison between two liquidity measures upon the Lehman Brothers crisis

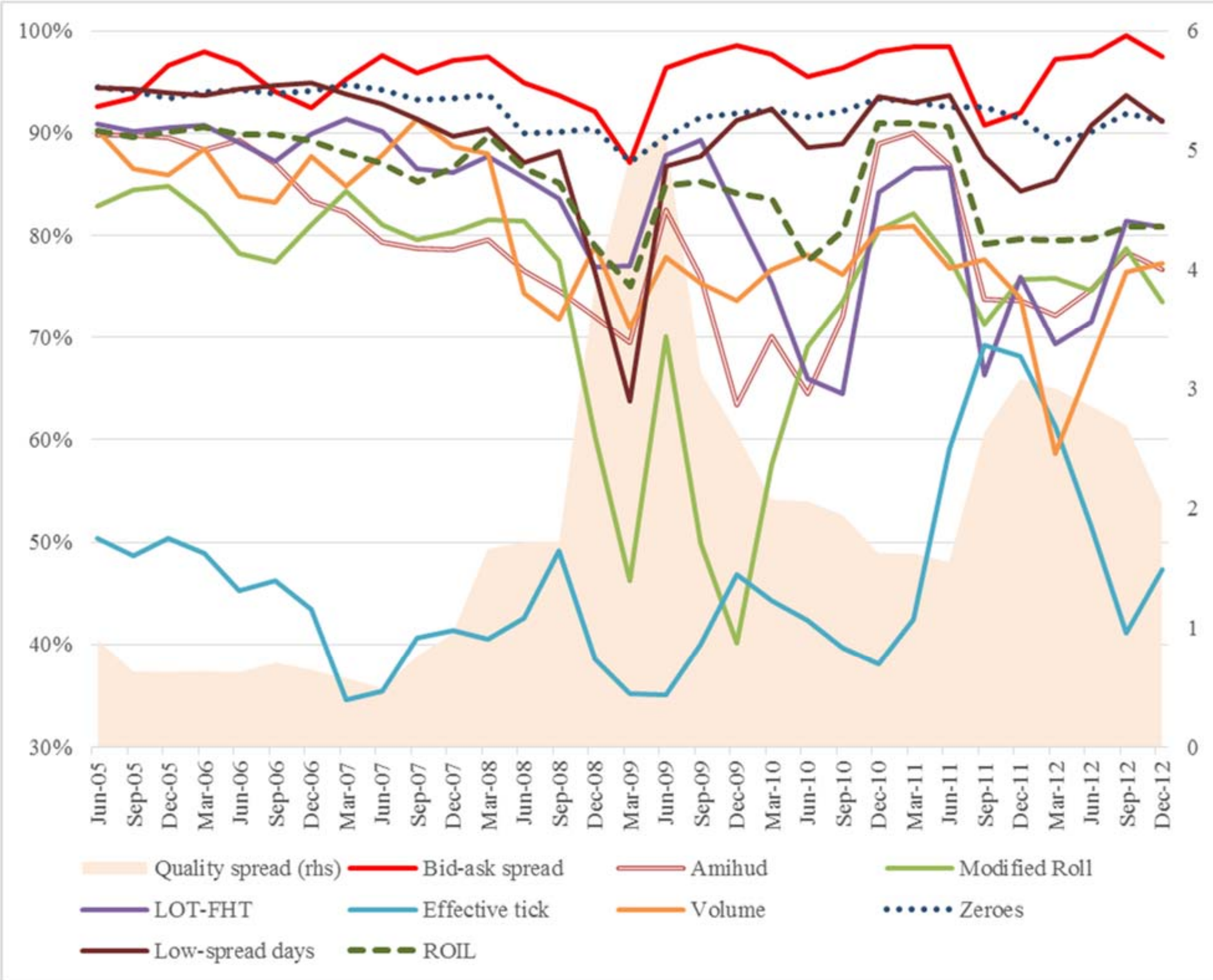

Figure 6 – Serial correlations (with the previous quarter) for different liquidity measures

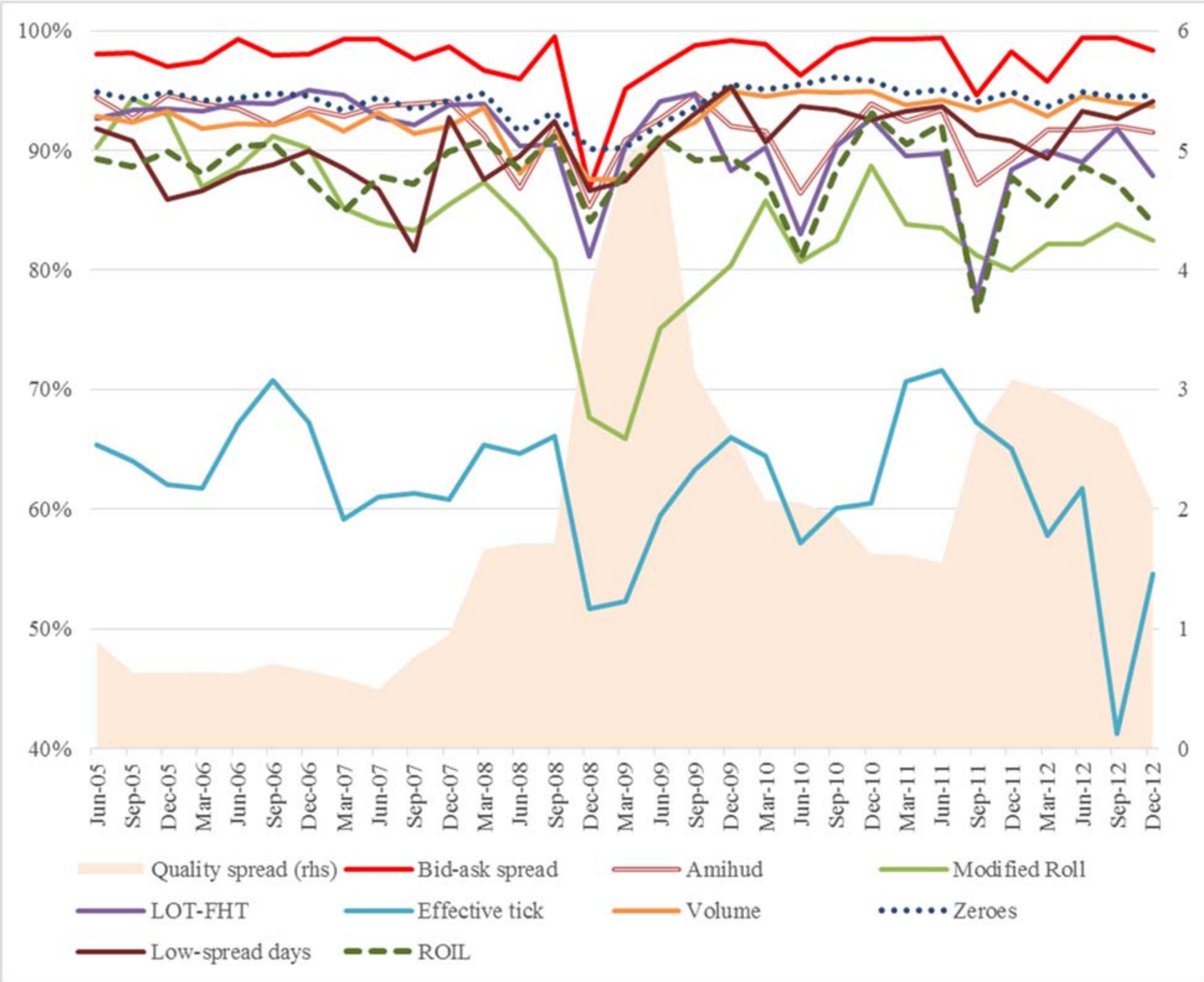

Figure 7 – Serial rank correlations (with the previous quarter) for different liquidity measures