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The liquidity of corporate and government bonds: drivers and sensitivity to different market conditions

Clara Galliani
Giovanni Petrella
Andrea Resti

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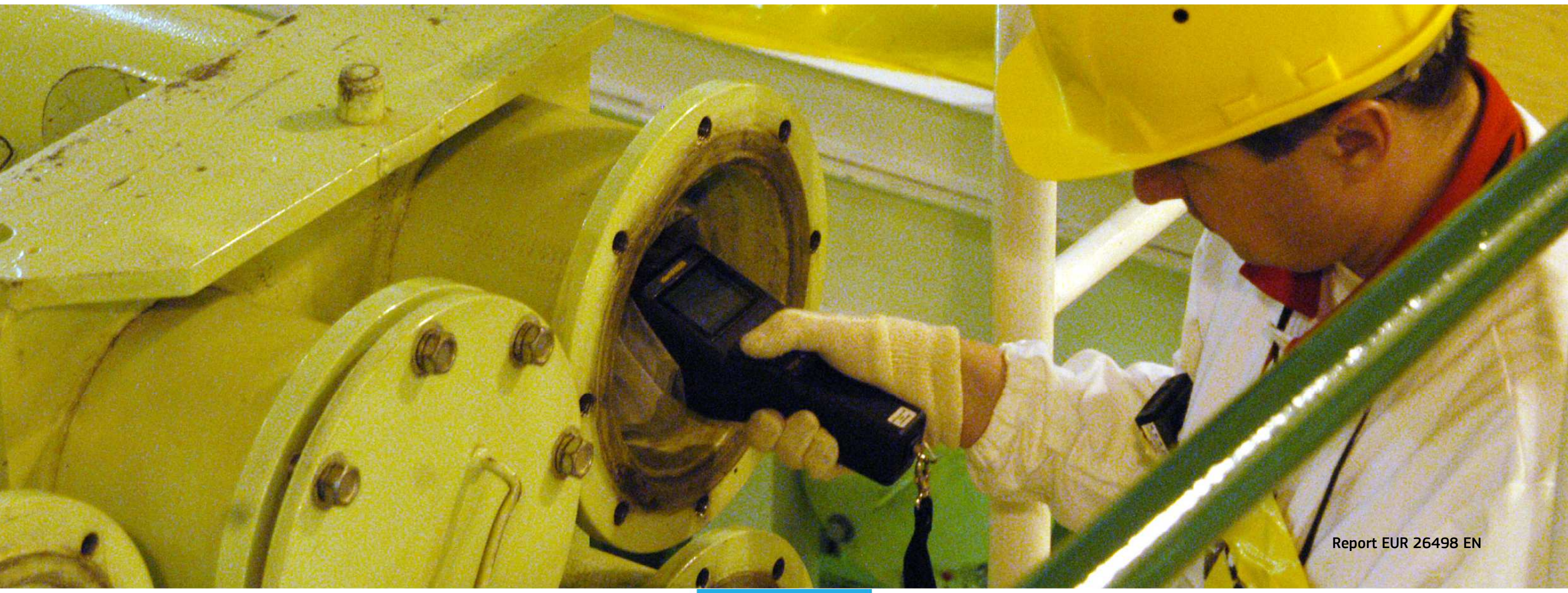

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Contact information
Florinela Cazan
Address: Joint Research Centre, Via Enrico Fermi 2749, TP 361, 21027 Ispra (VA), Italy
E-mail: florinela.cazan@ec.europa.eu
Tel.: +39 0332 78 5100
Fax: +39 0332 78 5733
https://ec.europa.eu/jrc
https://ec.europa.eu/jrc/en/institutes/ipsc

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Authors' affiliation

Clara Galliani

Since April 2013: European Commission Joint Research Centre, IPSC, Scientific Support to Financial Analysis Unit

From May 2013: European Commission DG Ecfin, Unit D.3 - Countries of the G-20 – IMF – G-Groups

Giovanni Petrella

Cattolica University and Consultative Working Group of the ESMA Secondary Markets Standing Committee

Andrea Resti

Bocconi University and EBA Banking Stakeholder Group

Abstract

In this report we investigate the liquidity of the European fixed income market using a large sample of government, corporate and covered bonds. We construct a robust liquidity index, based on PCA, to aggregate several measures and proxies for liquidity and estimate a multivariate regression models to identify the main factors driving bond liquidity in ordinary times as well as in times of market stress. We find that European bond liquidity is driven by bonds' specific characteristics such as duration, rating, amount issued and time to maturity. The sensitivity of bond liquidity to these factors is larger when markets are under stress.

We also analyze the link between the liquidity of individual bonds and the liquidity of the market as a whole. This is done through the estimation a liquidity market model that controls for bonds' duration and rating as well as for periods of market stress. Results show that the illiquidity of individual bonds follows the illiquidity of the market. This effect is more pronounced for bonds with longer duration and lower rating, especially in times of market stress.

Our results confirm the importance of rating in driving asset allocation decision (flight-to-safety) and suggest specific interventions that regulators might consider to introduce. First, provided that duration plays a very important role in bond liquidity, bond eligibility for the purposes of the LCR might be subject to a penalization based on duration. Second, given that the size of the bond issue affects the liquidity, regulators might create incentives for plain vanilla issues and re-openings of old issues.

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

1. Introduction

The recent financial crises highlighted the importance of sound liquidity risk management practices. The Basel Committee on Banking Supervision (or Basel Committee) introduced in 2010 a new regulation for liquidity risk to promote both short term bank resilience to liquidity shocks and long term equilibrium between asset and liability maturity structures. At the core of this regulation is the concept of liquid assets held by bank to face unexpected liquidity outflows.

From January 1, 2015 banks will be progressively required to hold High Quality Liquid Assets (HQLAs) in order to cover the 30-day cash outflows associated with a stress scenario. This requirement results from the Liquidity Coverage Ratio (LCR) introduced by the Basel Committee. The definition of HQLAs needed to comply with the LCR affects investors preferences in financial markets as some market participants might be forced to choose liquid assets and, thus, to penalise other assets. For example, an increase in HQLAs might trigger a decrease in credit to the real economy. Consequently, properly defining what is liquid in different market conditions is of high importance for the regulator in order to reduce the risk of biasing banks allocation decisions.

The current definition of HQLAs implies that certain asset categories (like corporate and covered bonds) are subject to limits, whereas banks can use domestic government bonds without any limitation – no matter what is the rating of such bonds – to fulfil the LRC requirement. This rule may be the source of unintended consequences especially when government bonds issued by different countries exhibit significantly different levels of risk.

The new liquidity rules for banks spurred a debate around key elements like the prevailing role of government bonds in fulfilling the liquidity standard and the actual liquidity associated to asset classes other than government bonds, disadvantages for Europe-like system compared to a US-like system.

In this report we investigate the actual level of liquidity for European government and corporate bonds in both normal and stressed market conditions. Specifically, we want to assess which assets' characteristics can increase liquidity during crisis times and which characteristics can cause extreme drops in liquidity.

Our policy-oriented objective is thus twofold: we intend to assess whether Basel criteria for defining high-quality liquid assets are appropriate and we also wish to identify alternative asset classes that regulators might consider for the inclusion in the HQLAs definition.

The rest of the report is organised as follows: the next Section provides a detailed description of the Liquidity Coverage Ratio, Section **3** presents a review of the literature covering the main liquidity measures, Section 4 describes the data and samples, whereas Section 5 presents the methodology used in the empirical analysis, Section 6 shows the results and Section 7 is devoted to conclusions and policy implications.

2. The regulatory framework

"Liquidity is the ability of a bank to fund increases in assets and meet obligations as they come due, without incurring unacceptable losses" [1]. The first document produced by the Basel Committee about supervision of liquidity was published in 1992. The paper brought together practice and techniques employed by major international banks in a single analytical framework, creating a useful guidance for all banks. The idea was that liquidity supervision is particularly effective if based on a dialogue between bank and supervisor.

An additional document on the same topics was published in 2000 and was organized around several key principles for effectively managing liquidity.

The global financial crisis that exploded in 2007 highlighted the importance of liquidity as a determinant of banking sector soundness. The Basel Committee then published the paper "Liquidity risk: Management and Supervisory Challenges" to review liquidity risk supervision practices in member countries taking into account the market developments originated during the first phase of the crisis. This paper pointed out risks faced by banks (funding risk, redemption risk) and outlined potential areas for updating the 2000 principles.

The new "Principles for Sound Liquidity risk Management and Supervision" were published in September 2008. The document took stock of the dangers originated during the crisis, when many of the most exposed banks had not an adequate risk management framework to account for liquidity risks associated to different asset classes. Moreover, banks had no reliable estimates of the amount of cash needed to meet contingent obligations under severe stress scenarios. For these reasons, the new Principles stressed the need to hold a cushion of liquid assets, to allocate liquidity costs and to carry out periodic stress tests.

The new international framework known as Basel III (2010) included two new liquidity ratios aimed at promoting a more resilient banking sector, increasing liquidity buffers and reducing unstable funding structures. The two ratios were meant to improve banks' short-term resilience to liquidity risk profile as well as to promote sustainable maturity structures of assets and liabilities.

In this report we focus on the first ratio, the Liquidity Coverage Ratio (LCR). This ratio is aimed at ensuring that banks have an adequate amount of high-quality liquid assets (HQLAs) that can be converted into cash under a severe stress scenario lasting 30 calendar days. The aim is "to buy time"

[1] Bank for International Settlement website http://www.bis.org/publ/bcbs144.htm

for management and/or supervisors to deploy adequate recovery plans, ensuring that in the meantime the bank can survive for some weeks.

The LCR is defined as follows:

$$\frac{\text{Stock of high} - \text{quality liquid assets}}{\text{Total net cash outflows over the next 30 calendar days}} \geq 100\%$$

Banks should meet the requirement continuously, except for periods of stress, when they are allowed to use their high-quality liquid assets (HQLAs) to meet contingent obligations.

The denominator is equal to the total expected cash outflows (minus inflows) under a 30-day "stress scenario". The latter is defined according to shocks experienced during the 2007-2009 financial turmoil, both idiosyncratic and market-wide. Stressed conditions include the run-off of a proportion of retail deposits, losses of unsecured wholesale funding and secured short-term financing, downgrade of the bank's credit ratings, increased market volatility affecting collaterals and derivative exposures. In practice, the total expected cash outflows are calculated by multiplying the outstanding amounts of various liabilities and off-balance sheet commitments by a set of "run-off" or "draw-down" rates dictated by the regulators.

The numerator of the LCR ratio includes two categories of HQLAs: Level 1 and Level 2 assets.

According to the 2010 rules, Level 1 assets can be used without limits and include:

- cash;
- central bank reserves;
- marketable securities representing claims on or claims guaranteed by sovereigns, central banks, non-central government Public Sector Entities (or PSEs), the Bank for International Settlements, the International Monetary Fund, the European Commission with specific conditions (for example, 0% risk-weight under the Basel II Standardised Approach for credit risk);
- for non-0% risk-weighted sovereigns, sovereign or central bank debt securities issued in domestic currencies by the sovereign or central bank in the country in which the liquidity risk is being taken or in the bank's home country ;
- for non-0% risk-weighted sovereigns, domestic sovereign or central bank debt securities issued in foreign currencies, to the extent that holding of such debt matches the currency needs of the bank's operations in that jurisdiction.

Level 2 assets can be included up to 40% of the stock of HQLA. Based on the 2010 rules, they are limited to the following assets:

- marketable securities representing claims on or claims guaranteed by sovereigns, central banks, non-central government PSEs or multilateral development banks that satisfy all of the following conditions
    - to be assigned a 20% risk weight under the Basel II Standardised Approach for credit risk;
    - to be traded in large, deep and active repo or cash markets characterised by a low level of concentration;
    - to have a proven record as a reliable source of liquidity in the markets (repo or sale) even during stressed market;
    - not to be an obligation of a financial institution or any of its affiliated entities.
- corporate and covered bonds that
    - are not issued by a financial institution or any of its affiliated entities (in the case of corporate bonds);
    - are not issued by the bank itself or any of its affiliated entities (in the case of covered bonds);
    - have a credit rating of at least AA- (or internally rated as having a probability of default corresponding to a credit rating of at least AA-);
    - are traded in large, deep and active repo or cash markets characterized by a low level of concentration; and
    - have a proven record as a reliable source of liquidity in the markets (repo or sale) even during stressed market conditions.

Based on these rules, the European Banking Authority (EBA) carried out a set of simulation assuming full implementation of the new liquidity ratios. This involved 155 banks that provided sufficient data to calculate the LCR according to the Basel III liquidity framework. The average LCR was found to be 72% for the largest institutions and 91% for the remaining ones. Overall, banks show an aggregated shortfall (i.e., the difference between high-quality liquid assets and net cash outflows[2]) of €1.17 trillion as of 31 December 2011[3]. Such a considerable amount suggests that, by inducing lenders to hold HQLAs, the LCR risks to trigger a cut in bank loans and in the overall credit to the real economy,

[2] The shortfall calculation does not reflect surplus of liquid assets at banks above the 100% requirement.
[3] Additional results are presented in "Report on the results of the Basel III monitoring exercise", full text available at http://www.eba.europa.eu/.

since credit institutions might neglect assets – like loans – that are not eligible for inclusion in the LCR.

In the 2010 version of the rules, the liquidity coverage ratio emphasized the role of government bonds as the main category of HQLAs, providing banks with the wrong incentives for risk diversification and creating the risk that other asset classes might suffer a drop in demand and secondary market liquidity.

A second version of the LCR, aimed at addressing at least in part the issues previously pointed out, was agreed by the Basel Committee on January 6, 2013. Based on this new version of the rule, the portfolio of eligible assets was enlarged and diversified. However, HQLAs still have to include at least 60% of “Level 1” assets – mainly cash, central bank reserves and certain sovereign debt – while other classes (including highly-rated corporate and covered bonds as well as blue chip stocks) are limited to 40% (in some cases, 15%) of the buffer and subject to haircuts.

Specifically, the definition of HQLAs has been expanded by including – subject to higher haircuts and a limit – the following Level 2B assets:

- corporate debt securities rated A+ to BBB– with a 50% haircut;
- certain unencumbered equities subject to a 50% haircut;
- certain residential mortgage backed securities rated AA or higher with a 25%haircut.

Level 2B assets, after haircuts, are subject to a limit of 15% of total HQLAs.

As for the timing of the rule, according to the 2013 agreement, the LCR will be introduced as planned on January 1, 2015, but the minimum requirement will begin at 60%, rising in annual steps of 10% each, to reach 100% on January 1, 2019. This “graduated” approach is designed to ensure that the LCR can be introduced without disruption to the orderly strengthening of banking systems or to the ongoing financing of economic activity.

3. Related research

Our study covers both corporate and government bonds. This section of the report reviews a selection of recent studies regarding the two categories of bonds covered in our empirical analysis.

As concerns corporate bonds, a number of empirical papers show that these assets pay a premium for expected illiquidity. (Houweling, Mentink, and Vorst 2005) test whether liquidity is priced in euro-denominated corporate bonds using daily data for more than 1,000 bonds in the period January 1999 – May 2001. Nine liquidity proxies are implemented: issued amount, listed, euro, on-the-run, age, missing prices, yield volatility, number of contributors and yield dispersion. For each liquidity proxy, the authors construct liquidity-sorted bond portfolios. The time series of portfolio returns are used in two (Fama and French 1993) regression models in order to test whether the constructed portfolios have significantly differently yields, after controlling for market and credit risks. The null hypothesis that the portfolios' liquidity premiums are jointly equal to zero is rejected for eight out of nine liquidity proxies. Only for the listed liquidity proxy the null hypothesis is not rejected. The highest premiums are found when liquidity is proxied through age and yield dispersion.

(Longstaff, Mithal, and Neis 2005) use the information on credit-default swap premiums to provide direct measures of the size of the default and non-default components in corporate yield spreads, where the non-default component also include a liquidity-related portion. Their data set includes CDS spreads for five-year maturity contracts and corresponding corporate bond prices for 68 firms actively traded in the credit derivatives market between March 2001 and October 2002. They show that the default component does not account for the entire credit spread. Cross-sectional and time-series analyses indicate that the non-default component of corporate bond spreads is strongly related to a number of bond liquidity measures such as the size of the bid/ask spread and the principal amount outstanding. More specifically, bond-specific illiquidity measures are important in explaining cross-sectional differences, while market-wide or macroeconomic measures of liquidity explain a sizable portion of the common variation in all corporate spreads over time.

(Chen, Lesmond, and Wei 2007) explore the association between corporate bond liquidity and yield spreads using 4,000 US corporate bonds spanning both investment grade and speculative grade categories. They employ Bloomberg and Datastream to estimate three liquidity measures (bid-ask spread, LOT and percentage of zero returns)[4] and find a significant association between corporate bond liquidity the yield spread with each of the three liquidity measures. Liquidity explains a larger fraction of the cross-sectional variation in bond yields for speculative grade bonds than for investment grade bonds. They also find that an increase in illiquidity is significantly and positively associated with an increase in yield spread even after controlling for changes in credit rating, macroeconomic variables or firm-specific factors.

(Lin, Wang, and Wu 2011) investigate the pricing of liquidity risk in corporate bonds focusing on whether expected corporate bond returns are significantly related to systematic liquidity risk, as opposed to the level of liquidity. The liquidity risk under their scrutiny is therefore the risk that the bond price will drop when the aggregate liquidity deteriorates. They estimate a linear factor model to assess the importance of liquidity risk relative to the effects of other risk factors, liquidity level, and bond characteristics on expected corporate bond returns. Based on a large data set of corporate bonds (almost 12,000) during the period 1994-2009, they show that liquidity risk is priced in corporate bond returns and find significant monotonic variations in returns of beta-sorted portfolios related to liquidity risk, controlling for the effects of default and term betas and ratings.

[4] Definitions and additional details on liquidity measures are provided in §4.

Moreover, there is also some evidence – albeit not very strong – that the same liquidity factors that price the cross section of equity returns (Pastor-Stambaugh and Amihud stock market liquidity measures) are also valid for the cross section of bond returns. Finally, lower-grade bonds have higher liquidity premiums. This relation is consistent with the phenomenon of investors' flight-to-liquidity in illiquid periods as in bad times investors rush to exit their position of low grade bonds this implies sharp falls in their price when market liquidity dries up (i.e., high liquidity risk betas).

(De Jong and Driessen 2012) also study liquidity risk as a determinant of expected returns on corporate bonds. They model liquidity as a risk factor and use a two-step estimation procedure: first, they estimate liquidity betas from a time-series regression of excess corporate bond returns on market and liquidity risk factors; second, they run a cross-sectional regression of the corporate bond excess returns on the betas in order to estimate the size of the liquidity risk premia. They consider two types of liquidity risk: one originating from the equity market (measured according to (Amihud 2002)) and one from the Treasury bond market (measured by changes in the bid-ask spread). Their results, based on US corporate bond data (1993-2002) and also validated by European corporate bond data (2000-2004), show that corporate bond returns have a significant exposure to liquidity factors or, alternatively stated, that liquidity factors significantly contribute to expected returns. The liquidity premium estimated for long maturity investment grade bonds is around 0.6% per annum, and around 1.5% per annum for speculative grade bonds.

(Acharya, Amihud, and Bharath 2012) use a regime-switching model to study the exposure of US corporate bond returns to liquidity shocks of stocks and Treasury bonds over the period 1973-2007. Their basic intuition is that the impact of liquidity shocks on asset prices is highly conditional, significantly stronger in bad times. Their results show that the pricing of liquidity risk in the bond market is conditional on the state of the economy. Consequently, the response of corporate bond prices to liquidity shocks varies over time in a systematic way: in times of economic and financial stress, liquidity risk becomes a significant determinant of bond prices, more than in normal times. They also find a pattern of flight-to-liquidity in the stress regime only. Junk bond returns respond negatively to illiquidity shocks in times of stress, whereas investment grade bond returns respond positively, as investors switch from less liquid junk bonds to more liquid investment grade bonds.

(Friewald, Jankowitsch, and Subrahmanyam 2012) also find – based on a sample of US corporate bonds covered by TRACE between October 2004 and December 2008 – that liquidity is priced and the effect of liquidity measures is stronger in times of crisis. This evidence is especially strong for bonds with high credit risk. (Dick-Nielsen, Feldhutter, and Lando 2012) use a sample of US corporate bonds with trade reports on TRACE during the period 2005-2009 to analyze how illiquidity has contributed to bond spreads before and after the onset of the subprime crisis. They employ a liquidity measure derived from a principal component analysis of eight liquidity proxies and find that the contribution of illiquidity to bond spreads increased strongly with the onset of the crisis. The increase is slow and persistent for investment grade bonds, while the effect is stronger but more short lived for speculative grade bonds.

There are also a few papers that have examined the liquidity of government bond markets. (Dunne, Moore, and Portes 2006) use limit order book and transaction data from the MTS trading platforms covering euro-denominated government bonds. Their analysis covers 2005 and some months of 2003 and 2004. They estimate a number of liquidity measures (effective spread, steepness of the order book, trade size, liquidity available at the best bid and ask quotes, liquidity available at the three best quotes) and find that execution quality is closely related to the size of the issuer, the issuance techniques, and the obligations imposed on primary dealers. In markets where obligations on primary dealers are stronger, the steepness of the order book is larger and this implies that execution quality for large trades suffers in these markets. They also find that greater transparency is associated with lower trade size and possibly involves higher spreads.

(Beber, Brandt, and Kavajecz 2009) examine the behavior of order flow for 10 Euro-area active sovereign debt markets and relate the sovereign yield spread (i.e., the difference between the sovereign bond yield and the swap yield) to differences in credit quality and liquidity. Liquidity is measured using bid-ask spread, average quoted depth, cumulative limit order book depth at the first three levels, as well as the ratio between limit order book depth and bid ask spread (or depth-to-spread ratio). They find that investors care about both credit quality and liquidity, but they do so at different times and for different reasons: the bulk of sovereign yield spreads is explained by differences in credit quality, though liquidity plays a non-trivial role especially for low credit risk countries and during times of heightened market uncertainty.

(R. Goyenko, Subrahmanyam, and Ukhov 2011) investigate the liquidity of US Treasury bond over an extensive time period that spans November 1967 to December 2005. They find that liquidity conditions in the bond market are significantly affected by the economic environment. For example, bond spreads increase during recessions. Moreover, the difference between spreads of long- and short-term bonds significantly widens during recessions, suggesting that investors shift funds into short-term bonds during this time. This is consistent with flight-to-quality and flight-to-liquidity phenomena. They also investigate the effect of liquidity on bond returns over the long run in a variety of economic conditions using a vector autoregression (VAR) analysis, which allows them to account for joint dynamics between liquidity and returns across different maturities. They find that short-term off-the-run liquidity is priced across all maturities, while on-the-run liquidity has no significant impact on prices. These results suggest that off-the-run illiquidity, rather than that of the on-the-run issues, is the source of the liquidity premium in the US T-bond market.

4. Liquidity measures

Following (Aitken and Comerton-Forde 2003), liquidity measures can be classified in two basic categories: trade-based and order-based measures.

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.

In this report, we estimate bond liquidity using trade-based measures, order-based measures and order-based proxies. Order-based proxies aims 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). Details for the measures and proxies considered in this report are provided below.

The **trading volume**, which is a trade-based measure, is the total euro value of the trades executed during the day.

The **bid-ask spread**, which is an order-based measure, 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.

(Roll 1984) develops an estimator of the effective bid-ask spread based on the serial covariance of price changes (i.e., returns). This is an order-based proxies 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 stock return is independent of buy/sell trades sequence.

The **Roll** measure for the spread (S) can be computed as follows:

$$S = 2\sqrt{-Cov(\Delta p_t, \Delta p_{t+1})}$$

where $\Delta p_t = p_t - p_{t-1}$ is the change in prices (or logprices) between two adjacent periods (usually, but not necessarily, trading days).

(Holden 2009) refines Roll's estimator to remove the systematic component of the stock return. Stock returns (adjusted for splits and dividends) can be decomposed into three parts: a systematic component associated to the market, an idiosyncratic component associated to the firm, and the bid-ask bounce. The starting point is the following Capital Asset Pricing Model (CAPM) regression model:

$ar_t - r_f = \alpha + \beta(r_{mkt} - r_f) + z_t,$

where ar_t is the adjusted return on date t, which accounts for stock splits and dividends, r_f is the daily risk free rate, r_{mkt} is the value-weighted market return on date t and z_t is the regression residual. Residuals are then used to compute the idiosyncratic adjusted price change:

$$\Delta P_t^* = z_t P_{t-1},$$

where P_{t-1} is the unadjusted price on date t-1.

The **Extended Roll** measure is then estimated as follows:

$$Extended\ Roll = \begin{cases} \dfrac{2\sqrt{-Cov(\Delta P_t^*, \Delta P_{t-1}^*)}}{\bar{P}}, & when\ Cov(\Delta P_t^*, \Delta P_{t-1}^*) < 0 \\ 0, & when\ Cov(\Delta P_t^*, \Delta P_{t-1}^*) < 0 \end{cases}$$

(Holden 2009) and (R. Y. Goyenko, Holden, and Trzcinka 2009) propose a weighted-average percent effective spread based on actual trade prices (and consequently belonging to the order-based proxies category) and observed ticks[5]. The underlying assumption, following (Harris 1991), is that trade prices tend to cluster on rounder increments ("price clustering"), so that the relative frequency of prices having different fractional parts (e.g., $\$\frac{1}{8}$ for prices of $\$3\frac{1}{8}$ or $\$5\frac{1}{8}$) can be used to estimated probabilities $\hat{\gamma}_j$ associated with different spread levels s_j.

The **Effective Tick** that can be calculated as follows:

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

$$S_{Holden} = \frac{\sum_{j=1}^{J} \hat{\gamma}_j s_j}{\bar{P}},$$

where $\bar{P}$ is the average trade price.

The proportion of days with zero returns 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.

The **zero trading days** measure can be calculated as follows[6]:

$$Zeros = z = \frac{\#days\ with\ zero\ returns}{Total\ number\ of\ trading\ days\ (in\ a\ month)}$$

The theoretical underpinning of this measure 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 lower than the bid-ask spread a trader will abstain from trading as the expected trading profits would be negative.

(Lesmond, Ogden, and Trzcinka 1999) derive an estimate of the bid-ask spread (LOT hereafter) based on the actual distribution of observed returns (including zero returns).

The idea underlying LOT estimator is that the observed stock return is the realization of an underlying (unobservable, potential or true) stock return process. As previously mentioned, stocks 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. (Fong, Holden, and Trzcinka 2011) simplify the estimation of the LOT measure by assuming that transaction costs are symmetric[7]. Accordingly, the observed return R on a given security and the "true", unobserved return R* are linked by the following relationships:

$$R = R^* + \frac{S}{2} \qquad when\ R^* < \frac{S}{2}$$

$$R = R^* \qquad when\ -\frac{S}{2} < R^* < \frac{S}{2}$$

$$R = R^* - \frac{S}{2} \qquad when\ \frac{S}{2} < R^*$$

[6] An alternative version of this measure can be constructed using the number of positive volume days with zero return at the numerator.

[7] This implies that S/2 is the cost of buying a stock and –S/2 is the cost of selling.

Finally, the observed returns are zero in the middle region where $-\frac{S}{2} < R^* < \frac{S}{2}$, that is when the expected profits from trading are not positive as trading costs are larger than the expected price changes.
To derive a quick formula for the estimation of S, (Fong, Holden, and Trzcinka 2011) assume that the unobservable true stock return process R^* is normally distributed with mean zero and variance σ^2. Thus, based on these parameters, the probability of observing a zero return (i.e., when the true return falls in the middle region indicated above) is given by:

$$N\left(\frac{S}{2\sigma}\right) - N\left(\frac{-S}{2\sigma}\right)$$

The empirically observed frequency of zero returns is given by the measure zeros (z) previously described. Equating to the empirically observed frequency of zero returns to the theoretical probability of a zero return implied by the formula and solving for S we obtain the **LOT(FHT)** measure:

$$LOT(FHT) = 2\sigma N^{-1}\left(\frac{1+z}{2}\right)$$

To capture the price impact of trades, (Amihud 2002) proposes an illiquidity proxy that measures the daily price response associated with one monetary unit of trading volume.
The **Amihud** measure can be computed as follows:

$$API_{i,t} = \frac{|r_{i,t}|}{Volume_t}$$

where $r_{i,t}$ is the return of bond *i* on day t, and $Volume_t$ is the monetary value of the trading volume on day t.

5. Data

5.1 Government bond data

Government bond data are taken from MTS Time Series database. MTS is a corporation running a number of major wholesale (i.e., interdealer) markets for fixed-income securities in Europe, including

EuroMTS – a pan European electronic market for Euro-denominated benchmark bonds (i.e., bonds with an outstanding value of at least €5 billion) – as well as a string of domestic markets.

We select bonds issued by national and supranational institutions traded in markets run by MTS (EuroMTS and MTS domestic markets). Our sample includes 2,151 bonds[8] and covers 3 full calendar years (2006, 2008 and 2011).

The MTS database contains daily traded volume, average daily bid-ask spread, closing price, closing midquote, yield to maturity based on the midquote, and a number of bond-specific control variables (modified duration, convexity, bond type, issue date, issuer name, maturity date, coupon). We add rating information provided by Standard & Poor's, taken from Datastream and Bloomberg.

5.2 Corporate and covered bond data

Corporate and covered bond data are taken from Bloomberg. We include in our sample all bonds that meet the following criteria:

- amount outstanding above 10 million in local currency;
- currency of denomination equal to USD, GBP, EUR;
- country of issue: EU-27 countries + Switzerland;
- issuer not belonging to one of the following categories: Government, Supranational, Government-Sponsored;

We exclude bonds with the following collateral types as classified by Thomson Datastream: government guaranteed, local government guaranteed, government liquid guaranteed, and mortgage backed.

For each of the bonds in our sample we collect daily quotes (bid, ask, mid) from Markit/Iboxx, as well as closing prices, daily quotes (bid and ask), and average traded volumes from ICMA/Trax[9]. Combining these two sources, we end up with a comprehensive final sample of 1,521 bonds. For each bond we also collect information on duration[10], issuer, issuer's nationality, issuer's industry[11], issue

[8] The sample does not include UK government bonds (Gilts) since an electronic market was launched by MTS platform only in July 2011.

[9] Markit/Iboxx and ICMA/Trax data are obtained through the Thomson Datastream database. Since January 2011, ICMA/Trax data are no longer available.

[10] Historical bond durations were also obtained from Datastream for each quarter. For bonds for which durations were not available, approximations were derived using a formula based on issue and redemption dates, coupon (datatype C), coupon frequency (datatype CD) and market return (set at 5% for simplicity). The robustness of this approximation was tested on the bonds for which duration values were indeed available.

date, maturity date, issued amount, bond type and coupon. S&P's historical ratings were obtained from Datastream (datatype ISPHRT). To complete the data set when S&P's ratings were not available, Moody's or Fitch's ratings were collected from Bloomberg (RATC function)[12].

5.3 Sample description

In this Subsection we provide an overview of the main characteristics of our samples. Note that, as our liquidity measures are computed on a quarterly basis, each observation in our data set – and consequently in the tables below – is a combination of bond (ISIN code) and quarter.

Table 1 shows the distribution by rating grade: most observations in our sample fall into the AAA grade category. Observations are far from being uniformly distributed across rating classes. Since non-investment grade bonds are rare in our samples, we pooled all bond-quarter observations with ratings below AA into one single group. As for the corporate bonds sample, 62 percent of the observations refer to the AAA category, reflecting a specific feature of the European corporate bond market with respect to the US corporate bond market.

Table 1 - Sample partition by issuer type and rating class

	AAA	**AA**	**<AA**	**na**
Govies	2503	743	1202	289
Corporate	10759	2083	2280	2098

Table 2 presents a breakdown of the sample by bond duration. The vast majority of corporate bonds does not exceed 7 years, while long maturities are less unusual in the case of govies. In fact, 27 percent of the observations in the government bonds sample exhibit a duration greater than 7 years, whereas this holds for only 16 percent of the corporate bonds sample.

[11] Bonds issued by banks vs. non-banks are identified based on Datastream filters. Non-banks appear to include a number of subsidiaries of banking groups, as well as several insurance companies. We discard these observations so to ensure that the non-banks category only includes issuers that are not related to the financial industry.

[12] When associating ratings to quarterly liquidity indicators, the prevailing rating grade during the quarter – based on the number of months for which it had been in place – was attributed to each quarter.

Table 2 - Sample partition by issuer type and duration

	Dur < 3	Dur 3-7	Dur > 7	n .d.
Govies	1986	1262	1265	224
Corporate	5870	7852	2830	668

The next two tables show the distribution of bonds across countries and calendar years. As mentioned above, MTS data do not cover UK Gilts. Additionally, our sample of government bonds only covers three years; however, those years were chosen to account for a first period of orderly operation of the market (2006), a second more problematic year including the Lehman collapse (2008), and a third year (2011) when the Eurozone crisis reached large countries like Italy and Spain, threatening the credibility of Europe's single currency.

Table 3 - Sample partition by issuer type and country of issue

	BE	DE	ES	FR	GB	IT	NL	Others
Govies	392	626	363	918	-	1018	324	1096
Corporate	12	5265	4695	3485	1119	322	664	1658

Table 4 - Sample partition by issuer type and year

	2005	2006	2007	2008	2009	2010	2011	2012
Govies		2048		1403			1286	
Corporate	833	1493	1965	2140	2448	3135	2515	2691

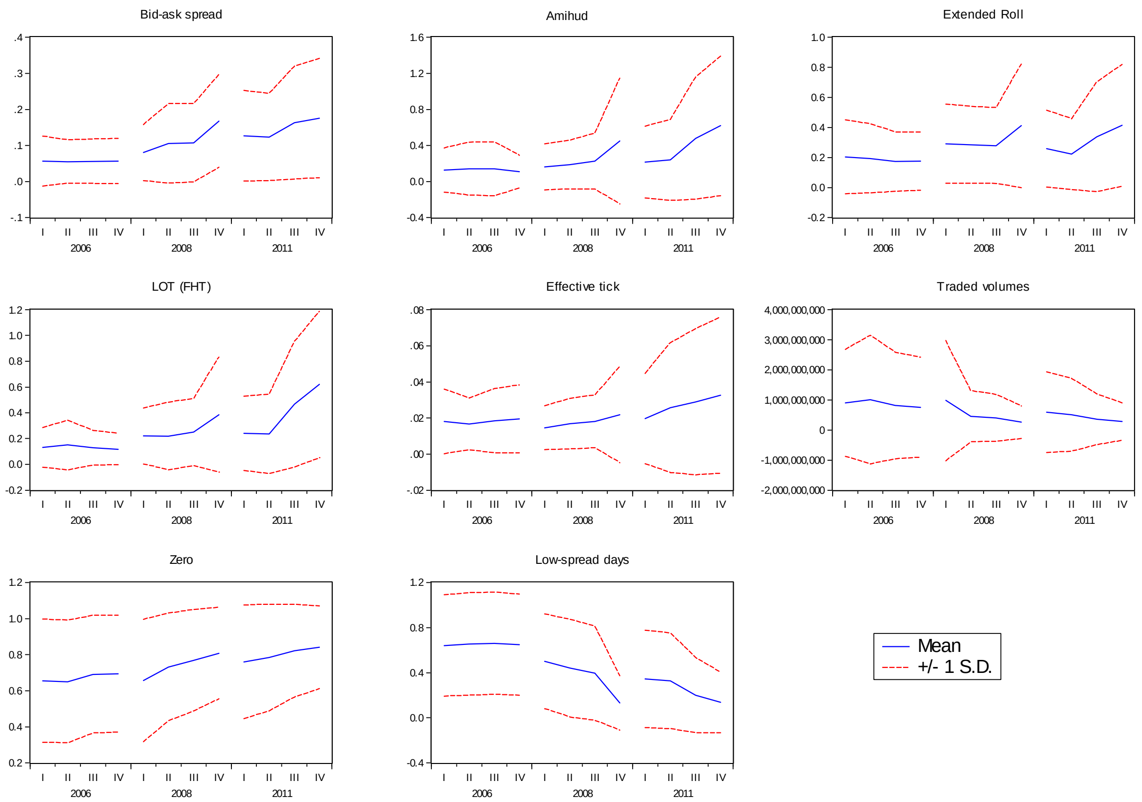
6. Methodology

In this Section we present the methodology that we apply to our data. First, we briefly describe the behavior of several liquidity measures that can be computed from our data sets. Second, we introduce a composite liquidity index that will be used, unless otherwise indicated, as our dependent variable. Third, we present the multivariate model that will be estimated in our empirical analysis to identify bond characteristics that drive (il)liquidity. Fourth, we investigate the link between the liquidity of individual bonds and the liquidity of the market as a whole: this is done through a liquidity market model that controls for bonds' duration and rating as well as for phases of market stress. Lastly, we perform a quantile regression analysis to identify the determinants of extreme illiquidity conditions.

6.1 Liquidity indicators

Our data on government bonds allow us to estimate eight individual bond liquidity indicators (including both measures and proxies): bid-ask spread, Amihud, Extended Roll, LOT (FHT), Effective Tick, Traded Volumes, Zero, Low-spread days[13]. Starting from observation sampled at daily frequency, we compute all liquidity measures on a quarterly basis. Their behavior in 2006, 2008 and 2011 is shown in Figure 1.

Figure 1 - Government bonds: the behavior of liquidity indicators over time



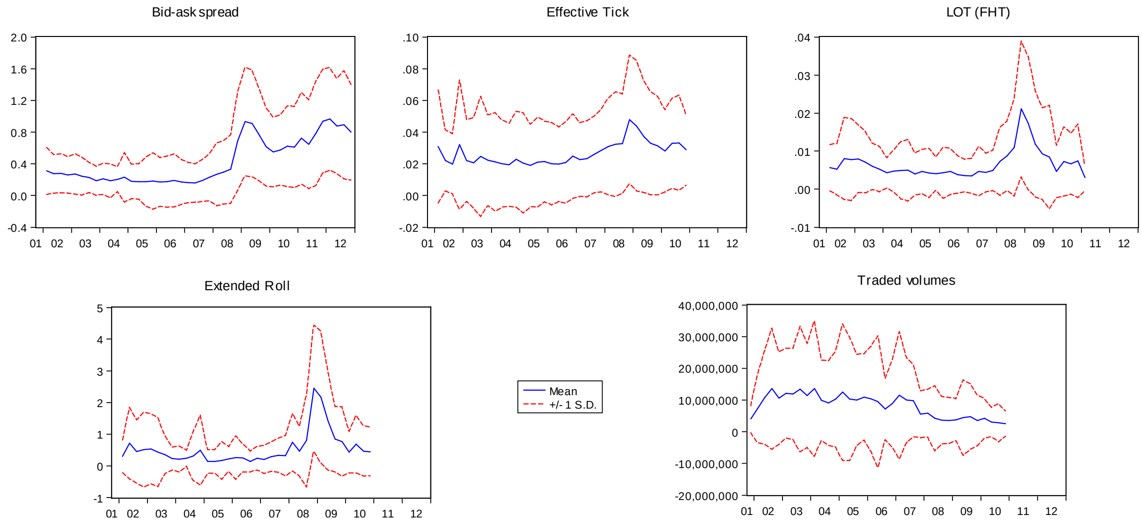
In 2006 market liquidity was high, with little variation across individual bonds (as indicated by the dotted line, lying one standard deviation away from the mean). Later on, in 2008, especially in the third and fourth quarter (Lehman Brothers' collapse, September 15), market conditions deteriorate. In 2011 liquidity conditions remain tense and get worse in the second half of the year, because of the sovereign debt crisis spreading to some large European countries.

Similar patterns can be found in Figure 2, where individual liquidity measures are shown for the corporate and covered bonds sample. Some indicators calculated for the government bond sample

[13] The low spread days measure is equal to the number of days during which the bid-ask spread is not greater than three basis point values (BPV). For the definition of the other liquidity indicators please refer to §4.

cannot be estimated for this sample (e.g. Amihud), since traded volumes are only available at monthly frequency. Accordingly, we calculate the following indicators: the bid-ask spread, Effective tick, LOT (FHT), Extended Roll and traded volumes. While the bid-ask spread is available for the entire 2005-2012 time period, other indicators end in January 2011, when Trax data ceased to be distributed through the Datastream platform.

Figure 2 - Corporate and covered bonds: the behavior of liquidity indicators over time



6.2 A robust liquidity index

Market microstructure scholars have proposed a number of liquidity measures and proxies (see Section 4). However, there is no consensus on what is the “best” liquidity indicator. Each indicator captures a specific dimension of market liquidity and each dimension can have a valuable information content, especially in specific market conditions and for certain traders.

In this report we have estimated a sizeable range of liquidity indicators. For the above mentioned reason (i.e., to avoid the one-size-fits-all bias), instead of relying on a single proxy, we prefer to use a composite liquidity index as dependent variable in our multivariate analysis.

In line with (Dick-Nielsen, Feldhutter, and Lando 2012), who combine eight different liquidity proxies, we use Principal Components Analysis (PCA) in order to ensure that we preserve as much information as possible when moving from individual indicators to a single indicator. We use the first principal component as our Robust Liquidity (“RoLiq” henceforth) index.

As previously mentioned (and as seen in Figures 1 and 2) we are able to construct different sets of liquidity indicators for sovereign and corporate bonds. Consequently, we run PCA twice and generate two different versions of RoLiq, one for each category of bonds.

Weights assigned to individual components are displayed in the Tables 5 and 6. The behavior of RoLiq over time as well as its empirical distribution are shown in Figures 3 and 4 for, respectively, the government bonds sample and the covered/corporate bonds sample. Like most liquidity indicators shown in Figures 1 and 2, RoLiq is an illiquidity index, meaning that high values point to low liquidity levels.

Table 5 - RoLiq for government bonds: liquidity indicators and weights associated with PCA

Individual liquidity indicator	Weight
Bid-ask spread	0.44
Amihud	0.44
Extended Roll	0.43
LOT (FHT)	0.48
Effective tick	0.28
Volume	-0.26
Zero	0.21
Low spread days	-0.07

Figure 3 - Government bonds: the behavior of RoLiq over time and its empirical distribution

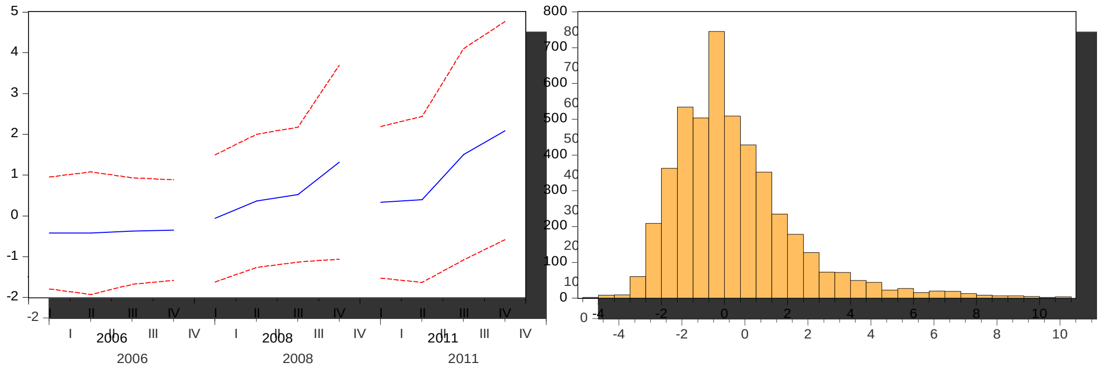
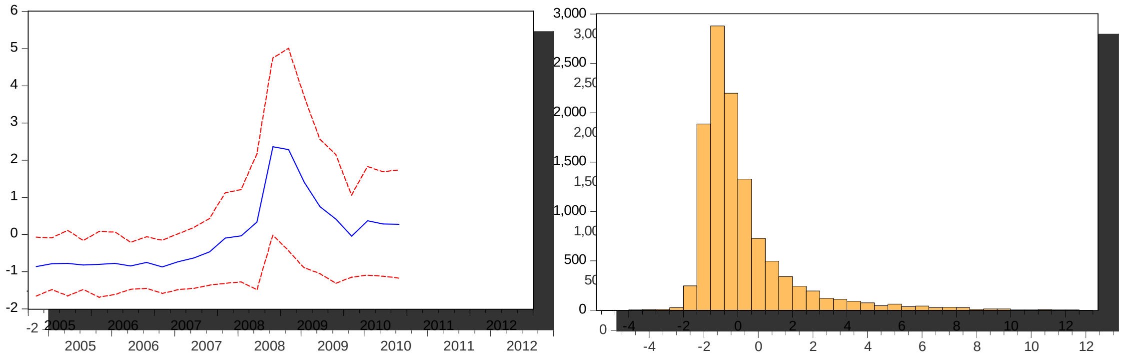


Table 6 - RoLiq for corporate and covered bonds: liquidity indicators and weights associated with PCA

Individual liquidity indicator	Weight
Bid-ask spread	0.48
Effective tick	0.39
LOT (FHT)	0.54
Extended Roll	0.54
Volume	-0.20

Figure 4 – Corporate and covered bonds: the behavior of RoLiq over time and its empirical distribution



6.3 Multivariate models

The RoLiq index is used as dependent variable in two regression models that aim at exploring the drivers of bonds illiquidity in normal times as well as in times of market stress.

The first model is the following:

$$RoLiq_{it} = \alpha + \sum_{j=1}^{J} \beta_j C_{jit} + \varepsilon_{it}$$

where C_{jit}, $j = 1, \ldots, J$ are bond-specific characteristics.

Table 7 lists the explanatory variables along with a short description and their expected sign. We expect higher illiquidity for bonds having higher duration, lower rating (higher probability of default), and smaller outstanding amounts. Additionally, we expect illiquidity to increase with the time elapsed since issuance and for unsecured bonds issued by banks and other financial institutions. Finally, we have no clear expectations regarding covered bonds: on one hand, they are secured by specific assets, and hence they should be perceived as safer and remain relatively more liquid in times of stress; on the other hand, most covered bonds are secured by real estate, which could have been a serious drawback during the recent financial crisis.

Table 7 – Explanatory variables: description and expected sign

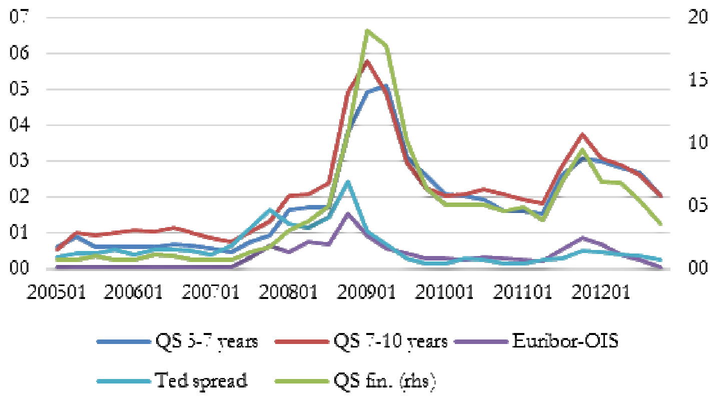
Symbol	**Name**	**Description**	**Expected sign**
$C_{1it}:DUR$	Duration	Modified duration of a bond i in quarter t	+
$C_{2it}:PD$	Probability of default	Probability of default associated with bond i's issuer rating.	+
$C_{3it}:DU\_OTR$	Dummy on the run	Dummy variable equal to 1 if bond i in quarter t has been issued by less than one year	-
$C_{4it}:AMT$	Amount issued	Natural log of the amount outstanding for bond i in quarter t	-
$C_{5it}:DU\_ZCB$	Dummy zero coupon	Dummy variable equal to 1 if bond i is a zero coupon bond (ZCB)	-
$C_{6it}:QS$	Quality spread	Difference between BBB yields and AAA yields in quarter t for a sample of bonds with duration between 5 and 7 years	+
		Only for corporate/covered bonds	
$C_{7it}:DU\_FinUn$	Dummy financial unsecured	Dummy variable equal to 1 if the bond is not collateralized	+
$C_{8it}:DU\_Covere$	Dummy covered	Dummy variable equal to 1 if the bond is a covered bond	?

Consistently with the Basel III framework, we are interested in assessing what factors most affect liquidity in periods of market stress. As a starting point for our analysis we select five indicators of market stress that are commonly used both in the literature and in the industry. First, we consider the TED Spread, which is the difference between the three-month LIBOR and the three-month T-bill interest rate. Second, we consider the difference between the three-month Euribor and the three-month Over-night Index Swap (OIS) rate. Both spreads measure the degree of tension – in terms of liquidity and perceived credit risk – in the inter-bank market. Lastly, we also consider three indicators of quality spread which measures the compensation (or risk premium) associated to low grade corporate bonds with respect to prime corporate bonds[14]. The behavior of the five market stress indicators in the

[14] Specifically, we consider the difference in redemption yield between the Bank of America-Merrill Lynch (BOFA-ML) Euro Corporate 5-7 yrs. BBB and the AAA companion index (QS_5_7), the difference in redemption yield between the BOFA-ML Euro Corporate 7-10

period 2005-2012 is displayed in Figure 5. They are very highly correlated and the quality spread measures are systematically larger than the TED and Euribor-OIS spreads.

Figure 5 - Market stress indicators



We employ the stress indicator as a multiplicative dummy in the following regression model:

$$RoLiq_{it} = \alpha + \sum_{j=1}^{J} \beta_j C_{jit} + STRESS_t \sum_{j=1}^{J} \gamma_j C_{jit} + \varepsilon_{it}$$

$STRESS_t$ is a dummy variable taking value one when the selected stress indicator exceeds the sample median. Thus, the *j-th* regressor has a β_j effect on liquidity in normal times and $\beta_j + \gamma_j$ effect in times of market stress. By running a statistical test on γ_j we can assess if the *j-th* regressor significantly increase (or decrease) its influence on liquidity in times of stress. This is in line with the strand of recent literature that investigates how liquidity premium depends on systemic risk (see (Lin, Wang, and Wu 2011); (Acharya, Amihud, and Bharath 2012); (Friewald, Jankowitsch, and Subrahmanyam 2012); (Dick-Nielsen, Feldhutter, and Lando 2012)).

Using the government bond sample, we also estimate the same regression adding the dummy IT, that takes value equal to one when the country of issue is Italy. Italian government bonds are expected to add liquidity to the market given it huge amount of public debt whose risk is appreciated by foreign investors.

yrs. BBB and the AAA companion index (QS_7_10), and the difference between in redemption yield between the BOFA-ML Euro Corporate Financials BBB and the AAA companion index (QS_FIN).

6.4 Liquidity market model and quantile regression

As a second step, we analyze if the degree of liquidity of individual bonds corresponds to the liquidity of the market as a whole. If liquidity is correlated with overall market conditions, less liquid bonds should have more market risk than more liquid bonds. We estimate a simple market model by regressing the liquidity of an individual bond on a measure of market liquidity:

$$Liq_{it} = \alpha + \beta Liq_{MKT\,t} + \varepsilon_{it} \,,$$

The liquidity beta is not a measure of liquidity per se, but indicates how individual bonds are exposed to liquidity risk. A unit β would suggest that the liquidity of single bonds is closely related to the liquidity of the entire market.

Two additional regressions are estimated adding control variables for market stress, rating and duration to check their effects on the liquidity beta.

Our last step is estimating quantile regressions, in order to validate results obtained before in times of high pressure on the market.

We run the quantile regression having the liquidity measure computed with PCA as dependent variable. Independent variables are the one considered for model [1]. Estimations are conducted over the median and over the folloqing quantiles: 0.6, 0.7, 0.8, 0.9, 0.95, 0.99. Results show that some specific bonds' characteristics continue to be significant in quantile regressions. Moreover, the process of coefficients estimated at various quantiles shows a clear relationship between the quantile value and the estimated coefficients.

7. Results

7.1 Government bonds

Descriptive statistics of some of the variables included in the analysis are provided in the table below.

Table 8: Descriptive statistics

	Mean	Median	Max	Min	Stdev	#obs	ρ/t
RoLiq	30.3%	-9.3%	1091.1%	-439.3%	196.8%	4647	-
Bid-ask spread	0.09	0.05	0.54	0.00	0.11	4737	83%
AMT	15.4	16.0	18.0	-6.9	2.4	6124	11%
DUR	4.8	3.4	46.8	0.0	5.0	5599	72%
Maturity at	12.4	10.3	51.0	0.1	10.0	9579	67%

launch							
Age	10.4	3.8	108.4	0.0	24.0	10150	-10%
Traded volume	618	66	25372	0	1418	10150	-49%
PD	0.2%	0.0%	9.1%	0.0%	0.9%	9354	17%
Dummy AAA	50.9%	100.0%	1.0	0.0	50.0%	10150	-9.7
Dummy ZCB	41.2%	0.0%	1.0	0.0	49.2%	10150	25.8

Multivariate analysis is performed through three regression models. Residual diagnostics show heteroskedasticity. Results displayed in the following table are derived using heteroskedasticity-consistent estimates for standard errors and covariances. It is worthwhile mentioning that there are not substantial changes concerning the significance of the parameters.

Table 9: Government bonds. Results of the multivariate analysis

	(I)		(II)		(III)	
	RoLiq		RoLiq		RoLiq	
Intercept	5.87	***	5.27	***	0.38	
Modified duration	1.38	***	1.19	***	1.17	***
PD	0.10	*	0.10	*	0.24	***
Dummy on-the-run	-0.21	***	-0.18	***	-0.18	***
Issued amount	-0.39	***	-0.35	***	-0.10	***
Dummy zero coupon	-0.14	***	-0.16	***	0.04	
Quality spread	0.84	***	0.65	***	0.62	***
Stress * Modified duration			0.65	***	0.69	***
Stress * PD			0.11	*	0.29	***
Stress * Dummy OTR			-0.04		-0.03	
Stress * Issued amount			-0.31	***	-0.45	***
Dummy IT					-0.51	***
Adjusted R-square	70%		73%		77%	
# of observations	3154		3154		3154	

Results explain that illiquidity, measured through the liquidity index RoLiq, is strongly influenced by duration, amount issued, and time to maturity at launch (Model (I)). Ratings are also influencing illiquidity, with significance at 95% level. Small bonds with higher duration, low issuer rating, issued long time ago request higher liquidity premium, confirming the expected signs reported in Table 7. Moreover, market conditions, measured with the quality spread, are also influencing the liquidity premium. All the explanatory variables except PD are highly significant (at 99% level).

In Model (II) the dummy STRESS is added and results confirm that the effects are even stronger when the market is in periods of stress.

The dummy variable controlling for Italy added in Model (III) signals that there is a negative 'Italy effect'.

Liquidity beta for government bonds is estimated for the standard model presented in Section 6.3 and for three additional models that add dummy variables and the effect of market stress. Results are presented in the following table:

Table 10: Government bonds. Liquidity beta

	(I)		(II)		(III)		(IV)	
	RoLiq		RoLiq		RoLiq		RoLiq	
Intercept	0.00	*	-0.45	***	-0.25	***	-0.24	***
Illiquidity (BAS) of the market (IM)	0.77	***	0.46	***	0.32	***	0.47	***
Dummy high duration (DHD)			0.91	***	0.89	***	0.89	***
Dummy rating below AA- (DRBAA)			-0.08	**	0.26	***	0.23	***
IM * DHD			0.47	***	0.50	***	0.48	***
IM * DRBAA			-0.01		0.25	***	-0.04	
Dummy Italy					-0.75	***	-0.72	***
Stress							0.17	
Stress * IM							-0.33	*
Stress * IM * DHD							0.03	
Stress * IM * DRBAA							0.31	***
Adjusted R-square	15%		48%		57%		58%	
# of observations	4647		4087		4087		4087	

Liquidity of individual bonds follows that of the market: this is clear from the beta associated to the Illiquidity (BAS) of the market (IM), that in the first regression is equal to one (in the table standardized beta are presented). Models (II) and (IV) show once again that we have higher betas for longer duration and ratings below AA- (IM*DHD and IM*DRBAA). In particular, the effect of low ratings is even higher when the market is under stress (Model (IV)). The dummy for the Italian sovereign market (added in Model (III)) is negative and highly significant showing, as expected, that it adds liquidity to the entire government market.

Results of the multivariate analysis presented in Table 9 are compared with the ones obtained in a quantile regression. We selected 7 quantiles of the distribution of the liquidity indicator RoLiq starting from the median. Results are presented below.

Table 11: Government bonds. Quantile regression

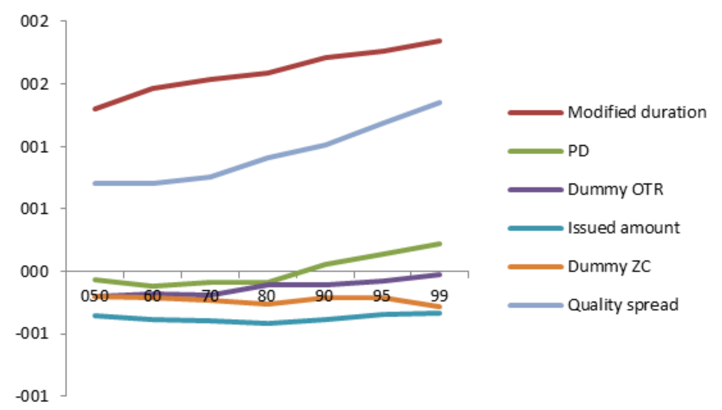
Quantile	50	60	70	80	90	95	99
Intercept	5.44	6.10	6.30	6.60	6.12	5.34	5.36
Modified duration	1.30	1.47	1.53	1.59	1.71	1.77	1.84
PD	-0.07	-0.12	-0.09	-0.08	0.06	0.14	0.22

Dummy on-the-run	-0.20	-0.18	-0.19	-0.11	-0.11	-0.08	-0.03
Issued amount	-0.35	-0.39	-0.40	-0.41	-0.39	-0.35	-0.33
Dummy zero coupon	-0.21	-0.21	-0.23	-0.27	-0.21	-0.21	-0.28
Quality spread	0.70	0.70	0.76	0.91	1.01	1.19	1.36
Pseudo R-square	*0.46*	*0.53*	*0.55*	*0.58*	*0.61*	*0.64*	*0.66*
# of observations	*3154*						

Green cells highlight variables that are significant at 99% level, significance at 97.5% level is displayed by orange cells, whereas significance at 95% level is highlighted in red. For variables in blank cells, the hypothesis of being equal to zero cannot be rejected. It is interesting to notice that modified duration and issued amount are key variables for determining illiquidity of govies. PD, as previously displayed in the OLS regressions, turns out not to be a key variable.

Coefficient estimates for modified duration, PD, dummy OTR, and quality spread show a clear positive relationship between the quantile value and the estimated coefficients, meaning that their effect is stronger in times of financial turbulence.

Figure 6 – Quantile regressions – coefficient estimates



The analysis of government bonds shows that liquidity is significantly affected by size, duration and age of the bond. These variables increase their effects under stress: once the stress variable is included in the regression and it interacts with previous regressors, it exacerbates the role of key explanatory variables.

7.2 Corporate and covered bonds

Some descriptive statistics for both RoLiq and the independent variables are presented in the table below.

Table 12: Descriptive statistics

	Mean	Median	Max	Min	Stdev	#obs	ρ/t
RoLiq	11.8%	-38.2%	1276.2%	-463.5%	171.7%	11296	-
Bid-ask spread	0.56	0.38	2.93	0.05	0.58	17084	76%
AMT	14.0	14.2	15.5	11.2	0.9	22531	-8%
DUR	4.2	3.8	21.2	0.0	2.7	20254	26%
Maturity at launch	8.8	7.5	49.2	0.8	5.4	22531	29%
Age	3.5	2.7	30.2	0.0	3.3	22531	2%
Traded volume	7.8	2.8	102.3	0.0	14.9	12928	-28%
PD	0.1%	0.0%	10.3%	0.0%	0.4%	19235	6%
Dummy AAA	65.1%	100.0%	1.0	0.0	47.7%	19235	9.66
Dummy financial unsec	21.9%	0.0%	1.0	0.0	41.4%	22531	-4.88
Dummy covered	67.6%	100.0%	1.0	0.0	46.8%	22531	9.59

Multivariate analysis is performed through three regression models. Results are displayed in the following table.

Table 13: Corporate/covered bonds. Results of the multivariate analysis

	(I)		(II)		(III)	
	RoLiq		RoLiq		BidAsk	
Intercept	3.42	***	3.34	***	1.13	***
Modified duration	0.61	***	0.47	***	0.15	***
PD	0.06	***	0.05	**	0.05	***
Dummy on-the-run	-0.29	***	-0.19	***	-0.07	***
Issued amount	-0.24	***	-0.22	***	-0.06	***
Dummy zero coupon	-0.01	***	-0.01	***	0.00	**
Quality spread	0.88	***	0.90	***	0.21	***
Dummy fin unsec	0.05		0.06	*	0.01	
Dummy covered	0.03		0.00		-0.01	
Stress * Modified duration			0.58	***	0.12	***
Stress * PD			0.04		0.08	***
Stress * Dummy OTR			-0.14	***	-0.01	**
Stress * Issued amount			-0.59	***	-0.16	***
Stress*Dummy fin unsec			-0.03		-0.01	
Stress*dummy covered			0.14		0.08	**
Adjusted R-square	43%		48%		34%	
# of observations	9280		9280		14392	

Results explain that illiquidity, measured through the liquidity index RoLiq, is strongly influenced by duration, rating, amount issued, and time to maturity at launch (Model (I)). Small bonds with higher duration, low issuer rating, issued long time ago request higher liquidity premium, confirming the expected signs reported in Table 7. Moreover, market conditions, measured with the quality spread, are also influencing the liquidity premium. All the explanatory variables are highly significant (at 99% level).

In Model (II) the dummy STRESS is added and results confirm that the effects are even stronger when the market is in periods of stress.

Results are robust to changes in liquidity metric and to sample extension including 2011 and 2012, as shown in Model (III). When the bid-ask spread is used replacing RoLiq, duration, dummy OTR, amount issued and PD still maintain their importance in explaining liquidity.

Liquidity beta for corporate/covered bonds is estimated for the standard model presented in Section 6.3 and for two additional models that add dummy variables and the effect of market stress. Results are presented in the following table:

Table 14: Corporate/Covered bonds. Liquidity beta

	(I)		(II)		(III)	
	Bid/Ask		Bid/Ask		Bid/Ask	
Intercept	-0.02	**	-0.04	***	-0.05	***
Illiquidity (BAS) of the market (IM)	0.28	***	0.23	***	0.24	***
Dummy stress			0.00		0.01	
Dummy high duration (DHD)			0.00		-0.01	
Dummy rating below AA- (DRBAA)			0.04	***	0.06	***
IM * DHD			0.14	***	0.16	***
IM * DRBAA			0.09	***	0.04	*
Stress * IM					-0.03	
Stress * IM * DHD					-0.02	
Stress * IM * DRBAA					0.04	***
Adjusted R-square	25%		38%		38%	
# of observations	16416		14392		14392	

Results show that the liquidity of individual corporate/covered bonds follows that of the market (beta equal to one in model (I) with non-standardized coefficients). Models (II) and (III) show once again that we have higher betas for longer duration and ratings below AA- (IM*DHD and IM*DRBAA). Model (III) shows that the effect of low ratings is even higher when the market is under stress.

Results of the multivariate analysis presented in Table 13 are compared with the ones obtained in a quantile regression. We selected 7 quantiles of the distribution of the liquidity indicator RoLiq starting from the median. Results are presented below:

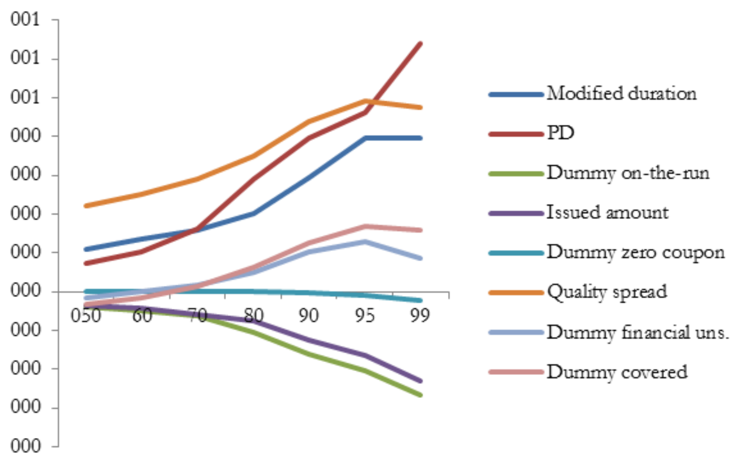
Table 15: Corporate/Covered bonds. Quantile regression

Quantile	50	60	70	80	90	95	99
Intercept	0.66	0.75	0.97	1.23	2.12	2.92	4.95
Modified duration	0.11	0.13	0.16	0.20	0.29	0.40	0.40
PD	0.07	0.10	0.16	0.29	0.40	0.46	0.64

Dummy on-the-run	-0.04	-0.05	-0.06	-0.11	-0.16	-0.20	-0.27
Issued amount	-0.04	-0.04	-0.06	-0.08	-0.12	-0.17	-0.23
Dummy zero coupon	0.00	0.00	0.00	0.00	0.00	-0.01	-0.02
Quality spread	0.22	0.25	0.29	0.35	0.44	0.49	0.47
Dummy fin unsec	-0.02	0.00	0.02	0.05	0.10	0.13	0.09
Dummy covered	-0.03	-0.01	0.01	0.06	0.13	0.17	0.16
Pseudo R-square	*0.24*	*0.24*	*0.25*	*0.25*	*0.27*	*0.28*	*0.26*
# of observations				*14392*			

Green cells highlight variables that are significant at 99% level, significance at 97.5% level is displayed with orange cells, whereas significance at 95% level is highlighted in red. For variables in blank cells, the hypothesis of being equal to zero cannot be rejected. Duration, PDs, age of the bond and amount issued are always highly significant with a clear positive relationship between coefficients estimates and quantile values. Dummies related to zero coupon bonds, financial unsecured and covered bonds turn out to be highly significant only when we consider the last quantiles. The relationship between quantiles and coefficients estimates is displayed in the figure below.

Figure 1: Corporate/Covered bonds. Quantile regression coefficients



Duration and probability of default are influencing positively illiquidity (RoLiq), and coefficients are increasing as we move toward the 0.99 quantile. The on-the-run dummy and issued amount have, on the contrary, negative coefficients whose absolute value is as well increasing moving in the right side of the RoLiq distribution.

Thus, results for corporate/covered bonds are comparable to the ones obtained by govies. Specific bonds' characteristics are influencing liquidity and their effects are more pronounced in periods of market stress.

8. Summary and policy implications

In this report we investigate the liquidity of the European fixed income market using a large sample of government, corporate and covered bonds. We construct a robust liquidity index, based on PCA, to aggregate several measures and proxies for liquidity and estimate a multivariate regression models to identify the main factors driving bond liquidity in ordinary times as well as in times of market stress.

We find that European bond liquidity is driven by bonds' specific characteristics such as duration, rating, amount issued and time to maturity. The sensitivity of bond liquidity to these factors is larger (i.e., non-linear effects are present) when markets are under stress.

We also analyze the link between the liquidity of individual bonds and the liquidity of the market as a whole. This is done through the estimation a liquidity market model that controls for bonds' duration and rating as well as for periods of market stress. Results show that the illiquidity of individual bonds follows the illiquidity of the market. This effect is more pronounced for bonds with longer duration and lower rating, especially in times of market stress.

Our results confirm the importance of rating in driving asset allocation decision (flight-to-safety) and suggest specific interventions that regulators might consider to introduce. First, provided that duration plays a very important role in bond liquidity, bond eligibility for the purposes of the LCR might be subject to a penalization based on duration. Second, given that the size of the bond issue affects the liquidity, regulators might create incentives for plain vanilla issues and re-openings of old issues.

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