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The determinants of liquidity commonality in the Euro-area sovereign bond market

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ABSTRACT
We examine time-series variation in liquidity commonality across sovereign benchmark bonds from 10 Euro-area countries, over a 7-year period using tick-by-tick data from the inter-dealer market and study how it is driven by supply determinants (funding constraints of financial intermediaries) and demand determinants (investor sentiment, uncertainty, and cross-market linkages with the equity market) of liquidity. Commonality in liquidity does change over time, tends to intensify in stress periods as well as around ECB policy meetings, and we find stronger evidence in favor of the supply side determinants.

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1. Introduction

How market liquidity behaves over time and spills across borders are important concerns of both investors and policy makers. However, the finance literature has had little to say about liquidity co-movements in fixed income markets and even less is known about what determines how it evolves over time. This paper provides a study of the determinants of liquidity co-movements in the Euro-area government bond market. We first test for and document a common component in liquidity variation across Euro-area government bonds, and then uncover which economic forces explain the time-series variation of liquidity co-movements in the Euro-area sovereign bond market by considering several supply and demand side determinants of commonality in liquidity as well as by examining liquidity-co-movements around announcements of key macroeconomic indicators.

An in-depth understanding of commonality in liquidity and its determinants is important for at least four reasons. First, commonality in liquidity implies a systematic and, non-diversifiable, factor influencing variation in trading costs of a large cross-section of assets rather than individual securities. Second, it may imply asset pricing effects, because investors need to be compensated for holding a security that becomes illiquid when the market, in general, becomes illiquid (Pástor and Stambaugh 2003; Acharya and Pedersen 2005). Third, it has important implications for market viability as an illiquidity shock in one market may affect liquidity conditions in other asset classes. The 2007-2009 global financial crisis and the 2011 European debt crisis underlined the importance of such cross-market illiquidity effects as investors sought the safety of government securities and market illiquidity amplified shocks originating elsewhere and led to a contagious propagation of shocks within, as well as across, asset classes. Last, sovereign bond markets are important in ensuring arbitrage conditions in other markets (Pasquariello 2014) and market liquidity in sovereign bond markets is closely connected to central bank operations and interventions, either in the form of interest rate setting, or quantitative easing, and their unwinding (Pelizzon et al. 2016). From a central bank's perspective, an implication of sovereign bonds liquidity co-movements is that providing liquidity to specific bonds may potentially lead to flight-to-liquidity

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and spillover effects to other sovereign bonds as well (De Santis 2014; Clancy, Dunne, and Filiani 2019; O'Sullivan and Papavassiliou 2020).

In this study, we examine the time-series determinants of liquidity co-movements of a large number of Euro-area government bonds, issued by 10 large Euro-area economies, over a 7-year period of 2011–2018 using tick-by-tick data from MTS (Mercato Telematico dei titoli di Stato), the largest Euro-area inter-dealer fixed income market. We focus on benchmark bonds as they are the most liquid bonds and are the focus of price discovery (Remolona and Yetman 2019).

Our study mainly relates to two strands of microstructure literature. The first is the literature on the microstructure of the European sovereign bond markets. A number of studies using high frequency data from MTS have previously studied various aspects of market liquidity in Euro-area sovereign bond markets such as the relationship between sovereign yield dynamics and order flows (Menkveld, Cheung, and De Jong 2004; Cheung, Rindi, and De Jong 2005), the identification of benchmark status (Dunne, Moore, and Portes 2007), the determinants of yield differentials between sovereign bonds (Favero, Pagano, and Von Thadden 2010), the price impact of trades (Dufour and Nguyen 2012), price discovery (Caporale and Girardi 2013), the interrelation between market liquidity and credit risk (Beber, Brandt, and Kavajecz 2009; Favero, Pagano, and Von Thadden 2010; Pelizzon et al. 2016), the effect of macroeconomic announcements on market liquidity (Paiardini 2014), informed trading (Paiardini 2015), liquidity spill-over effects (Clancy, Dunne, and Filiani 2019), the linkage between expected issuance fees in the primary market and bond liqudity in the secondary market (Buis et al. 2020), and commonality in liquidity and its pricing implications (O'Sullivan and Papavassiliou 2020). However, we know relatively little about the fundamental sources that drive co-movements in liquidity of fixed-income securities over time, i.e. the determinants of commonality in liquidity across Euro-area government bonds has not been examined. Our study contributes to the literature by empirically examining which underlying economic sources generate time-series variation on commonality in liquidity in European sovereign bond markets.

The study which our paper is closest to is that of O'Sullivan and Papavassiliou (2020). O'Sullivan and Papavassiliou (2020) test for and document commonality in liquidity in European sovereign bond markets. In addition, they examine liquidity spill-overs across different maturities over calm and crisis periods, and test for the pricing implications of commonality in liquidity. Our study corroborates the results of O'Sullivan and Papavassiliou (2020) by documenting significant liquidity co-movements in the Euro-area government bond market (O'Sullivan and Papavassiliou 2020) and further contributes to the literature by providing the first empirical examination of the effect of macroeconomic announcements and of several supply- and demand-side variables on time-series variation of liquidity co-movements in the Euro-area sovereign bond market.

The second strand of literature that our paper contributes to, is that of examining the determinants of commonality in liquidity. Several studies in equity markets (Coughenour and Saad 2004; Hameed, Kang, and Viswanathan 2010; Hasbrouck and Seppi 2001; Kamara, Lou, and Sadka 2008; Huberman and Halka 2001; Karolyi, Lee, and Van Dijk 2012; Koch, Ruenzi, and Starks 2016) and a handful of studies in relation to FX markets (Karnaukh, Ranaldo, and Söderlind 2015; Sensoy, Uzun, and Lucey 2021) have examined several variables that help explain time-series and cross-sectional variation on commonality in liquidity. To the best of our knowledge, no previous study has examined the determinants of commonality in liquidity in fixed-income markets.[1]

The institutional structure of the Euro-area market for government bonds is unique in the sense that it allows us to test for co-movements in liquidity of sovereign bonds at the national as well as the international level. As a comparison, the US Treasury market is a mature, large, and liquid market in which government securities are issued from a single issuer, the US government, and for this reason are exposed to the same credit risk and the same underlying macroeconomic fundamentals with liquidity provided by a set of common financial intermediaries. In contrast, the Euro-area market for government bonds is characterized by significant market fragmentation and liquidity is provided by a set of common financial intermediaries for all Euro-area countries as well as by country-specific liquidity providers. In addition, government securities have multiple sovereign issuers, and share the same monetary policy within the monetary union. However, there are significant differences among Euro-area debt issuers in terms of the level of public debt, sovereign credit risk, and macroeconomic fundamentals.

We initially test for commonality in liquidity along three dimensions. First, we test for commonality in liquidity within countries. However, commonality in liquidity across government bonds issued from the same country is likely to be strong given the securities share common underlying features (Fleming 2003). Second, we test for commonality in liquidity across benchmark government bonds that belong to the same maturity bracket but were issued from different countries. To this end, we consider benchmark bonds with maturities over the entire term structure.[2] Third, we also test for commonality in liquidity across different benchmark government bonds, irrespective of issuing country *and* maturity at issue, i.e. at the pan-European level. By doing so, we attempt to uncover a pan-European liquidity common factor influencing liquidity variation of Euro-area government bonds as a whole, rather than individual securities, despite the fragmented structure of the market, the heterogeneity of market participants, the differences in debt size and quality as well as the exposure of each individual issuing country to different macroeconomic fundamentals.[3]

We test for commonality in liquidity by running market-model time-series regressions and we use the methodology of both Chordia, Roll, and Subrahmanyam (2000) and Korajczyk and Sadka (2008) to extract market-wide liquidity. In measuring liquidity, we use tick-by-tick data to construct daily estimates of liquidity for each benchmark bond in our data set. We capture different facets of market liquidity by calculating quoted spreads and depths, effective spreads and price impacts, as measured by the Amihud ratio. We use the adjusted R^2 of regressions of the liquidity of individual bonds on market-wide liquidity as a measure of the extent to which the liquidities of individual bonds move together.

We find strong evidence of commonality in liquidity at the national level in all four liquidity measures we consider, with quoted spreads and depths exhibiting strong co-movements. With respect to commonality in liquidity at the national level, the average across countries of the adjusted R^2 is equal to 68% and 42% for spreads and depths respectively, with these percentages dropping to approximately 47% and 26% when examining commonality across bonds that belong to specific maturity brackets but were issued from different countries. Although there is significant commonality in liquidity of benchmark bonds at the national level and the maturities level, there is also some cross-sectional variation of the commonality in liquidity both among issuing countries and among maturity brackets. Strikingly, the average across all bonds in our dataset (i.e. irrespective of issuing country or maturity at issue) of the adjusted R^2 remains relatively high. On average, 40% and 23% of the variation in quoted spreads and depths of each individual bond is explained by the changes in the pan-European, market-wide liquidity. This last finding strongly supports the hypothesis that commonality in liquidity spills across borders. Overall, these results support the view that commonality in liquidity is a pervasive phenomenon in Euro-area sovereign fixed-income markets. Similar results are also reported by O'Sullivan and Papavassiliou (2020).

However, a clear understanding of the fundamental sources of co-movements in liquidity of fixed-income securities is still missing. Commonality in liquidity can theoretically have two basic sources: co-variation in liquidity supply or co-movement in liquidity demand. However, with respect to equity markets, the empirical evidence provides heterogeneous results. Some empirical studies have found support for supply-side sources of commonality in liquidity related to the funding costs of financial intermediaries (Coughenour and Saad 2004; Hameed, Kang, and Viswanathan 2010). Other studies have explored demand-side factors driven by correlated trading activity (Karolyi, Lee, and Van Dijk 2012), the level of institutional ownership (Kamara, Lou, and Sadka 2008; Koch, Ruenzi, and Starks 2016), investor sentiment (Huberman and Halka 2001), and cultural and behavioral factors (Moshirian et al. 2017). With respect to FX markets, Karnaukh, Ranaldo, and Söderlind (2015) find stronger co-movements of FX liquidity in distressed markets, especially when funding is constrained and volatility is high. Sensoy, Uzun, and Lucey (2021) find that commonality in FX markets increases significantly before (after) ECB (Fed) monetary policy announcements. Similarly, in a yet unpublished study, Moinas, Nguyen, and Valente (2018) examine the link between funding liquidity and market liquidity of European government bonds. In particular, they found a two-way response occurring between funding and illiquidity shocks of European government bonds suggesting that market illiquidity for individual bonds reacts differently to tightening funding conditions. Our main contribution to the literature differs from Moinas, Nguyen, and Valente (2018) as we empirically examine which underlying economic forces generate time-series variation of the common, pan-European liquidity factor related to various supply- and demand-side explanations of commonality in liquidity. Our focus is on the determinants of the co-movement of a large cross-section of bonds, rather than the determinants of liquidity of individual bonds.

On the supply side, we investigate whether bond liquidity deteriorates with funding constraints and higher volatility, as postulated by recent theoretical models (Gromb and Vayanos 2002; Morris and Shin 2004; Brunnermeier and Pedersen 2009). These theoretical models predict that when a volatility shock occurs, lenders may tighten their terms of funding (for example, in terms of higher repo rates). Thus, financial intermediaries, who act as liquidity providers in financial markets, face higher funding costs and a difficulty in obtaining leverage. Financial intermediaries are then forced to liquidate positions or withdraw liquidity across many securities. This reduces market-wide liquidity, a cross-section effect, and triggers price drops leading to higher price impact and higher volatility. The liquidation of positions and the drop in market liquidity then affects individual bonds via their liquidity betas and results in an increase in commonality in liquidity. There is therefore a self-reinforcing feedback mechanism linking volatility shocks, funding costs and commonality in liquidity.

On the demand side, we consider three potential explanations for commonality in liquidity. First, we examine whether demand shocks, related to investor sentiment, can give rise to commonality in liquidity. Second, commonality in liquidity can arise as uncertainty about a government's economic policy may affect both asset valuation and volatility, increase information asymmetries and potentially lead to liquidity dry-ups. In addition, investors care not only about the mean and variance of asset returns, but also about the uncertainty of events over which the future return distribution occurs (Bali, Brown, and Tang 2017). Third, various studies suggest that there are significant cross-market linkages between equity and fixed income markets, either through liquidity spillovers between two markets in which arbitrageurs and specialized dealers coexist (Cespa and Foucault 2014) or through shifting wealth between stock and bond markets, with the effect leading to liquidity co-movements under both channels.

The results of time-series regressions of the supply-side hypotheses that evaluate the potential role of funding constraints of financial intermediaries acting as liquidity providers are strong. After controlling for market volatility, market liquidity and trading activity we find evidence that changes in commonality in quoted spreads are statistically significantly correlated with shocks in four out of the five variables we use as proxies of the funding conditions. Specifically, we find that monthly changes in commonality in quoted spreads are positively associated with shocks in both the TED and LOIS spread, suggesting that distress in money markets is correlated with stronger commonality in quoted spreads in Euro-area fixed income markets.

Furthermore, we find evidence that changes in commonality in spreads is negatively associated with the financial health of liquidity providers, as measured by the returns on portfolios of their stocks, and positively correlated with ECB's excess liquidity. Both findings are consistent with the supply-side explanation of commonality in liquidity which suggests that dealers lower market liquidity when they hit their funding constraints. Importantly, the positive correlation between ECB's excess liquidity and commonality in liquidity is consistent with the finding by Pelizzon et al. (2016) that the Long-Term Refinancing Operations of the ECB weakened the sensitivity of market makers' liquidity provision to credit risk highlighting the importance of funding liquidity measures as determinants of market liquidity. However, we find no evidence that changes in commonality in spreads or depths is greater in times of higher interest rates. Evidence on changes in commonality in depths and our proxies for the funding conditions of liquidity providers is weaker as compared to commonality in spreads. Given the fragmented structure of the market, a possible explanation might be that traded quantities are negotiated and agreed bilaterally.

Our demand-side proxies, on the other hand, do not help to explain time-series variation in commonality in liquidity. In particular, we find no association between any of our investor sentiment proxies and commonality in liquidity (either in spreads or in depths). We find that our proxy for US economic policy uncertainty is positively associated with commonality in liquidity in quoted spreads but not in depths, whereas the proxy for economic policy uncertainty in Europe does not help to explain the variation in commonality in either spreads or depths.

Last, we find a strong relationship between European as well as US equity market volatility shocks and changes in commonality in liquidity in fixed income markets. This last finding suggests that liquidity provision in these markets is, to some extent, inter-linked and a liquidity shock in one of these markets can also affect liquidity condition in the other market. Overall, our results suggest supply-side factors are more influential than demand-side factors in explaining time-series variation in commonality in liquidity.

The evidence that our proxies for funding conditions can help better explain the dynamics of changes in commonality in liquidity as compared to variables that proxy for demand-side explanations should not come as a surprise. Given infrequent trading and the use of government bonds as safe assets during periods of market stress as well as a source of immediate funding (i.e. when used as collateral to obtain financing in repo markets) it is natural that government bonds as an asset class tend to exhibit particularly strong links between volatility, funding conditions, and market liquidity.

We further test whether commonality in liquidity intensifies around announcements of key macroeconomic indicators in the Euro-area, a period in time in which new information is released and incorporated into prices. We employ as our measure of co-movement of liquidity in the event window the measure of synchronicity, originally proposed by Morck, Yeung, and Yu (2000), and as modified by Brockman, Chung, and Pérignon (2009). We find strong statistical evidence that some announcements materially increase commonality with the stronger effect stemming from ECB policy meetings on rate decisions. The average co-movement in spreads is 63.55% across all trading days and all benchmark bonds while this percentage increases to 67.87% during interest rate setting announcements, the difference in means being statistically significant at the 1% confidence level. This finding highlights the important linkage between interest rate changes and secondary-market liquidity. Similar results are reported by Sensoy, Uzun, and Lucey (2021) in relation to commonality in liquidity in FX markets and monetary policy announcements.

Overall, the existence of a pan-European common liquidity factor and the identification of the sources generating time-series variation in this factor are important for academics, practitioners, and policy makers. For academics, our results point to specific directions that are likely to be fruitful in improving our current understanding of fixed-income market liquidity by providing better insights into time-series, cross-section as well as the cross-market dynamics of market liquidity. For practitioners, understanding the implications of Euro-area market-wide commonality in liquidity aids the decisions of fixed income portfolio managers. A common liquidity factor is undiversifiable and implies pricing effects. Finally, policy markers may be able to draw policy-relevant implications from this study and central banks may be able to minimize the risk of liquidity crises in stress periods by timely improving funding conditions of financial intermediaries. Our results suggest that commonality varies over time and intensifies in stress periods corroborating the view that market liquidity can be a driving force for financial contagion.

The remainder of the study is organized as follows: Section 2 discusses the Euro-area secondary sovereign bonds market, Section 3 describes the data set and measures of liquidity. Section 4 presents our empirical approach for testing for commonality in liquidity and the effect of macroeconomic announcements and of several supply- and demsnd-side variables on commonality in liquidity. Section 5 discusses our results and Section 6 concludes.

2. The European sovereign bond market

Euro area sovereign issuers operate in the markets through a primary dealership system, i.e. an appointed group of financial institutions, either domestic or foreign, usually referred to as *Primary Dealers* with the objective to perform certain specialized operations in the government securities market.[4] These operations, which differ from country to country, mainly include participating in primary issues, placing the government securities with final investors, and maintaining a liquid secondary market subject to some regulatory requirements.[5] The number of primary dealers per country varies over time and across countries, with some degree of cross-country overlap. The existence of common primary dealers across countries is an important feature as it may induce cross-country spillovers in liquidity in both the primary and secondary markets. On average, each European country operates in the markets through 17 primary dealers with this number ranging between 5 and 39.[6]

Usually, primary dealers are incentivized to incur the additional risks associated with market making by the prospect of the gains received by the preferential treatment offered by issuers. This preferential treatment generally involves the granting of some form of exclusivity such as the exclusive right to participate in some treasury auctions, and/or the right to serve as a counterparty to the central bank when it conducts open market operations, and/or access to a line of credit or permission to borrow particular issues from the central bank. Dealers with no market-making requirements can participate in the market as price-takers. Dealers (either primary or not) can purchase securities for their own portfolio, on behalf of their customers, or for resale in the secondary market. In terms of instruments, sovereign issuers mainly access markets through conventional instruments (e.g. fixed coupon bonds), despite some differences across countries, mainly driven by overall borrowing needs as well as differences in investor base.[7]

In terms of size, the European sovereign debt market is one of the largest in the world with the total government debt securities outstanding at the end of 2017 being equal to €9.79 tn and €7.44 tn[8] for the EU-28 (64% of EU-28 GDP) and Euro-Area (67% of EA GDP) countries respectively.[9] Comparatively, the total government debt securities outstanding of US at the end of 2017 was $20.5tn. Despite differences in macroeconomic fundamentals, levels of debt and credit quality, government debt has some similar characteristics across countries: (i) most government debt is issued by the central government (approx. 80% among Euro-area countries) (ii) most of the debt consists of tradable securities (e.g. bonds and T-bills), with loans accounting for a small portion (apart from bailout countries) (iii) the debt is predominately denominated in Euros (iv) debt is traded through a fairly similar market structure across countries and (v) securities are typically regulated by domestic law (with the exception of Greek debt which is governed by English law). Since the focus of this study is the liquidity of the secondary market, we proceed by describing the structure and size of the secondary market without referring to primary markets.

In general, the structure of the secondary market for sovereign bonds across European countries is fairly similar in that trading is divided into two segments, the dealer-to-dealer segment and the dealer-to-customer segment with the inter-dealer segment being seen as the core of the market. In the inter-dealer segment, trading is taking place either through an opaque, quote-driven, OTC market or through an observable exchange-traded (predominantly electronic) market. The market is predominantly an institutional market with retail participation being largely indirect (through e.g. pension funds, insurance companies, mutual funds, asset managers).

The market has undergone significant structural change over the last 40 years driven by the widespread introduction of new trading technologies, the harmonization of debt management practices and by regulatory reforms. Despite the share of electronic trading in the European bond market being below that observed for other asset classes, recent estimates suggest that share to be approximately 60% for 2015 and expected to further increase in the future.[10] A key factor behind the slower adoption of electronic trading in European sovereign bond markets has been the heterogeneity of the traded instruments and the resulting difficulty in finding matches in supply and demand. In addition, since the 2008–2009 financial crisis and the post-crisis global regulatory reforms, dealers are facing higher funding and capital adequacy costs.

Little information is publicly available regarding trading volumes. However, the market share of both market segments depends on the issuing country and is not always (publicly) known. Because bond trading is not centralized in any particular location, information on actual traded volumes is not readily available despite DMOs publishing some statistics on volumes but sizes are often not directly comparable. AFME[11] estimates an average daily trading volume (excluding bills) of approximately €72.2 bn across EU-28 countries for the period 2014–2017 with most of the trading activity in the secondary market concentrated in the period between 9:00 and 17:00 CET.

3. Hypotheses

Commonality in liquidity can theoretically have two basic sources: co-variation in liquidity supply or co-movement in liquidity demand. In this section, we discuss and formulate the hypotheses for our empirical test by considering various supply and demand-side explanations of commonality in liquidity. Section 3.1 discuss the relevant literature on the effect of market volatility on aggregate market liquidity. Sections 3.2 and 3.3 discuss, respectively, the relevant literature on the supply- and demand-side explanations. Last, in Section 3.4 we also examine whether commonality in liquidity is intensified around macroeconomic announcements, a period of time in which new information is released and incorporated into prices.

3.1. Market volatility

Previous theoretical and empirical research indicates that market liquidity and volatility are linked. Traditionally, theoretical market microstructure models examine liquidity provision through the lenses of information asymmetries and inventory risk (although, these are not mutually exclusive). From the perspective of asymmetries in information, higher volatility increases the likelihood that market makers will transact with informed traders and suffer larger losses (see, for example, Glosten and Milgrom 1985). By splitting orders, informed traders hide their information and only partially reveal it to the market with each additional trade. New information is thus disseminated sequentially to traders, with liquidity traders not being able to perfectly deduce the presence of informed trading. The sequential arrival of new information to the market generates both trading volume and price volatility, with both increasing by information shocks. To protect themselves, market makers widen the spread and/or quote limited quantities when fearful of informed traders, thus lowering market liquidity.

From the perspective of inventory models, market makers are exposed to risk through the inventory of a security. The market maker either has limits on the quantity of inventory held or a desired inventory level and a cost of deviating from it (see, for example, Stoll 1978; Ho and Stoll 1981). Best bid and ask prices determine the stochastic arrival rate of sellers and buyers, and market makers adjust prices dynamically to optimize their inventory levels. At a single point in time, the aggregate inventory position across market makers measures the amount of risk market makers have taken on. Models with limited risk-bearing capacity (for example Gromb and Vayanos 2002) suggest that when large dealers hold undesired inventories, whether long or short, they face greater risk exposure and lower risk-bearing capacity and, consequently the higher the volatility the more reluctant these dealers are to provide liquidity.

From a demand-side perspective, the high liquidation risk implied by volatile prices can keep prospective investors out of the market (Pagano 1989) lowering market liquidity. Thus, when volatility increases, liquidity will tend to evaporate.

However, the volatility effect may be asymmetric, i.e. commonality in liquidity might be much stronger when the market experiences large declines as compared to large market increases. The argument is that during stress periods, given the funding constraints of liquidity providers, a large negative market return reduces the amount of capital that is tied to marketable securities and hence reduces the supply of liquidity. Such an effect is consistent with the theoretical predictions of Brunnermeier and Pedersen (2009) and Gromb and Vayanos (2002). Hameed, Kang, and Viswanathan (2010) provide relevant empirical evidence pertaining to the US equity markets and show that commonality in liquidity intensifies during market declines, especially when funding costs are higher. Similar results are reported by Karolyi, Lee, and Van Dijk (2012) in relation to international stock markets and by Marshall, Nguyen, and Visaltanachoti (2013) in relation to commodities. Kamara, Lou, and Sadka (2008) find that commonality in liquidity change over time and that these changes are affected by market volatility as well as market returns. Hameed, Kang, and Viswanathan (2010) argue that, in stress periods, a large negative market return may lead to greater commonality in liquidity through an effect on the wealth and the collateral of investors and liquidity providers, that commonality should increase during periods of large market declines and the effect of volatility should be asymmetric.

In the cross-section, all of the above arguments imply a positive relationship between changes in volatility and changes in commonality in liquidity. Moreover, they predict that commonality is higher during periods of high market volatility, and, in particular, during large market declines. We investigate these conjectures by studying the link between volatility and commonality in liquidity empirically before we turn our attention to other variables.

3.2. Supply-side hypothesis: funding constraints

Recent theoretical (Brunnermeier and Pedersen 2009) and empirical (Moinas, Nguyen, and Valente 2018) studies suggest that there might be situations in which volatility may act as a catalyst in the market and exaggerate the effect of shocks originating elsewhere. Brunnermeier and Pedersen (2009) show theoretically that commonality in liquidity can arise as a result of forces related to the supply of liquidity and amplified by market volatility. According to their model, in order for market makers to provide liquidity and to finance their inventories, they need to obtain leverage by either posting margins or by pledging securities that they hold as collateral. For example, to finance the purchase of a bond, a dealer may need to raise cash by pledging the same bond as collateral in the repo market. When the dealers find an interested buyer, they can simply stop rolling over the overnight repo (or terminate open ones) so as to obtain the collateral (bond) back when the sale is settled and then deliver the bond to the buyer. Thus, as government bonds are often used as high-quality collateral in repo transactions, it is reasonable to conjecture that liquidity of the sovereign bond market would be directly affected by funding liquidity shocks.

When, for example, interest rates rise or a volatility shock occurs, obtaining financing may become more expensive or generate losses in their collateral values, forcing dealers to become reluctant to take on positions, especially capital intensive positions in high-margin securities. This can result in dealers withdrawing market liquidity (either by lower market participation, by quoting less depth and/or wider spreads, by liquidating their positions across many securities or a combination of these). In turn, lower market liquidity suggests that asset prices are more sensitive to the impact of individual dealers' demand, with shocks leading to higher price impact and higher volatility leading to further losses and/or margin increases, thus creating an illiquidity spiral that further restricts market makers ability to supply liquidity. In the cross-section, this feedback loop between market liquidity, volatility and funding liquidity implies a positive relationship between the funding conditions of market makers and commonality in liquidity.

We investigate the relevance of market makers' funding conditions in explaining time-series variation in commonality in liquidity of European government bonds over our sample period. This supply-side explanation predicts that commonality in liquidity should be positively related to financial market stress and to the level of interest rates. Commonality in liquidity should also be negatively correlated to the stock returns of financial intermediaries who act as market makers, which are likely to be inversely related to the tightness of capital in the market.

3.3. Demand-side hypotheses

3.3.1. Investor sentiment

The first demand-side explanation we consider links commonality in liquidity to investor sentiment. The investor sentiment literature assumes that irrational investors generate sentiment-based demand shocks that affect prices and may be important sources of commonality in liquidity. For example, Huberman and Halka (2001) argue that commonality in liquidity arises because of the 'presence and effects of noise traders'. Baker and Stein (2004) show theoretically that when noise traders receive private signals regarding future cash flows they tend to overweight them and underreact to the information contained in aggregate order flow (since they consider others to be less well-informed) and be more active in the market. Thus, prevailing market-wide sentiment makes investors move together, thereby causing increased correlated demand for liquidity. Baker and Wurgler (2006) show that investor sentiment affects the cross-section of stock returns with sentiment traders shifting from safe to speculative securities when sentiment increases, and from speculative to safe securities when sentiment declines. Hameed, Kang, and Viswanathan (2010) recognize that panic selling by investors may be a sentiment-based cause of commonality in liquidity. In relation to the fixed-income market, Beirne and Fratzscher (2013) report that there was herding contagion in advanced and emerging economies during the European sovereign debt crisis with sharp and simultaneous increases in sovereign yields across countries.

Motivated by the findings in the equity markets, we attempt to link investor sentiment to commonality in liquidity in fixed income markets. In order to test this sentiment based explanation, we include various Sentix indices as proxies for variation in investor sentiment in our time-series regressions.[12] Sentix Indices are used to measure investor sentiment in equity (Schmeling 2007), foreign exchange (Heiden, Klein, and Zwergel 2013), and fixed income markets (Afonso et al. 2018). In our analysis we use the Sentix Euro Area Aggregate Index, Sentix Euro Area Breakup Index, Sentix Contagion Index as well as regional (e.g. global, US, Asia) indices. The sentiment hypothesis does not offer clear predictions on whether investor sentiment is positively or negatively correlated with changes in commonality in liquidity, thus we are a priori agnostic about the direction of the postulated relationship (Karolyi, Lee, and Van Dijk 2012).

3.3.2. Economic policy uncertainty

The second demand-side hypothesis we consider proposes that uncertainty related to a government's economic policy may determine how correlated the demand for liquidity is across government bonds, and thus commonality in liquidity. On frictionless and complete markets, with information available to all market participants, and a full set of state-contingent assets, there is no illiquidity. However, markets are not perfect. There are information asymmetries between liquidity providers and informed traders. The larger these information asymmetries are, the less willing are investors to participate in the market. Krishnamurthy (2010) show theoretically that market participants when faced with risks they do not fully understand, as in stress periods, may be less willing to trade assets whose characteristics and/or behaviour are not well known. They choose to disengage from risks and seek liquid investments. In stress periods, when uncertainty related to a government's economic policy increases, trading could become impossible causing market liquidity to dry up. A market may altogether disappear (the most extreme form of illiquidity) if information is sufficiently asymmetric (Adrian and Shin 2008).

In addition, investors care not only about the mean and variance of asset returns, but also about the uncertainty of events over which the future return distribution occurs (Bali, Brown, and Tang 2017). Since the return distribution is affected by the state of the economy, an increase in uncertainty regarding a governments' economic policy makes investors concerned about future outcomes and it may lead to less than optimal levels of consumption and investment. To hedge against unfavourable shifts in the economy, investors prefer to hold assets that have higher covariance with economic uncertainty. Thus, anticipation of future liquidity dry-ups or uncertainty regarding future macroeconomic fundamentals, may affect current investment decisions and lead to increased correlated demand for liquidity of government bonds. The above hypotheses predict a positive correlation between economic uncertainty and commonality in liquidity. In our time-series regressions, we use the Economic Policy Uncertainty (EPU) index developed by Baker, Bloom, and Davis (2016) of both the US and Europe as a proxy for aggregate government policy uncertainty.

3.3.3. Cross-market illiquidity effects

The third demand-side explanation we consider is based on cross-market liquidity interdependence flowing from volatility to liquidity between equities and fixed income markets. If illiquidity is a systematic risk factor across markets, a liquidity shock to one of the markets will affect its relative attractiveness resulting in trading activity affecting liquidity demand in both markets. Fleming, Kirby, and Ostdiek (1998) report strong volatility linkages between equities and fixed-income markets. Chordia, Sarkar, and Subrahmanyam (2005) and Goyenko and Ukhov (2009) examine the time-series properties of stock and bond liquidity and they find evidence of cross-market dynamics and common influences in both markets. In particular, they find that innovations to stock volatility forecast an increase in bond spreads. Mink and De Haan (2013) examined the impact of news about a Greek bailout on bank stock prices using data for 48 European banks and found a significant effect on bank stock prices, even on stock prices of banks without any exposure to Greece or other highly indebted euro area countries. There are two potential channels through which the state of the stock market may affect liquidity conditions of fixed income markets.

According to the first channel, a negative stock volatility shock may affect liquidity provision in both markets by impacting the inventory risk of market makers,[13] thus increasing commonality in liquidity in the cross-section. Kyle and Xiong (2001) and Cespa and Foucault (2014) show that if financial intermediaries providing liquidity in two markets are suffering trading losses in one market or if they are hitting their funding constraints in one asset, then they may reduce liquidity provision in both markets. This illiquidity spillover effect arises from cross-asset learning when dealers specialising in different asset classes learn from each other's prices. Prices are informative because they reflect information about fundamentals known to dealers specialising in each asset. However, prices are also affected by temporary demand pressures and even more so when the cost of illiquidity increases. Thus, when one asset becomes less liquid, its price becomes less informative for dealers specialised in the other asset. These dealers then face more uncertainty and require larger spreads to absorb liquidity traders' order imbalances generating price impact and volatility. Thus, an increase in illiquidity in one asset propagates to the second asset, generating a feedback loop which amplifies the initial shock. This mechanism relies on the sensitivity of price informativeness of each asset price to illiquidity and culminates beyond some critical values of dealers' risk tolerance.

Although this illiquidity propagation mechanism is mostly a supply-side effect, Cespa and Foucault (2014) show that when arbitrageurs, who are uninformed but trade in both markets, and specialized dealers *coexist*, cross-asset learning is a source of liquidity spillovers for exactly the same reasons as in the baseline model. Arbitrageurs respond to liquidity demand in one asset by hedging their position in other assets and thus transmit temporary demand shocks for one asset to the other asset. However, the model predicts that co-movements in liquidity should decrease with the capital allocated to cross-market arbitrage as arbitrageurs increase the overall risk-bearing capacity of liquidity providers.

The second channel is through portfolio rebalancing and cross-market hedging effects. A number of asset allocation strategies shift wealth between stock and bond markets (see, for example, Fox 1999; Barberis 2000). In addition, in times of market uncertainty (i.e.increased market volatility), investors tend to rebalance their portfolios and shift towards less risky (flight-to-quality) and more liquid assets (flight-to-liquidity), especially in fixed-income markets (Beber, Brandt, and Kavajecz 2009). Hartmann, Straetmans, and Vries (2004) empirically study the linkages between stock and government bond markets with a focus on crisis periods and their results suggest that stock-bond contagion is approximately as frequent as flight to quality from stocks into bonds with cross-border linkages being approximately equal in magnitude to national linkages. Thus, investors by hedging their positions in other assets, they transmit shocks to demand for one asset to the other asset.

In our time-series regressions, we use two volatility proxies for European equity markets: the monthly standard deviation of Stoxx50 daily returns as well as the realized volatility calculated from five-minute intervals.[14] We hypothesize a positive correlation between stock market volatility and commonality in liquidity in fixed income markets.

3.4. Macroeconomic announcements

In the last part of our analysis, we examine the impact of macroeconomic news announcements in the Euro-area on the European market-wide commonality in liquidity. We assume two different channels through which macroeconomic announcements may affect commonality in liquidity. The first is through the effect of portfolio rebalancing. As new information is released regarding underlying macroeconomic fundamentals, it may lead investors to revalue their portfolios and trigger portfolio rebalances, thus intensifying the correlation in demand for liquidity for government bonds, and thus also the co-movement in liquidity. The second channel is through the effect of adverse selection. The release of new macroeconomic information is usually associated with an increase in trading activity and the presence of informed traders which, in turn, may induce dealers to protect themselves by withdrawing market liquidity, in terms of wider spreads and lower depth, for a large cross-section of government bonds. Although we cannot effectively disentangle the effects of these two channels, we test whether commonality in liquidity overall is intensified during the event window. In addition, unanticipated surprises may potentially have a stronger effect on liquidity commonality of government bonds as compared to anticipated surprises. Forward-looking investors are expected to instantly adapt their expectations, revalue, and rebalance their portfolios and trading positions as unanticipated information about fundamental asset values becomes available in the marketplace.

4. Data

In this section we describe the data source and our data set, the limitations of the data, the screening and filtering procedures, the identification of the term structure of benchmark bonds as well as the liquidity variables we use to construct our measures of commonality in liquidity.

4.1. The MTS trading platform

We gained access to a granular dataset from MTS that includes historical data for almost all Euro-area countries from June 2011 to June 2018. MTS is considered as the major interdealer market for trading Euro-area government bonds and for that reason it provides a good, but not complete, picture of interdealer activity. It is sourced from a trading community of approximately 500 unique counterparties and reports an average daily volume, across MTS platforms and fixed-income securities of approximately €100bn (i.e. both sovereign and non-sovereign).[15]

MTS is an entirely electronic and order-driven interdealer market. European sovereign bonds can be traded on two parallel markets: EuroMTS and/or domestic MTS, with the former only trading Euro-area benchmark sovereign bonds and the latter trading both benchmark and non-benchmark sovereign bonds. Market participants can also trade quasi-government bonds, corporate bonds and repurchase agreements. Both platforms are electronic limit order markets in which mainly banks participate, who are either market makers with a two-sided quoting obligation (primary dealers) or price takers (dealers). Most market makers are active on both platforms, which ensures market liquidity in the domestic and EuroMTS platforms are closely connected, despite their technical fragmentation (Cheung, Rindi, and De Jong 2005).

Financial institutions must satisfy strict requirements about traded volumes and net asset values to qualify as market makers. Market makers are assigned a subset of securities for which they have to post two-sided quotes called *proposals*. Market makers' quotes can be hit or lifted by other market participants via market orders. Price takers are also allowed to submit single-sided limit orders (either buy or sell). Regarding market structure and trading protocol, see also Dufour and Skinner (2004). All MTS quotes are transactable. Before the 2007–2009 global financial crisis, MTS imposed strict requirements on dealers. Market makers were required to provide firm quotes for a minimum number of hours during the trading day, for a maximum spread, and for minimum quantities ranging from €2.5 m to €10 m, depending on the maturity and benchmark status of the instrument. With the onset of the 2007–2009 global financial crisis, MTS relaxed dealers' obligations (e.g. minimum quote and trade size of €1 m) and introduced more flexible requirements recognizing that market makers were facing higher liquidity and credit risk. Instead of imposing fixed obligations, MTS monitors average quoting times and average spreads of each individual market maker, which must be in line with market averages computed across all dealers.

4.2. Data set

The sample period for our study is June 2011 to June 2018. This time period is of particular interest to the study of the behavior of Euro-area fixed-income markets both unconditionally as well as because a number of significant market events took place in that period such as the peak and aftermath events of the 2011 European debt crisis, the ECB's quantitative easing program, the Brexit referendum, and the uncertainty period surrounding Italian elections.

Our MTS data set includes tick-by-tick data for more than 2600 individual fixed income securities with approximately 2.65 million trades in the sample period. We select sovereign bonds issued from 10 Euro-area countries, namely Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal and Spain[16] (536 bonds were dropped), which capture about 98 percent of the market universe of medium- and long-term bonds with original maturities larger than two years.[17]

We further constrain our focus to standard, fixed-coupon sovereign securities in order to avoid the confounding effects related to specific bond characteristics. Particularly, we exclude non-sovereign issuers (109 bonds were dropped), sovereign securities with original maturity less than two years (1095 bonds were dropped), with less common coupon types (such as floating, step coupon), inflation and index-linked bonds, with coupons and/or principals stripped from a conventional bond, and under special types of transactions such as bond buyback and exchanges (242 bonds were dropped). After the filtering, we are left with about 1.45 million trade records from 625 unique euro-denominated sovereign bonds in the sample period.

The dataset includes trade and quote information as well as security identification information. For the trade information, the dataset contains the ISIN[18] code for the bond, the date and time of all trades, the price and size of each trade as well as the direction of each trade. The quote information includes the ISIN code for the bond, the type of the order, the bid and ask prices and corresponding depth at each price on the limit-order book. Note that all MTS quotes are transactable, thus we do not have to rely on proxies for an accurate measurement of liquidity. The security identification information includes various metadata such as the issuing country, issuer type, issue and maturity date, coupon rate, benchmark status etc.

As with any high-frequency data set, it is important to note that prior to using the raw data, one must first clean the data with the objective of discriminating between noisy and valid data entries. Trades and/or quotes that are out of sequence, that are recorded outside normal trading hours (defined as CET 8:30 am–17:30 pm), or that have special settlement conditions are discarded. Observations during weekends and public holidays are also removed. Negative bid-ask spreads, depths and trade prices are also eliminated from the data set. We further use the Brownlees and Gallo (2006) algorithm to clean the MTS data. This filtering procedure removes rare and obvious outliers. A similar approach is used by Mancini, Ranaldo, and Wrampelmeyer (2013), Marshall, Nguyen, and Visaltanachoti (2013), and Karnaukh, Ranaldo, and Söderlind (2015).

As a final step, we aggregate the irregular spaced raw data to a one minute sampling frequency. At the end of each minute, we reconstruct the order book, and following Pelizzon et al. (2016) we compute the global best bid and ask prices, along with their associated depths, across the two platforms for each country (i.e. regardless of whether the trading or quoting activity took place on the domestic or the European market), taking into consideration only active quotes. In addition, for each minute of trading activity we also calculate the midquote, the total trading volume as well as net order flow. The logarithmic return is calculated based on midquote changes. These data allow us to construct liquidity measures for each security.

4.3. Liquidity measures

A secondary market is viewed as liquid when market participants can execute large-volume transactions at low cost, quickly and with minimum impact on market prices. We thus break down our measures into three categories, namely, trading cost (price dimension), market depth (quantity dimension) and price impact (elasticity dimension) in an attempt to capture all aspects of market liquidity. This section details the liquidity measures used in our study.

4.3.1. Trading costs

Our first measure attempts to capture the cost of executing a trade. A market can be regarded as liquid if trading costs are low and as illiquid if trading costs are high. Measuring trading costs is not simple as they depend on the size of a trade, its timing, the trading venue, and the counterparties (Fleming 2003). The proportional quoted bid-ask spread, L^{PQS}, is a commonly used measure of market liquidity. It directly measures the cost of executing a small trade, with the cost typically calculated as:

$$L^{PQS} = (P^A - P^B)/P^M$$

where the superscripts A, B, and M indicate the best ask, the best bid, and mid quotes, respectively per €100 of face value. The latter is defined as $P^M = (P^A + P^B)/2$. We calculate the proportional quoted spread per bond at the end of each minute and daily estimates are obtained by averaging across all minutes per day. A drawback of the bid-ask spread is that bid and ask quotes are good only for limited quantities and periods of time. The spread therefore only measures the cost of executing a single trade of limited size at a specific point in time.

The quoted bid-ask spread reflects the liquidity available at a given point in time, although an alternative would be to measure trading costs using the prices actually obtained by investors. In practice, trades are not always executed at the posted bid or ask quotes.[19] Instead, deals frequently transact at better prices. The effective spread better captures the cost of a round-trip order by including both price movement (dealers coming in to execute orders at a better price than previously quoted) and market impact (spread widening due to the size of the order itself). Effective costs can be computed by comparing transaction prices with the quotes prevailing at the time of execution. The percentage effective cost of a trade is defined as:

$$Ł^{PES} = \begin{cases} (P - P^M)/P^M, & \text{for buyer-initiated trades,} \\ (P^M - P)/P^M, & \text{for seller-initiated trades,} \end{cases}$$

with P denoting the trade price. The wider the effective spread, the less liquid is the asset. Since our data includes quotes and trades, we do not have to rely on proxies for the effective spread, but can compute it directly from observed data. Daily estimates of illiquidity are obtained by averaging the effective cost of all trades that occurred on each day.

4.3.2. Market depth

Our second measure captures the quantity dimension of market liquidity. The quantity of securities that can be traded at the bid and ask prices is the depth of the market and complements the bid-ask spread as a measure of market liquidity. The average quoted depth, L^{AQD}, is a commonly used measure of market depth, typically calculated as:

$$L^{AQD} = (D^A + D^B)/2$$

where D^A denotes the ask depth, i.e. the quantity that liquidity providers are willing to sell at the best ask price and D^B denotes the bid depth, i.e. the quantity that liquidity providers are willing to buy at the best bid price in millions of euros. Intuitively, this characterizes the average quantity that a trader can trade at the best prices. The larger the average depth, the more liquid the market is considered to be and the lower the likely execution cost for a large order. In other words, depth denotes the size of transaction that can be absorbed without affecting prices. A drawback of this estimate, however, is that market participants often do not reveal the full quantities they are willing to transact at a given price, so the observed quote sizes at the best prices may underestimate true market depth. Concerns that sovereign depth is uninformative are mitigated by the fact that the ratio of hidden to displayed orders in our dataset is extremely low (e.g. less than 2%).

4.3.3. Price impact

The fourth liquidity measure we calculate combines the cost and quantity dimensions and captures the marginal cost of trading an extra unit of the asset. Conceptually related to Kyle's (1985) λ, the price impact of a trade measures how much the bond price changes in response to a given order flow. The higher the price impact, the more the bond price moves following a trade, reflecting lower liquidity. Roşu (2009) develops a dynamic model that predicts that more liquid assets should exhibit narrower spreads and lower price impact. Despite the granularity of our dataset, regressing net order flow on intraday bond returns to obtain an accurate estimation of price impact is not feasible due to infrequent trading. An alternative is to gauge the sensitivity of returns to trading volume.[20] To this end, we calculate Amihud's illiquidity ratio at the daily frequency defined as:

$$L^{AIR} = \frac{|R_{i,t}|}{Vol_{i,t}}$$

where $|R_{i,t}|$ denotes the absolute daily log return and $Vol_{i,t}$ denotes the daily trading volume in euros for bond i in day t. It can be interpreted as the daily price response associated with one euro of trading volume. A higher value of the measure indicates lower liquidity. We scale up daily L^{AIR} by multiplying by 10^6 as the original magnitude of the measure is too small to be used in empirical analysis. Goyenko and Ukhov (2009) show empirically that the Amihud ratio is a good proxy for price impact, as it is highly correlated with high-frequency measures of price impact. Kamara, Lou, and Sadka (2008) and Karolyi, Lee, and Van Dijk (2012) use Amihud's ratio to test and document commonality in liquidity is US equity markets, Marshall, Nguyen, and Visaltanachoti (2013) in commodity markets, and Benos, Payne, and Vasios (2020) to measure the liquidity of interest rate swap contracts.

4.3.4. Commonality measure

Price impact, together with the spread and depth measures, provides a fairly complete picture of market liquidity (Fleming 2003). We use the adjusted R^2 of regressions of the liquidity of individual bonds on market-wide liquidity as a measure of the extent to which the liquidity of individual bonds move together. There are two approaches in the literature in extracting market-wide liquidity: averaging (Chordia, Roll, and Subrahmanyam 2000) and principal component analysis (Korajczyk and Sadka 2008). For robustness, we use and report results separately for both approaches in the next section of this study. To obtain a monthly time-series average of the adjusted R^2 measures, for each month, we use the equally-weighted average adjusted R^2 of regressions of the liquidity of each individual benchmark bond series on market-wide liquidity to obtain a measure of commonality in liquidity in a given month. We require a minimum number of at least 15 daily observations to estimate the adjusted R^2 of a benchmark bond series in a given month as well as a minimum number of 50 bonds for the calculation of these aggregate adjusted R^2 measures in calculating commonality in liquidity across all bonds in our sample (i.e. irrespective of issuing country or maturity at issue) in a given month. Our raw commonality measure is not suitable to use as the dependent variable in regressions, because their values always fall within the interval [0,1]. Following Karolyi, Lee, and Van Dijk (2012) and Moshirian et al. (2017), we use the logistic transformation of the R^2 measures, $ln[R^2/(1-R^2)]$, in our time-series regressions.

4.4. Liquidity measures of benchmark bonds

We generate liquidity measures for benchmark sovereign bonds across time and countries at daily frequency. Traditionally, an on-the-run bond is the most recently auctioned bond of a particular maturity. It attains the 'benchmark' status when it becomes the most heavily traded bond at that maturity for an adequate period of time, and normally without government intervention (Remolona and Yetman 2019). However, the existing literature (see, for example, Paiardini 2014; Pelizzon et al. 2016; O'Sullivan and Papavassiliou 2020) typically considers as a benchmark bond at a particular maturity the one that is most actively for the greatest part of the sample period under examination.

This approach, in the case in which a new benchmark bond is issued in the sample period and thus should have become the new benchmark in the respective maturity, results in treating the ex-benchmark bond as still being the benchmark bond. This misuse may bias the empirical results of the analysis if there is significant liquidity difference between the on- and off-the-run bonds (Pasquariello and Vega 2009). Moreover, trading volume of non-benchmark bonds can be temporarily more active than the benchmark peers if these are subject to idiosyncratic factors such as at the dates of bond re-openings. Thus, we manually identify the switching dates for each of the 2-year, 3-year, 5-year, 7-year, 10-year, 15-year, 20-year and 30-year maturities, when a new benchmark bond replaces the former one in Bloomberg.

Missing observations are recorded when benchmark bonds do not exist in certain periods for some countries.[21] Missing benchmark bonds are replaced with bonds that are issued by the same sovereign, that have the closest remaining maturity, and that are not considered as benchmark bonds in other maturities.[22] Remaining missing observations are kept if no replacement bonds are found which satisfy these conditions. We end up with 73 balanced benchmark bond series.[23] Lastly, using the ISINs, the panel of benchmark bonds across time and maturities are matched with the liquidity measures.

We partition our dataset along three dimensions. Firstly, we separate the bonds in our dataset by issuing country, i.e. we have eight time series each representing a different maturity within a country for each of the 10 countries. The second dimension involves separating the bonds in our dataset by maturity at issue, i.e. we have 10 time series each representing a different country for each of the eight maturity brackets. The final partition is an unconditional partition which includes all benchmark bond series, irrespective of issuing country or maturity at issue. By partitioning our dataset with respect to these three dimensions, we test for commonality in liquidity at the [1] national level, [2] across maturities, and at the [3] pan-European level.

4.5. Summary statistics

Using the large data set described above, we calculate the four liquidity measures (bid-ask spread, effective cost, market depth and price impact) for each trading day and each sovereign bond. Table 1 shows means and standard deviations for the four measures of liquidity across all bonds of the same maturity but issued from different countries. For all sovereign bonds, the quoted spread and the Amihud illiquidity ratio increase as time to maturity increases whereas the quoted depth decreases as the time to maturity increase. This observation suggests that bonds with shorter maturities are more liquid than bonds with longer maturities. Similar results are reported by Pasquariello and Vega (2009) for US Treasury bonds and by O'Sullivan and Papavassiliou (2020) for Euro-area government bonds. Effective costs are less than half the bid-ask spread, implying within-quote trading.

5. Empirical approach

In Section 5.1, we present the empirical method in testing for commonality in liquidity. In Section 5.2 we discuss our empirical approach in examining the effect of several supply- and demand-side determinants on

Table 1. Daily liquidity measures per maturity.

	2Y	3Y	5Y	7Y	10Y	15Y	20Y	30Y
L^{PQS}								
Mean	31.30	36.13	43.28	49.78	51.61	51.10	59.49	61.00
Std. Dev.	105.16	114.86	124.42	130.89	130.02	39.74	54.88	57.07
L^{PES}								
Mean	2.06	3.41	4.80	4.68	8.28	7.27	6.01	12.59
Std. Dev.	8.50	20.07	13.12	16.50	16.67	13.83	16.13	20.91
L^{AQD}								
Mean	19.70	17.65	15.93	15.33	13.01	8.31	6.86	6.57
Std. Dev.	12.49	10.07	8.06	7.59	6.95	3.75	2.43	2.33
L^{AIR}								
Mean	0.004	0.006	0.010	0.017	0.026	0.028	0.045	0.069
Std. Dev.	0.044	0.066	0.074	0.094	0.108	0.099	0.192	0.209

Notes: This table shows summary statistics for various daily measures of liquidity across all bonds of the same maturity but issued from different countries. The percentage quoted spread (L^{PQS}) denotes the average relative bid-ask spread computed using intraday data for each trading day. The percentage effective spread (L^{PES}) is the average relative difference between the transaction price and the bid/ask quote prevailing at the time of the trade. The average quoted depth (L^{AQD}) is the average depth quoted at the best bid and ask prices computed using intraday data for each trading day. The Amihud illiquidity ratio (L^{AIR}) is the ratio of absolute daily log return and daily trading volume. The sample period is 2011:06–2018:6 and includes 1,804 daily observations.

commonality in liquidity. In Section 5.3 we present the test for the effects of macroeconomic announcements on commonality in liquidity.

5.1. Testing for commonality in liquidity

We use the adjusted R^2 of time-series regressions of the liquidity of individual bonds on market-wide liquidity as a measure of the extent to which the liquidity of individual bonds move together. Specifically, daily percentage changes[24] in liquidity variables for an individual benchmark bond series are regressed on the daily percentage change in market-wide measures of liquidity, i.e.

$$\Delta L_{j,t}^{(\cdot)} = \alpha_j + \beta_{1j}\Delta L_{M,t}^{(\cdot)} + \beta_{2j}\Delta L_{M-1,t}^{(\cdot)} + \beta_{3j}\Delta L_{M+1,t}^{(\cdot)} + Controls + \epsilon_{j,t}, \tag{1}$$

where $\Delta L_{j,t}^{(\cdot)}$ is, for benchmark bond series j on day t, the percentage change (Δ) from trading day $t-1$ to t in liquidity measure $L^{(\cdot)}$, $\Delta L_{M,t}^{(\cdot)}$ is an estimate of market-wide liquidity of the same variable, $\Delta L_{M,t-1}^{(\cdot)}$ and $\Delta L_{M,t+1}^{(\cdot)}$ are the lag and lead percentage changes in market-wide liquidity and are intended to capture any lagged adjustment in commonality.

Following Chordia, Roll, and Subrahmanyam (2000), the contemporaneous, leading and lagged market return and the contemporaneous change in the individual benchmark bond series absolute return are included as control variables. The market return is intended to remove spurious dependence induced by an association between returns and the bid-ask spread.[25] Finally, the absolute return is induced to proxy for volatility, which is positively correlated with liquidity. We use the Bloomberg Barclays Pan-European Aggregate Bond Index as a proxy for the market.[26]

There are two approaches in the literature in estimating market-wide liquidity: averaging (Chordia, Roll, and Subrahmanyam 2000) and principal component analysis (Korajczyk and Sadka 2008). For robustness we implement both methods, but most of the analysis is based on the second approach.

5.1.1. Averaging

In the first approach, market-wide liquidity $L_{M,t}^{(\cdot)}$ is computed as the equally-weighted cross-sectional average[27] of liquidity at the individual benchmark bond series level, i.e.

$$L_{M,t}^{(\cdot)} = \frac{1}{N}\sum_{j=1}^{N} L_{j,t}^{(\cdot)}. \tag{2}$$

where N is the number of benchmark bond series and $L^{(\cdot)}_{j,t}$ is the liquidity of the benchmark bond series j on day t. Chordia, Roll, and Subrahmanyam (2000) and Pástor and Stambaugh (2003) use this method for determining market liquidity in equity markets and Marshall, Nguyen, and Visaltanachoti (2013) in commodities markets. Note that in each individual regression when computing the market-wide liquidity measure, $\Delta L^{(\cdot)}_{M,t}$, benchmark bond series j is excluded, so the explanatory variable in (1) is slightly different for each benchmark's bond time series regression. This removes a potential mechanical correlation.

5.1.2. PCA

The second approach for extracting a market-wide measure of liquidity is based on principle component analysis. Korajczyk and Sadka (2008) used this approach to document liquidity commonality in US equity markets and Mancini, Ranaldo, and Wrampelmeyer (2013) in FX markets. As a first step, we calculate the cross-sectional average of a liquidity measure on a daily basis and we compute the time-series mean and standard deviation of this series. We then standardize each of the time-series observations by subtracting from each observation the cross-sectional average and dividing by the standard deviation of the cross-sectional mean series calculated in the first step. Following Korajczyk and Sadka (2008) and Mancini, Ranaldo, and Wrampelmeyer (2013), for each liquidity measure we extract the first three principal components across all benchmark bond series. Principal components can be interpreted as liquidity factors for an individual bond. The first principal factor is the one that is most likely to capture systematic liquidity, and for this reason, is viewed as representing market-wide liquidity. In order to test for the degree of commonality across benchmark bond series for each liquidity measure, we regress for each benchmark bond series j the time-series of daily liquidity measure $L^{(\cdot)}_{j,t}$ on the first three extracted factors and record the p-values of the factor loadings and the adjusted R^2 value. The size of these factors is measured as the cross-sectional average adjusted-R^2. In addition, we perform market-type regressions using as market-wide liquidity the first principle component. The regression results are reported in Table 2. The size of the liquidity factors is reported in Table 3. We apply these methods for each liquidity measure separately and we test for liquidity commonality across the benchmark bond series of (i) each individual country (national level) (ii) across different maturities as well as (iii) across countries *and* maturities (pan-European level).

Figure 1 shows market-wide liquidity, for all sovereign bonds in our sample over time. Decreased market-wide liquidity was observed surrounding the EU debt crisis time period, while being significantly ameliorated in more recent years. Finally, market-wide liquidity seems to be negatively affected around stress periods as, for example, around the 2018 Italian elections.

5.2. Time-series regressions

We examine the effect of several supply- and demand-side determinants on commonality in liquidity by running time-series regressions of the monthly average commonality in spreads and in depths on 73 benchmark bond series - denoted by $R^2_{COM,t}$ – on various variables aimed to proxy for different demand and supply-side explanations of commonality in liquidity. Thus, for commonality for a given liquidity measure we run the following regression:

$$\Delta R^{2,(\cdot)}_{COM,t} = \alpha + \beta \Delta \text{Proxy}_t + \gamma \Delta \text{Controls} + \epsilon_{j,t}, \tag{3}$$

We regress in differences, when necessary, to address the issue of the dependent variable being stationary and some of the explanatory variables being non-stationary. A constant term in a time-series regression on first-differences implies a linear time trend in levels. We include the constant term to examine whether commonality in liquidity has increased or decreased over time. All equations are estimated using OLS with Newey–West standard errors.

We complement the monthly measure of commonality in quoted spreads and depths with low-frequency proxies for various demand and supply-side explanations of commonality in liquidity. These proxies are collected from Haver Analytics and Bloomberg at the monthly frequency for the period 2011:06–2018:06. All monthly observations are calculated as monthly averages. Following Karolyi, Lee, and Van Dijk (2012) and Moshirian et al. (2017), we also include in our time-series regressions changes of the average monthly market return of

Table 2. Market-wide commonality in liquidity.

	PCA				Averaging			
	L^{PQS}	L^{PES}	L^{AQD}	L^{AIR}	L^{PQS}	L^{PES}	L^{AOD}	L^{AIR}
Panel A: Across Countries *and* Maturities								
$L_{M,t}$	0.408	0.129	0.143	0.205	0.854	0.471	0.680	0.267
	(5.10)	(5.31)	(3.25)	(4.39)	(12.92)	(3.66)	(5.22)	(2.32)
% positive	98.63	93.15	84.93	79.45	100.00	97.26	97.26	90.41
% significant	84.93	64.38	58.90	24.66	100.00	80.82	87.67	54.79
$L_{M,t-1}$	0.192	0.028	0.015	0.001	0.018	0.152	0.020	0.176
	(1.52)	(1.97)	(0.15)	(0.76)	(0.44)	(1.74)	(0.11)	(0.92)
% positive	79.45	80.82	46.58	64.38	53.42	80.82	49.32	67.12
% significant	47.95	49.32	16.44	9.59	13.70	43.84	9.59	39.73
$L_{M,t+1}$	0.053	0.031	0.009	0.001	0.012	0.134	0.018	0.146
	(0.24)	(2.08)	(0.40)	(1.61)	(0.26)	(1.57)	(0.07)	(1.25)
% positive	6.16	76.71	36.99	80.82	49.32	75.34	52.05	71.23
% significant	4.11	50.68	15.07	23.29	13.70	45.21	5.48	30.14
Adjusted R^2	0.456	0.082	0.240	0.045	0.113	0.042	0.021	0.022
Panel B: Within a Country and across Maturities								
$L_{M,t}$	0.537	0.402	0.395	0.100	0.638	0.268	0.458	0.159
	(32.15)	(26.90)	(14.35)	(7.34)	(18.16)	(4.86)	(9.81)	(2.85)
% positive	98.63	98.63	98.63	86.30	100.00	98.63	100.00	84.93
% significant	97.26	95.89	89.04	63.01	100.00	86.30	98.63	54.79
$L_{M,t-1}$	0.240	0.100	0.038	0.010	0.014	0.102	0.039	0.083
	(2.08)	(2.07)	(0.62)	(1.06)	(0.30)	(2.09)	(0.78)	(1.36)
% positive	67.12	71.23	61.64	63.01	42.47	78.08	72.60	65.75
% significant	69.86	63.01	34.25	21.92	17.81	45.21	19.18	30.14
$L_{M,t+1}$	0.116	0.081	0.027	0.002	0.007	0.099	0.037	0.065
	(1.24)	(2.01)	(0.53)	(1.53)	(0.27)	(1.80)	(0.75)	(1.47)
% positive	64.38	69.86	68.49	64.38	50.68	68.49	78.08	75.34
% significant	68.49	63.01	35.62	30.14	8.22	35.62	12.33	28.77
Adjusted R^2	0.686	0.256	0.414	0.179	0.194	0.041	0.066	0.028
Panel C: Within a Maturity and across Countries								
$L_{M,t}$	0.436	0.133	0.494	0.060	0.444	0.156	0.109	0.117
	(24.04)	(8.42)	(11.96)	(5.38)	(8.89)	(2.43)	(1.83)	(1.56)
% positive	100.00	68.49	75.34	72.60	100.00	90.41	93.15	80.82
% significant	86.30	53.42	60.27	32.88	100.00	61.64	42.47	32.88
$L_{M,t-1}$	0.331	0.035	0.007	0.002	0.035	0.090	0.006	0.060
	(1.50)	(0.59)	(0.36)	(0.35)	(0.63)	(1.82)	(0.19)	(0.84)
% positive	71.23	56.16	43.84	54.79	58.90	82.19	56.16	64.38
% significant	47.95	32.88	28.77	12.33	20.55	46.58	9.59	20.55
$L_{M,t+1}$	0.325	0.036	0.016	0.004	0.036	0.098	0.009	0.046
	(1.58)	(0.23)	(0.47)	(0.44)	(0.71)	(1.56)	(0.17)	(1.06)
% positive	71.23	56.16	39.73	56.16	65.75	84.93	58.90	72.60
% significant	58.90	36.99	28.77	19.18	17.81	34.25	5.48	16.44
Adjusted R^2	0.508	0.164	0.274	0.132	0.069	0.026	0.003	0.016

Notes: Daily proportional changes in an individual benchmark bond series liquidity measure are regressed in time series on proportional changes in market-wide liquidity, extracted either as [1] the equally-weighted average liquidity for all benchmark bond series ('the market', L_M), as well as [2] the first principle component. In each individual regression, the market average excludes the dependent variable benchmark bond series. All equations are estimated using OLS, cross-sectional averages of time series slope coefficients are reported with *t*-statistics in parentheses below coefficient estimates. % positive reports the percentage of positive slope coefficients, while % significant gives the percentage with *p*-values lees than 0.05. There are 1,804 daily observation in our sample period. The lead, lag and contemporaneous values of the market return and the proportional daily change in individual benchmark bond series absolute return (a measure of volatility) were additional regressors; coefficients are not reported to conserve space.

the fixed-income market, trading volume, market volatility, market liquidity, and credit risk as proxies for the overall capital market conditions.[28]

For example, based on the inventory explanation for liquidity, increased trading activity should result in narrower spreads because inventory balances and risks per trade can be attained at lower levels whereas when informed traders are present in the market, spreads should widen with the number of transactions.[29] These conditions can also affect changes in commonality in liquidity through various supply-side channels – for example,

Table 3. Size of within-measure common factors.

Variable	Statistic	Factor 1	Factor 2	Factor 3
Panel A: Across Countries *and* Maturities				
L^{PQS}	Adjusted R^2-mean	40.65	45.84	58.42
L^{PES}	Adjusted R^2-mean	3.52	6.04	14.69
L^{AQD}	Adjusted R^2-mean	23.18	28.51	31.97
L^{AIR}	Adjusted R^2-mean	2.53	4.06	5.96
Panel B: Within a country and across maturities				
L^{PQS}	Adjusted R^2-mean	68.08	78.57	82.04
L^{PES}	Adjusted R^2-mean	22.08	36.17	50.16
L^{AQD}	Adjusted R^2-mean	41.91	53.57	63.70
L^{AIR}	Adjusted R^2-mean	15.84	29.66	44.45
Panel C: Within a maturity and across countries				
L^{PQS}	Adjusted R^2-mean	46.98	55.80	67.08
L^{PES}	Adjusted R^2-mean	12.77	25.22	39.11
L^{AQD}	Adjusted R^2-mean	25.87	36.97	46.59
L^{AIR}	Adjusted R^2-mean	11.45	23.29	34.31

Notes: This table reports statistics of time-series regressions. Within-measure common factors are extracted separately for four different liquidity measures. Then for each variable and each benchmark-bond series, a time-series regression of the variable on its common factors in executed. The liquidity measures analyzed are: the percentage quoted spread (L^{PQS}), the percentage effective spread (L^{PES}), the average quoted depth (L^{AQD}) and the Amihud illiquidity ratio (L^{AIR}). Prior to the extraction of common factors and regression analysis, for each benchmark bond series, is normalized every month by its mean and standard deviation calculated up to the prior month (with at least three prior monthly observations). The table reports the mean adjusted R^2 of these regressions using one, two and three factors.

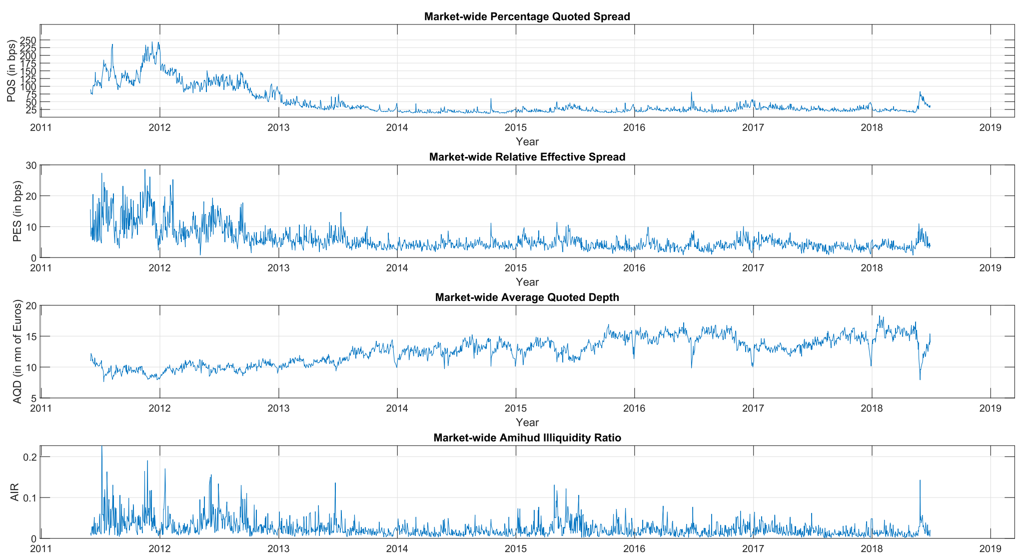

Figure 1. Market-wide liquidity.

Market-wide liquidity. The figure plots daily estimates of market-wide liquidity. Market-wide liquidity, for each liquidity measure, is extracted as the first principal component across all benchmark bond series. The upper left graph shows the first principal component extracted for percentage quoted spreads (L^{PQS}) across all benchmark bond series, the upper right shows the market-wide estimate of percentage effective spreads (L^{PES}), the lower left graph shows market-wide estimated of average quoted depths (L^{AQD}) and the lower right graph shows the market-wide estimate of daily price impacts, as captured by the Amihud illiquidity ratio (L^{AIR}). The sample is June 2011 to June 2018.

by affecting the funding liquidity of financial intermediaries – or demand-side channels, such as the extent of correlated trading by institutional investors. Thus, we need to include these proxies to account for changes in the capital market environment, in general, before we explore the explanatory power of other variables. We measure the economic magnitude of the estimated coefficients by the effect of an increase of the standard deviation in the time-series variable of interest, expressed as a fraction of the time-series standard deviation of $R^2_{COM,t}$.[30]

5.3. Macroeconomic announcements

As we cannot use the monthly $R^2_{COM,t}$ values to measure liquidity at daily frequency, we elect to use a different measure of liquidity co-movements that can capture daily co-movements in liquidity of government bonds. We employ as our measure of co-movement in the event window the measure of synchronicity originally proposed by Morck, Yeung, and Yu (2000) and as subsequently modified by Brockman, Chung, and Pérignon (2009).[31] As in Chordia, Roll, and Subrahmanyam (2001) and Brockman, Chung, and Pérignon (2009), we use a three-day event window with the announcement day being the last day in the event window (days −2 to 0) in order to capture the effects of pre-announcement portfolio rebalancing on market liquidity. We measure the daily co-movement of liquidity by first counting the number of benchmark bonds with positive and negative changes in their liquidity measure for each trading day and then dividing the larger of these two numbers by their sum. We delete trading days in which the number of benchmark bonds with unchanged liquidity measures exceeds 50% of total number of bonds.[32] Then we average daily co-movement percentages (i) across all trading days (column 1 in Table 9), and (ii) across only those trading days with Euro area macro news releases (columns 2–5). We report results for spread and depth co-movements in Panel A and in Panel B, respectively. We further split our cross-section of issuing countries between core and periphery markets[33] and we perform the same analysis and present separate results.

Moreover, in order to examine the effect of unanticipated announcement surprises, following Balduzzi, Elton, and Green (2001) and Paiardini (2014), we calculate announcement surprises as the difference between the actual announcement (α_t) and the market expectation of the announcement ($E(\alpha_t)$) scaled by the cross-sectional standard deviation of the forecast error ($\alpha_t - E(\alpha_t)$). Our unanticipated news component is created from consensus forecasts, thus the shocks we use are the average of shocks across investors, meaning that there is a motive to trade as there may exist a positive shock for one investor and a negative shock for another. We extent our event-window to include two days after the announcement day (i.e. days −2 to 0 and to +2), in order to additionally capture the effects of post-announcement portfolio rebalancing on market liquidity. For each announcement we distinguish between large and low announcement surprises and recalculate the measure of co-movement as defined above. We report results for large and low announcements surprises for spreads and depths co-movements separately and across core and periphery markets in subpanels in Table 9.

6. Empirical results

In this section, we report the estimation results of the market-type regressions, with market-wide liquidity extracted as the cross-sectional average and the first principal component. We further report the estimation results of monthly time-series regressions of commonality in liquidity (based on daily data) on various proxies for volatility, time-variation in supply- and demand-side factors. These estimation results are estimated by using the first principal component as the preferred method to extract market liquidity.[34] We also report the results of the effect of macroeconomic announcements on commonality in liquidity.

6.1. Commonality in liquidity

Table 2 reports the estimated β_j coefficients, from Equation (1) for both approaches used in extracting market-wide liquidity (i.e. averaging and PCA). Both sets of results provide strong evidence of commonality in liquidity. However, we mainly focus on the PCA results as the PCA can better capture the variability of the liquidity measures as compared to the simple average. The PCA results indicate that there is strong positive relation between the first principle component derived for all four liquidity measures.[35]

The change in the percentage quoted spread, $L^{PQS}_{j,t}$, in the left-hand side of Table 2 in Panel A where we test for commonality in liquidity across all benchmark bond series irrespective of issuing country or maturity at issue, i.e. at the pan-European level, displays an average value of 0.408 for the contemporaneous β_j's in (1) and an associated average t-statistic of 5.10, with 85% of these individual β_j's being positive and statistically significant at the 5% confidence level. In addition, although the leading and lagged terms are usually positive and often significant, they are small in magnitude. The results for the remaining liquidity measures, i.e. percentage effective spread, the average quoted depth, and the Amihud illiquidity ratio are similar to those of the percentage quoted spread and suggest that they also exhibit co-movement. These results provide strong evidence in support of the hypothesis that there is commonality in liquidity across borders, irrespective of issuing country or maturity at issue.

In terms of explanatory power, the strongest commonality is observed for quoted spreads and depths. The average adjusted R^2 for percentage quoted spreads and average quoted depths is approximately 45% and 25%, respectively, whereas for the effective spread and the Amihud ratio it is approximately 8% and 5%. As additional support, the cross-sectional average of the adjusted R^2, reported in Table 3, increases further when two or three principle components are included as explanatory variables.

In relation to commonality in liquidity at the national level (left-hand side, Panel B) and across maturities (left-hand side, Panel C), the results also provide evidence of liquidity co-movements. For example, for the percentage quoted spread the average contemporaneous coefficient is equal to 0.537 and 0.436 at the national and maturities level respectively and an associated average t-statistic of 32.15 and 24.04. Approximately 97% and 86% respectively of these individual β_j's are positive and statistically significant at the 5% confidence level. The results for the remaining liquidity measures are fairly similar to those of the percentage quoted spread and suggest that they also exhibit co-movement.

These results suggest the existence of strong liquidity commonality at the national level as well as across maturities. In terms of explanatory power, the average adjusted R^2 of the percentage quoted spread is approximately 69% and 51% when measuring commonality in liquidity within national markets and across maturities respectively, suggesting the commonality is stronger at the national level. We obtain similar results for the market depth, the effective spread, and the Amihud ratio. Overall, the PCA results suggest that there is significant commonality across benchmark bond series for most liquidity measures for all three dimensions used to partition our dataset.

Again, we obtain similar results when the cross-sectional average is used in calculating market-wide liquidity. For example, for the percentage effective spread at the pan-European level, the average estimated contemporaneous coefficient is 0.854 with an average t-statistic of 12.92, with 100% of these individual contemporaneous coefficients being positive and statistically significant at the 5% confidence level. We obtain similar results for the average quoted spread, the percentage effective spread, and the Amihud illiquidity ratio. In terms of explanatory power, the average adjusted R^2 is low for both four liquidity measures considered, with the percentage quoted spread exhibiting the higher value. The average adjusted R^2 of the percentage quoted spread is approximately 10%.

Although the explanatory power of the typical individual regression is not high, it is significantly higher as compared tothe reported average adjusted R^2 from similar regressions from other asset classes. For example, Chordia, Roll, and Subrahmanyam (2000) report an adjusted R^2 of 0.017 for US equity markets and Marshall, Nguyen, and Visaltanachoti (2013) reports an adjusted R^2 of 0.015 for commodity markets. Evidently, there is either a large component of noise and/or other influences on daily changes in individual benchmark bond series liquidity.

In terms of the percentage effective spread and the average quoted depth, the average adjusted R^2 is roughly 4% and 2% and seems consistent to the results reported by Chordia, Roll, and Subrahmanyam (2000) and Marshall, Nguyen, and Visaltanachoti (2013). Again, commonality at the country level is stronger at the national level as compared with commonality across maturities and the pan-European level.

These results imply that commonality in liquidity in the Euro-area sovereign bond market is stronger as compared to commonality in equity markets and weaker as compared to commonality in FX and commodity markets. Studies related to US equity markets report adjusted R^2 ranging between 2% and 30%. Marshall, Nguyen, and Visaltanachoti (2013) report an average adjusted average equal to 46% and 40% with respect to proportional quoted and effective spreads respectively in commodity futures markets, and Mancini, Ranaldo, and Wrampelmeyer (2013) report a cross-sectional average of 80% and 90% in FX spot markets at the daily frequency.

Overall, we find strong evidence of commonality in liquidity at the national level, across maturities, and the pan-European level. In terms of liquidity measures, all four liquidity measures we consider show significant co-movements, with percentage quoted spreads and average quoted depths exhibiting stronger correlation, across the three different dimensions we test for commonality. In terms of dimensions, as expected, commonality is stronger at the national level, with some cross-sectional differences, and lower at the pan-European level.

6.2. Time-series variation in commonality in liquidity

The regression results above document significant commonality in quoted spreads and depths, irrespective of issuing country *and* maturity at issuance, suggesting a Pan-European liquidity factor. We use the PCA as the preferred methodology to extract market-wide liquidity as it better captures the variability of the liquidity measures as compared to the simple average. However, this result does not reveal anything regarding how volatile this commonality is over time. To address this question, for each month, we use the equally-weighted average adjusted R^2 of regressions of the liquidity of individual benchmark bonds on market-wide liquidity to obtain a measure of commonality in liquidity in a given month. Figure 2 plots the average adjusted $R^2_{COM,t}$, for both the commonality in quoted spreads and depth, in a given month. The figure shows that commonality is significantly different in some periods than in others for both series, but without any apparent trend, as well as that the two series do not seem to behave in the same manner over time ($\rho = 0.41$), with the commonality in quoted spreads being more volatile as compared to the commonality in depth.

In an attempt to potentially relate the peaks and troughs of the $R^2_{COM,t}$ series to market events, we then sort according to the calculated $R^2_{COM,t}$ in a given month for both series and report the extreme observations in Table 4. We do not report the months with lowest $R^2_{COM,t}$ in Table 4 as they all appear to be unrelated to specific market events. Nevertheless, we observe interesting patterns in the time-variation of $R^2_{COM,t}$ of both series.

The results suggest that commonality tends to intensify during stress periods. Nine out of the 12 highest values of the series in quoted spreads can all be related, to some extent, to political and crisis events in the European Union. Commonality in depth exhibits a similar pattern. In addition, there are seven common months in

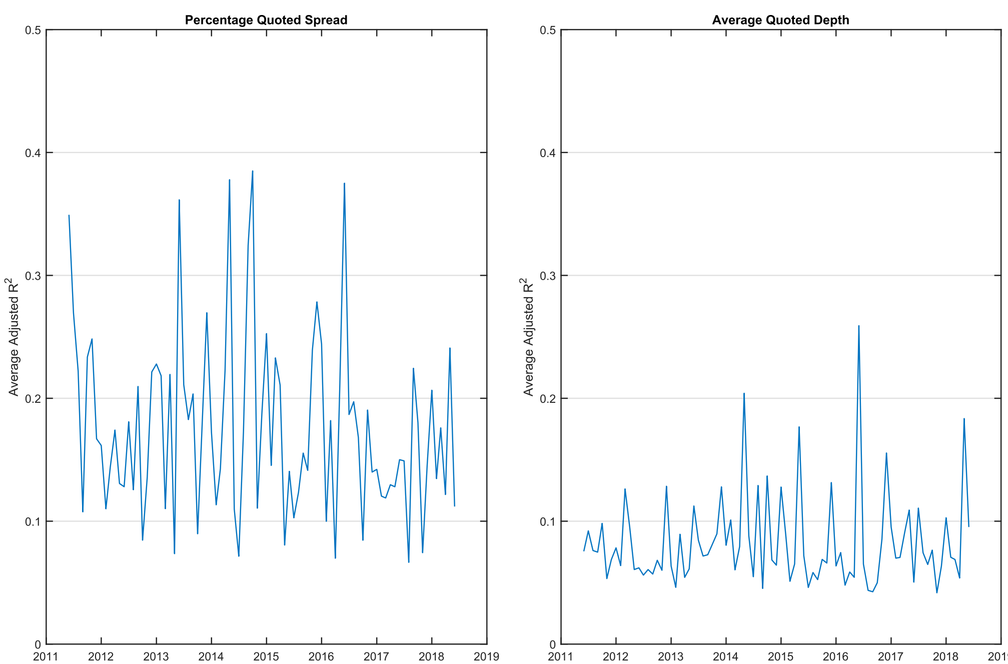

Figure 2. Time-series variation in commonality in liquidity.

Time-series variation in commonality in quoted spreads and depths at the pan-European level. This figure depicts the average commonality in liquidity ($R^2_{avg,t}$) for each month during the sample period 2011:06–2018:06. Commonality in liquidity of individual benchmark bond series is measured by the adjusted R^2 of monthly regressions of the daily percentage changes of a liquidity variable on the lead, lag, and contemporaneous daily percentage changes in market liquidity. We measure liquidity by calculating two liquidity variables, i.e. percentage quoted spreads (L^{PQS}) and average quoted market depth (L^{AQD}), for each individual benchmark bond series. For each liquidity measure, the first principal component is extracted and interpreted as market liquidity.

Table 4. Ranked monthly commonality.

Rank	Month	$R^2_{COM,t}$	Event
Panel A: Commonality in spreads (L^{PQS})			
1	October 2014	0.385	US Treasuries Flash Crash
2	May 2014	0.378	Greek Elections
3	June 2016	0.375	UK EU Referendum
4	June 2013	0.362	US Taper Tantrum
5	June 2011	0.349	European Debt Crisis
6	September 2014	0.324	T-LTRO 1
7	December 2015	0.278	Spanish & French Elections
8	December 2013	0.270	FED Tapening Announcement
9	July 2011	0.269	Greek sovereign debt restructuring
10	January 2015	0.253	ECB's QE Officially Announced
11	November 2011	0.248	EU/IMF announces bailout loan to Ireland
12	May 2018	0.244	Italian Elections
Panel B: Commonality in depth (L^{AQD})			
1	June 2016	0.269	UK EU Referendum
2	May 2014	0.214	Greek Elections
3	May 2018	0.194	Italian Elections
4	May 2015	0.187	Bund Tantrum
5	December 2016	0.166	
6	October 2014	0.137	US Treasuries Flash Crash
7	December 2015	0.131	Spanish & French Elections
8	August 2014	0.129	
9	December 2012	0.128	
10	December 2013	0.128	FED Tapering Announcement
11	January 2015	0.128	ECB's QE Officially Announced
12	March 2012	0.121	

Notes: Ranked average monthly commonality in quoted spreads and depths at the pan-European level. This table reports the extreme observations of sorting, from largest to lowest, the average monthly commonality in liquidity ($R^2_{COM,t}$) for each month during the sample period 2011:06–2018:06. Commonality in liquidity of individual benchmark bond series is measured by the adjusted R^2 of monthly regressions of the daily percentage changes of a liquidity variable on the lead, lag, and contemporaneous daily percentage changes in market liquidity. We measure liquidity by calculating two liquidity variables, i.e. percentage quoted spreads (L^{PQS}) and average quoted market depth (L^{AQD}), for each individual benchmark bond series. For each liquidity measure, the first principal component is extracted and interpreted as market liquidity. We do not report the months with lowest commonality in a given month as they all appear to be unrelated to specific market events.

the two ranked series, suggesting that market events affect different aspects of market liquidity simultaneously but to a different extent. Another observation is that both series seem to be affected by central bank announcements in the Euro-area and the US related to their asset purchase programmes. The ECB's announcement on quantitative easing in January 2015, the first allotment of TLTRO I in September 2014, and the Fed's tapering announcement in 2013 are all events coinciding with increased commonality in liquidity in the Euro-area sovereign bond markets. Central banks injected a sizable amount of excess liquidity into the financial system in order to repair monetary policy transmission channels.

The patterns we observe in Figure 2 could also just be a manifestation of statistical noise in our commonality measures. Also, much of the variation in commonality in Figure 2 cannot be directly linked to stress periods suggesting that other forces may also contribute to the variation of these series. Thus, we proceed by adopting a more systematic approach and considering several variables in an attempt to identify potential drivers of the commonality in liquidity over time.

6.3. Market volatility

Our time-series regressions include five specific volatility proxies: the equally-weighted absolute intraday log return of the benchmark bonds used in this study (noted as MTS Volatility), the standard deviation of the daily percentage changes of a bond index (in our case of the Bloomberg-Barclays Pan-European Aggregate Bond

Index), the MOVE index (a measure of implied Treasury volatility) as well as the VIX[36] and VSTOXX indices (two measures of implied equity volatility related to the US and European markets respectively).

Table 5 reports the results of time-series regressions of changes in monthly average commonality in spreads and in depths among 73 benchmark bond series – denoted by $R^2_{COM,t}$ – on various proxies for volatility. Each model specification adds one proxy for volatility to the base model of control variables. Model (1) in Table 5 shows the regression results of the effects of the general capital market environment on changes in commonality in spreads and in depths, suggesting a significant link between changes in market-wide liquidity and changes in

Table 5. Changes in volatility and in commonality in liquidity.

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Changes in Commonality in Spreads							
Market Return	0.018	0.034	0.028	0.047	0.020	0.021	0.063*
	(0.46)	(0.99)	(0.77)	(1.17)	(0.52)	(0.55)	(1.66)
ΔTrading Volume	0.017***	0.016***	0.015***	0.015***	0.017***	0.016***	0.012***
	(3.63)	(3.70)	(3.13)	(3.12)	(3.55)	(3.48)	(2.67)
ΔMarket Liquidity	0.011***	0.010***	0.005*	0.010***	0.011***	0.011***	0.005*
	(4.34)	(4.76)	(1.75)	(4.29)	(4.02)	(4.09)	(1.83)
ΔCredit Risk	0.002	0.001	0.002	−0.008	0.009	0.001	−0.001
	(0.52)	(0.33)	(0.60)	(−0.25)	(0.25)	(0.10)	(−0.31)
ΔBond Index Volatility		0.015**					0.010
		(2.34)					(1.51)
ΔMTS Volatility			0.069***				0.062***
			(2.84)				(2.69)
ΔMOVE				0.010**			0.004*
				(2.11)			(1.67)
ΔVIX					0.008		−0.012
					(0.55)		(−0.42)
ΔVSTOXX						0.011	0.010
						(1.04)	(0.44)
Constant	−0.016	−0.016	−0.016	−0.016	−0.016	−0.016	−0.016
	(−0.33)	(−0.35)	(−0.34)	(−0.36)	(−0.33)	(−0.34)	(−0.38)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.15	0.18	0.17	0.19	0.14	0.14	0.20
Panel B: Changes in Commonality in Depth							
Market Return	0.011	0.015	0.022	0.043	0.011	0.014	0.054*
	(0.32)	(0.46)	(0.70)	(1.30)	(0.34)	(0.40)	(1.67)
ΔTrading Volume	−0.020	−0.023	−0.025	−0.043	−0.020	−0.025	−0.054
	(−0.49)	(−0.42)	(−0.62)	(−1.05)	(−0.51)	(−0.63)	(−1.41)
ΔMarket Liquidity	−0.179**	−0.167**	−0.122	−0.131*	−0.179**	−0.172**	−0.055
	(−2.31)	(−2.02)	(−1.44)	(−1.71)	(−2.29)	(−2.31)	(−0.69)
ΔCredit Risk	0.001	0.001	−0.009	−0.002	−0.001	−0.001	−0.004
	(0.05)	(0.02)	(−0.22)	(−0.57)	(−0.12)	(−0.28)	(−0.79)
ΔBond Index Volatility		0.385					0.804
		(0.69)					(0.14)
ΔMTS Volatility			0.030*				0.003*
			(1.76)				(1.72)
ΔMOVE				0.016***			0.017***
				(3.06)			(2.63)
ΔVIX					0.003		−0.040
					(0.39)		(−1.14)
ΔVSTOXX						0.011	0.033
						(0.83)	(0.96)
Constant	−0.024	−0.025	−0.025	−0.025	−0.024	−0.024	−0.025
	(−0.69)	(−0.70)	(−0.74)	(−0.65)	(−0.68)	(−0.69)	(−0.64)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.06	0.06	0.11	0.12	0.05	0.06	0.15

Notes: This table reports results of time-series regressions of the change in monthly average commonality in liquidity among 73 benchmark bond series – denoted by $R^2_{COM,t}$, computed as the logistic transformation of commonality in liquidity in month t – over the period 2011:06–2018:06 on changes of various aggregate volatility proxies. The reported regressions are in monthly changes. All equations are estimated using OLS with Newey-West standard errors, with lag length $T^{1/3}$, where T is the indicated sample size. t-statistics are given in parentheses below coefficient estimates. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

commonality in liquidity. The results suggest that negative shocks to market-wide liquidity (either in spreads or depths) result in the liquidity of all sovereign benchmark bonds to start moving together more closely.

Models (2)–(7) in Table 5 overall suggest a significant correlation between changes in market volatility and changes in commonality in either quoted spreads or depths, even after controlling for market returns, changes in market-wide liquidity, trading volume and credit risk. Three and two out of the five proxies for volatility are statistically significant and positively correlated to commonality in quoted spreads and depth respectively. Models (2)–(6) in Table 5 show that shocks to the MOVE Index, to bond index volatility, and to the MTS volatility each help explain monthly changes in commonality in quoted spreads and depths. A positive and statistically significant relation between volatility and commonality in liquidity is also reported for US equity markets (Karolyi, Lee, and Van Dijk 2012) as well as FX markets (Mancini, Ranaldo, and Wrampelmeyer 2013).

The economic impact of market volatility on commonality is substantial. An increase of one standard deviation in volatility, as measured by the MTS volatility variable, relative to the mean is associated with an increase in commonality in quoted spreads of 2.62%, equal to 0.24 times the standard deviation of commonality in liquidity in spreads, i.e. $\sigma(R^{2,PQS}_{COM,t})$. Similarly, the economic magnitude of the bond index volatility and MOVE index variables on commonality in spreads is $0.21 \times \sigma(R^{2,PQS}_{COM,t})$ and $0.24 \times \sigma(R^{2,PQS}_{COM,t})$ respectively. Similarly important is the economic impact of market volatility in commonality in quoted spreads. An increase of one standard deviation in MTS volatility and MOVE index is associated with an increase in commonality in quoted depths of $0.26 \times \sigma(R^{2,AMD}_{COM,t})$ and $0.30 \times \sigma(R^{2,AMD}_{COM,t})$ respectively.

Interestingly, the estimated coefficients of VIX and VSTOXX proxies, although positive, are found to be not statistically significant. One possible explanation might be that those two proxies measure equity implied volatility and, for that reason, may not be suitable proxies for capturing volatility in fixed income markets. The largest adjusted-R^2 of 19% in terms of quoted spreads and of 12% in terms of quoted market depth are both attained by the MOVE index. In Model (7) all volatility proxies are considered simultaneously. The results suggest that changes in implied Treasury volatility and in MTS volatility are more strongly correlated with changes in commonality in both quoted spreads and depths over time as compared to the remaining volatility proxies used.

However, the results do not suggest any significant relation between trading volume and commonality in depth. Given the fragmented structure of the market, a possible explanation might be that traded quantities are negotiated and agreed bilaterally. Finally, all models in Table 5 include a constant term (implying a linear time trend in levels). The constant has a positive but insignificant coefficient for both quoted spreads and depths. This result suggests that $R^2_{COM,t}$ has been relatively constant over our sample period. These findings show that commonality in liquidity is high during periods of high market volatility and high market-wide trading activity.

These findings show that commonality in liquidity is high during periods of high market volatility and high market-wide trading activity. Motivated by the related literature, we examine whether commonality in liquidity in fixed income markets is stronger during periods of large market declines, as opposed to periods of large market increases. We define large negative (positive) market returns as returns that are in the bottom (top) quartile of market returns.[37] We also include MTS volatility as a control variable to proxy for market-wide volatility. A shock in market volatility is associated with stronger commonality in liquidity. Regression results are reported in Table 6.[38]

Hameed, Kang, and Viswanathan (2010) argue that, in stress periods, a large negative market return may lead to greater commonality in liquidity through an effect on the wealth and the collateral of investors and liquidity providers, that commonality should increase during periods of large market declines and the effect of volatility should be asymmetric. Regression results in Table 6 do not show any strong negative relation between $R^2_{COM,t}$ in spreads and large negative market returns, which would imply that $R^2_{COM,t}$ tends to increase during large market declines. However, we do find a positive and statistically significant relation, at the 10% confidence level, between changes in $R^2_{COM,t}$ in depths and large market increases. This result suggests that commonality in depth tends to increase with sharp market upswings. A potential explanation for this finding may be that during our sample period the ECB bought a large volume of government bonds with purchases carried out in several stages.

For both set of results, we find that shocks to market volatility can affect monthly changes in commonality in both spreads and depths. Overall, the results show that monthly changes in commonality in liquidity in both

Table 6. Changes in market returns and in commonality in liquidity.

Model	(1)	(2)	(3)	(4)
Panel A: Changes in commonality in spreads				
Market Return	0.028	0.060	−0.001	−0.013
	(0.77)	(1.21)	(−0.12)	(−0.08)
Market Return$*D_{Down}$		−0.080		0.074
		(−0.60)		(0.51)
Market Return$*D_{Up}$			0.072	0.005
			(0.77)	(0.02)
ΔTradring Volume	0.015***	0.014***	0.014***	0.014***
	(3.13)	(3.11)	(3.16)	(3.13)
ΔMarket Liquidity	0.005*	0.005*	0.005*	0.005*
	(1.75)	(1.77)	(1.85)	(1.83)
ΔCredit Risk	0.002	0.002	0.001	0.002
	(0.60)	(0.50)	(0.46)	(0.47)
ΔMTS Volatility	0.069***	0.067***	0.631***	0.630***
	(2.84)	(2.60)	(2.52)	(2.55)
Constant	−0.016	−0.015	−0.016	−0.016
	(−0.34)	(−0.23)	(−0.32)	(−0.18)
Observations	84	84	84	84
Adjusted R^2	0.17	0.22	0.22	0.22
Panel B: Changes in commonality in depths				
Market Return	0.022	−0.013	0.067	0.079
	(0.70)	(−0.25)	(1.34)	(1.84)*
Market Return$*D_{Down}$		0.090		−0.018
		(0.82)		(−0.09)
Market Return$*D_{Up}$			−0.083	0.021*
			(−1.28)	(1.69)
ΔTradring Volume	−0.025	−0.024	−0.023	0.023
	(−0.62)	(−0.56)	(−0.55)	(0.55)
ΔMarket Liquidity	−0.122	−0.119	−0.117	−0.117
	(−1.44)	(−1.41)	(−1.43)	(1.42)
ΔCredit Risk	−0.009	−0.005	−0.003	−0.004
	(−0.22)	(−0.12)	(−0.09)	(−0.10)
ΔMTS Volatility	0.030*	0.030*	0.033***	0.030***
	(1.76)	(1.84)	(1.97)	(1.94)
Constant	−0.025	−0.024	−0.024	−0.024
	(−0.74)	(−0.42)	(−0.68)	(−0.32)
Observations	84	84	84	84
Adjusted R^2	0.11	0.17	0.17	0.17

Notes: This table reports results from regressions of the monthly changes in commonality in quoted spreads and depths on monthly market returns. The dummy variable D_{Down} is equal to 1 if the market return is in the bottom quartile of market returns and 0 otherwise. Similarly, the dummy variable D_{Up} is equal to 1-D. The control variables include, changes in trading volume, market-wide liquidity, credit risk, and market volatility. All equations are estimated using OLS with Newey-West standard errors, with lag length $T^{1/3}$, where T is the indicated sample size. t-statistics are given in parentheses below coefficient estimates. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

spread and depths are driven by both changes in volatility and we find no significant evidence of the asymmetric effect of market returns on monthly changes commonality in liquidity.

6.4. *Supply-side: funding constraints*

Our time-series regressions include five specific proxies for the local and global funding constraints of market makers: the EONIA rate (the interest rate at which banks lend funds in the overnight interbank money market in the Euro-area), the TED spread (the difference between the three-month Treasury bill and the three-month LIBOR based on US dollars), the LOIS spread (the difference between three-month LIBOR and the three-month Overnight Indexed Swap rate), the stock-returns of financial intermediaries (Euro Stoxx Banks Index) and ECB's excess liquidity (defined as the sum of excess reserves held by financial institutions and the net deposit facility of the ECB).[39] Nowadays, financial intermediaries can easily obtain leverage internationally, and for that reason we use a mix of proxies estimated based on European as well as US data.

The EONIA rate is the basis of the term structure of Euro interest rates and the underlying rate of various derivatives contracts. It is calculated on a daily basis as a weighted average of all overnight unsecured lending transactions in the interbank market in euro, initiated within the euro area by the contributing banks. Under normal circumstances the ECB provides liquidity such that EONIA fixes close to the re-financing rate. Hence the ECB uses EONIA as the instrument for its monetary policy stance. We hypothesize a positive correlation between shocks to the EONIA rate and monthly changes in commonality in spreads and depths, as they reflect more constrained credit conditions and higher costs of obtaining leverage.

The second proxy of the funding costs of the market makers, is the TED Spread, defined as the difference between the three-month Treasury bill and the three-month LIBOR based on US dollars. Because a 3-month US Treasury bill is considered a risk-free security, the difference between it and the interest rate on interbank loans, which is a gauge of international banks' confidence in lending each other, is a good measure of credit risk in bank funding markets.[40] By comparing the risk-free rate to the interbank rate, one can determine the perceived difference in risk. In times of uncertainty, banks increase the interest rates on interbank loans, driving up the LIBOR. A flight to quality would then manifest itself as a widening of the TED spread which, would suggest a higher default risk of interbank loans and, thus be more costly for the financial intermediaries to obtain leverage.

Another measure of distress in money markets is the difference between three-month LIBOR and the three-month Overnight Indexed Swap rate (OIS). A bank entering into the OIS exposes the bank to future fluctuations in the reference rate. However, the bank can guarantee itself longer-term funding while still paying close to the overnight rate. Because the alternative would be rolling over the funds on a daily basis at changing overnight rates, banks are willing to pay a premium. This is reflected in the LIBOR-OIS spread (Sengupta and Tam 2008). In times of stress, the LIBOR, referencing a cash instrument, reflects both credit and liquidity risk, but the OIS has little exposure to default risk because these contracts do not involve any initial cash flows. The OIS rate is therefore an accurate measure of investor expectations of the effective interest rate (and hence a central bank's target) over the term of the swap, whereas LIBOR reflects credit risk and the expectation on future over night rates. When the LOIS spread increases it implies that banks are less willing to lend to each other, it is a signal of shrinking liquidity, and of increased funding costs.

The fourth measure of funding costs is the stock returns of local and global financial intermediaries who act as funding agents. As the balance sheets are continuously marked to market, changes in asset prices show up immediately on balance sheets and have an instant impact on the net worth of all constituents of the financial system. When asset prices increase, financial intermediaries' balance sheets generally become stronger, and - without adjusting asset holdings – their leverage tends to be low. The financial intermediaries then hold surplus capital and it is easier for them to finance their inventories and provide liquidity to the market (Adrian and Shin 2010). Thus, the stock returns can be interpreted as proxies for aggregate funding liquidity and are likely to be inversely related to the tightness of capital in the market (Karolyi, Lee, and Van Dijk 2012) as well as to commonality in liquidity.

The last proxy for funding liquidity is the ECB's excess liquidity. In essence, ECB's excess liquidity is a measure of the cash in excess of banks' immediate needs that is flowing in the financial system and it is viewed as a measure of tightness in money markets. We hypothesize a positive relationship between excess liquidity and commonality in liquidity. This assumption is mainly derived by the nature of increases in excess liquidity, which mainly arises from the ECB's longer-term liquidity operations and Asset Purchase Programme.

Christensen and Gillan (2018) show that quantitative easing has a very direct effect of reducing liquidity risk premiums in markets where central banks are buying bonds. Pelizzon et al. (2016) find that ECB liquidity injections attenuate the link between the credit risk and market liquidity of sovereign bonds. For the former, the ECB lends money to financial intermediaries which reportedly use the financing to purchase government bonds with similar maturity to the lending. For the latter, the ECB provides stable demand for Euro-area government bonds via its Public Sector Purchase Programme (Eser and Schwaab 2016). Both operations from the ECB arguably contribute to co-movement in Euro-area bond market liquidity.

Table 7 presents the estimated results of time-series regressions relating monthly average $R^2_{COM,t}$ on the supply-side factors. Our regressions are estimated with Newey-West standard errors with lag length $T^{1/3}$ (where

Table 7. What drives time-series variation in commonality? (Supply-side).

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Changes in commonality in spreads							
Market Return	0.028	0.026	0.035	0.029	0.018	0.022	−0.007
	(0.77)	(0.64)	(1.00)	(0.83)	(0.48)	(0.65)	(−0.12)
ΔTrading Volume	0.015***	0.015***	0.016***	0.016***	0.016***	0.013***	0.024***
	(3.13)	(3.36)	(3.82)	(3.58)	(3.68)	(2.61)	(2.96)
ΔMarket Liquidity	0.005*	0.005*	0.006*	0.006**	0.006**	0.004	0.002
	(1.75)	(1.72)	(1.86)	(2.00)	(2.10)	(1.52)	(0.32)
ΔCredit Risk	0.002	0.002	0.005	−0.006	−0.003	−0.012	−0.022
	(0.60)	(0.62)	(0.14)	(−0.20)	(−0.17)	(−0.29)	(−0.37)
ΔMarket Volatility	0.069***	0.066**	0.064**	0.061**	0.062**	0.070***	0.109**
	(2.84)	(2.15)	(2.51)	(2.35)	(2.45)	(3.30)	(2.39)
ΔEONIA Rate		0.204					0.278*
		(1.18)					(1.69)
ΔTED Spread			0.003*				−0.001
			(1.83)				(−0.59)
ΔLOIS				0.004**			0.005**
				(1.93)			(1.99)
ΔECB's Excess Liquidity					0.003***		0.006***
					(2.04)		(2.99)
Dealer's Stock Returns						−0.012**	−0.010*
						(−2.08)	(−1.79)
Constant	−0.016	−0.016	−0.016	−0.016	−0.015	−0.016	−0.013
	(−0.33)	(−0.31)	(−0.34)	(−0.34)	(−0.29)	(−0.35)	(−0.18)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.17	0.16	0.18	0.18	0.18	0.19	0.25
Panel B: Changes in commonality in depth							
Market Return	0.022	0.036	0.022	0.022	0.021	0.017	0.029
	(0.70)	(1.03)	(0.71)	(0.68)	(0.63)	(0.54)	(0.90)
ΔTrading Volume	−0.025	−0.036	−0.026	−0.028	−0.024	−0.037	−0.052
	(−0.62)	(−0.85)	(−0.61)	(−0.64)	(−0.57)	(−0.92)	(−1.20)
ΔMarket Liquidity	−0.122	−0.114	−0.121	−0.118	−0.121	−0.108	−0.094
	(−1.44)	(−1.36)	(−1.43)	(−1.36)	(−1.42)	(−1.39)	(−1.14)
ΔCredit Risk	−0.009	−0.012	−0.009	−0.004	−0.011	−0.004	−0.004
	(−0.22)	(−0.31)	(−0.21)	(−0.09)	(−0.24)	(−0.73)	(−0.75)
ΔMarket Volatility	0.030*	0.036**	0.032*	0.033*	0.032*	0.030**	0.037**
	(1.76)	(2.21)	(1.75)	(1.78)	(1.76)	(1.77)	(2.26)
ΔEONIA Rate		0.121**					0.152**
		(2.10)					(2.17)
ΔTED Spread			0.001				−0.002
			(0.04)				(−0.08)
ΔLOIS				−0.001			−0.013
				(−0.59)			(−0.51)
ΔECB's Excess Liquidity					0.003		0.009
					(0.21)		(0.48)
Dealer's Stock Returns						−0.010*	−0.011
						(−1.70)	(−1.46)
Constant	−0.025	−0.024	−0.025	−0.025	−0.024	−0.027	−0.024
	(−0.47)	(−0.74)	(−0.69)	(−0.73)	(−0.68)	(−0.69)	(−0.67)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.11	0.12	0.10	0.10	0.10	0.12	0.11

Notes: This table reports results of time-series regressions of the change in monthly average commonality in liquidity among 73 benchmark bond series – denoted by $R^2_{avg,t}$, computed as the logistic transformation of the average commonality in liquidity in month t – over the period 2011:06-2018:06 on changes of various proxies for funding conditions. All equations are estimated using OLS with Newey-West standard errors, with lag length $T^{1/3}$, where T is the indicated sample size. t-statistics are given in parentheses below coefficient estimates. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

T is the indicated sample size). To be consistent in our modeling across specifications, we include the market return, trading volume, aggregate liquidity, credit risk, and market volatility as control variables in all models as well as a constant.

Each model specification adds one variable related to the supply-side explanations to the base model of control variables and we perform these regressions for percentage quoted spreads and average quoted market depth separately.

Model (1) for spreads and depth in Table 7 is the same as the model (3) and (4) in Table 5 and shows a significant correlation between changes in market volatility and changes in commonality in liquidity. The empirical evidence that tightness in funding conditions affects quoted spreads is fairly consistent across several different proxies and the explanatory power of these variables is reasonably good. The economic magnitude of funding tightness proxies is substantial. Relative to commonality in depth, explanatory power is low, some variables have unexpected signs and thus the evidence is much weaker. A common point between commonality in spreads and depths is the effect of the stock returns of financial intermediaries who act as funding agents.

More specifically, the results show that shocks to the MTS volatility help explain monthly changes in commonality in quoted spreads and depths. The estimated coefficient has a positive sign that it is significant at the 1% confidence level relative to commonality in spreads and at the 10% confidence level relative to commonality in depths and of the same sign. The values of the adjusted-R^2 in the baseline model for spreads and depths are 17% and 11% respectively.

Models (2)–(6) expand model (1) by including more direct proxies for the funding liquidity of market makers while in model (7) we consider all proxy variables simultaneously. Monthly changes to the EONIA rate are significantly correlated to changes in commonality in depths but not to changes in commonality in spreads. Shocks to the TED spread and ECB's excess liquidity are positively correlated with $R^2_{COM,t}$ in spreads at the 10% and 5% significance level respectively, but they are not statistically significant with respect to commonality in depths. An increase of one standard deviation in the TED spread and in ECB's excess liquidity is associated with an increase in commonality in quoted spreads of $0.16 \times \sigma(R^{2,PQS}_{COM,t})$ and $0.17 \times \sigma(R^{2,PQS}_{COM,t})$ respectively. Moreover, the estimated coefficient on LOIS spread is positive and statistically significant at the 5% significance level in relation to $R^2_{COM,t}$ in spreads, but it is not found to be significantly correlated with changes in commonality in quoted depths. The negative sign of the estimated coefficient of LOIS goes against the prediction of the supply-side hypothesis. An increase of one standard deviation in the LOIS spread is accompanied by a change in commonality in quoted spreads of $0.14 \times \sigma(R^{2,PQS}_{COM,t})$.

The stock returns of a portfolio of European dealer-banks appear to have a significant influence on commonality in liquidity. The coefficient on European dealer-banks returns is negative and statistically significant at the 5% and 10% confidence level in relation to changes in commonality in quoted spreads and depths respectively. The economic magnitude of these coefficients is considerable and equal to $-0.20 \times \sigma(R^{2,PQS}_{COM,t})$ and $-0.19 \times \sigma(R^{2,AMD}_{COM,t})$ respectively.

Model (7) indicates that the effect of four out of the five proxies for the funding conditions does not change even when these variables are considered simultaneously. Noticeable is the increase in the adjusted-R^2 from 17% in the baseline model (1) to 25% in model (7). However, the effects of these proxies in relation to the commonality in depth disappear, with the exception of the EONIA rate and underline the role of changes in market-wide volatility. In sharp contrast to the increase in the adjusted-R^2 values with regard to spreads, the adjusted-R^2 values for models (1) to (7) in relation to depths remain constant.

Overall, the evidence that our proxies for funding liquidity can explain the dynamics of commonality in quoted spreads in our sample is strong but weak in explaining the dynamics of commonality in depth.

6.5. Demand-side determinants

Table 8 presents the estimation results of time-series regressions relating monthly average $R^2_{COM,t}$ to the demand-side factors. Again, model (1) for spreads and depth in Table 8 are the same as the model (3) and (4) in Table 5 and shows a significant positive correlation between changes in market volatility and changes in commonality in liquidity for both quoted spreads and depths.

Models (2) and (3) indicate that the sentiment indices used do not help to explain time-series variation in monthly changes in commonality for both quoted spreads and depths. Models (4) and (5) suggest that overall European government policy uncertainty shocks have no significant effect on monthly changes in commonality

Table 8. What drives time-series variation in commonality? (Demand-side).

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Changes in commonality in spreads							
Market Return	0.028	0.052	0.028	0.036	0.027	0.037	0.032
	(0.77)	(0.59)	(0.77)	(0.95)	(0.69)	(1.06)	(0.82)
ΔTrading Volume	0.015***	0.016***	0.015***	0.013***	0.013***	0.014***	0.014**
	(3.13)	(3.13)	(3.10)	(2.49)	(2.81)	(3.03)	(2.45)
ΔMarket Liquidity	0.005*	0.005*	0.005*	0.004	0.003	0.005*	0.004
	(1.75)	(1.76)	(1.76)	(1.57)	(1.36)	(1.68)	(1.60)
ΔCredit Risk	0.002	0.010	0.009	0.010	0.002	0.001	−0.007
	(0.60)	(0.25)	(0.52)	(0.27)	(0.41)	(0.13)	(−0.16)
ΔMarket Volatility	0.069***	0.068***	0.071***	0.070***	0.070***	0.069***	0.063***
	(2.84)	(2.85)	(2.75)	(2.83)	(2.67)	(2.98)	(2.58)
ΔSentix Euro−Area		−0.007					−0.006
		(−0.67)					(−0.52)
ΔSentix USA			−0.003				0.007
			(−0.22)				(0.72)
ΔEPU Europe				0.011			0.004
				(1.36)			(0.41)
ΔEPU USA					0.003		0.008
					(1.36)		(0.41)
ΔStoxx50 RV						0.101***	0.093*
						(2.85)	(1.85)
Constant	−0.016	−0.016	−0.015	−0.015	−0.012	−0.016	−0.016
	(−0.33)	(−0.32)	(−0.33)	(−0.33)	(−0.32)	(−0.34)	(−0.32)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.17	0.16	0.16	0.17	0.17	0.20	0.16
Panel B: Changes in commonality in depth							
Market Return	0.022	0.027	0.023	0.033	0.022	0.028	0.036
	(0.70)	(0.85)	(0.69)	(0.93)	(0.65)	(0.81)	(0.90)
ΔTrading Volume	−0.025	−0.033	−0.026	−0.053	−0.035	−0.030	−0.060
	(−0.62)	(−0.81)	(−0.63)	(−1.45)	(−0.87)	(−0.72)	(−1.42)
ΔMarket Liquidity	−0.122	−0.125	−0.122	−0.085	−0.105	−0.113	−0.129*
	(−1.44)	(−1.45)	(−1.42)	(−1.13)	(−1.33)	(−1.43)	(−1.79)
ΔCredit Risk	−0.009	−0.001	−0.009	−0.002	−0.002	−0.002	−0.002
	(−0.22)	(−0.13)	(−0.20)	(−0.46)	(−0.37)	(−0.44)	(−0.28)
ΔMarket Volatility	0.030*	0.032*	0.032*	0.041*	0.031*	0.032*	0.023
	(1.76)	(1.72)	(1.74)	(1.79)	(1.73)	(1.71)	(1.64)
ΔSentix Euro−Area		0.006					0.008
		(1.02)					(1.25)
ΔSentix USA			0.0075				0.004
			(0.06)				(0.33)
ΔEPU Europe				0.001			0.001
				(1.02)			(0.81)
ΔEPU USA					0.002		0.001
					(0.82)		(0.02)
ΔStoxx50 RV						0.057	0.059
						(0.95)	(1.05)
Constant	−0.025	−0.025	−0.025	−0.025	−0.025	−0.024	−0.024
	(−0.47)	(−0.75)	(−0.73)	(−0.67)	(−0.72)	(−0.74)	(−0.66)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.11	0.10	0.10	0.11	0.11	0.11	0.06

Notes: This table reports results of time-series regressions of the change in monthly average commonality in liquidity among 73 benchmark bond series – denoted by $R^2_{avg,t}$, computed as the logistic transformation of the average commonality in liquidity in month t – over the period 2011:06–2018:06 on changes of various proxies on demand-side determinants. All equations are estimated using OLS with Newey-West standard errors, with lag length $T^{1/3}$, where T is the indicated sample size. t-statistics are given in parentheses below coefficient estimates. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

in quoted spreads and depths. The realized volatility of Stoxx50 variable in Model (6) seem to help to explain monthly changes in commonality in spreads but not in depths. The estimated coefficient is positive and statistically significant at the 1% confidence level providing evidence on the cross-market liquidity interdependence between stock and bond markets. A one standard deviation in the Stoxx50 realized volatility is associated with an increase in commonality in quoted spreads of $0.11 \times \sigma(R^{2,PQS}_{COM,t})$.[41]

In Model (7), where we consider all demand-side variables simultaneously, only shocks to trading volume and market volatility accompanied by stock market volatility help to explain time-variation in commonality in spreads. In relation to commonality in depth only bond market volatility retains its information content. Overall, the evidence that our demand-side proxies can explain the behavior of commonality in liquidity in our sample is weak.[42]

6.6. Macroeconomic announcements and commonality in liquidity

We collect macroeconomic news announcements that relate to interest rate setting, inflation, unemployment and GDP in the Euro area in the sample period from Bloomberg. For the announcements on inflation and GDP, we keep only the release of flash estimates as they move the markets the most compared to the release of final data prints and revisions. The final dataset comprises 85 CPI announcements, 28 GDP announcements, 71 ECB meetings on policy rate decisions, and 84 unemployment announcements in the Euro area.

In Table 9 we report the results the average daily co-movement percentages i) across all trading days (column 1), and ii) across only those trading days with Euro area macro news releases (columns 2–5). We report results for spread and depth co-movements in Panel A and in Panel B, respectively. We further split our cross-section of issuing countries between core and periphery markets[43] and we perform the same analysis and present separate results. We report results for large and low announcements surprises for spreads and depths co-movements separately and across core and periphery markets in subpanels in Table 9.

Chordia, Roll, and Subrahmanyam (2001) report significant pre-announcement liquidity effects for US unemployment and GDP releases while Brockman, Chung, and Pérignon (2009) find that both domestic and US macro news increase exchange-level and global liquidity commonality in equity markets. In line with previous literature, we find a heterogeneous liquidity response to macroeconomic news announcements with some announcements having a stronger impact on commonality in liquidity than others. For example, the results in Panel A of Table 9 suggest that macroeconomic announcements related to interest rates and GDP significantly affect co-movements in liquidity in proportional quoted spreads. The average co-movement in spreads is 63.55% across all trading days and all benchmark bonds. This percentage increases to 67.87% during interest rate setting announcements. Interestingly, it reduces to 61.57% during GDP announcements, while inflation and unemployment news releases seem to have no significant effect on liquidity co-movements. We find similar results for both periphery and core economies.

Turning to Panel B, the average co-movement in depths is 56.48% across all trading days and all benchmark bonds. This percentage increases to 61.77% for interest rate announcements with inflation, GDP and unemployment announcements having no significant effect on liquidity co-movements. Interestingly, when examining the division between periphery and core economies, the results suggest that inflation and unemployment announcements in periphery economies and GDP announcements in core economies are associated with a lower average co-movement in depths. We find similar results when examining the effect of announcements surprises on liquidity commonality of government bonds. It should be noted however that the effects of interest rate policy meetings and GDP announcements are stronger on days with large announcement surprises in relation to spreads.

Overall, our findings show that ECB meetings on rate decision clearly drive up co-movement in spreads and depth and highlight the important link between interest rate changes and Euro-area secondary-market liquidity.

7. Alternative methodology and endogeneity

For a better understanding of the joint dynamics of commonality in liquidity and the various variables that proxy for the supply and demand-side determinants we further explore these relationships by estimating a vector autoregressive (VAR) model. In the previous sections of this paper we run simple OLS time-series regressions of the monthly average commonality in spreads and in depths on various variables aimed to proxy for different demand and supply-side explanations of commonality in liquidity. Although our objective is not to test for causation, the possibility of endogeneity due to simultaneity should be taken under consideration. As we estimate these effects contemporaneously at the monthly frequency, we implicitly assume that the causality runs from the

Table 9. Macroeconomic announcements and commonality in liquidity.

Market	Unconditional sample average	Inflation	GDP	Interest rates	Unemployment
Panel A: Commonality in spread and Euro area macroeconomic news					
Whole market	63.55%	62.70%	61.57%*	67.87%***	62.68%
Periphery	67.09%	66.67%	65.56%	70.63%**	66.63%
Core	64.86%	64.31%	62.59%**	68.60%**	66.29%
Subpanel A.I: Large announcement surprises					
Whole market	62.91%	62.14%	61.51%**	68.82%***	62.05%
Periphery	65.75%	65.47%*	64.25%*	71.48%***	65.30%
Core	62.91%	62.57%	61.28%***	69.22%***	64.30%
Subpanel A.II: Low announcement surprises					
Whole market	61.64%	57.06%	61.02%	67.19%**	61.43%
Periphery	66.42%	60.67%	65.30%	69.22%**	64.63%
Core	64.21%	58.52%	62.09%	66.54%**	62.31%
Panel B: Commonality in depth and Euro area macroeconomic news					
Whole market	56.48%	56.23%	56.29%	61.77%*	56.19%
Periphery	59.99%	58.89%**	59.60%	60.09%	58.72%***
Core	57.63%	57.40%	56.42%**	57.58%	57.46%
Subpanel B.I: Large announcement surprises					
Whole market	55.97%	55.89%	56.23%	62.63%*	55.63%
Periphery	58.97%	58.07%***	58.17%	60.81%	57.55%**
Core	56.19%	56.14%	55.24%***	58.10%	55.74%
Subpanel B.II: Low announcement surprises					
Whole market	54.84%	51.17%	55.78%	61.21%	55.07%
Periphery	59.51%	53.59%	59.36%	59.13%	56.96%*
Core	57.23%	52.23%	55.97%*	56.26%	53.73%

Notes: This table reports results of the liquidity co-movement measure averaged across all trading days over the whole sample period (i.e. unconditional sample average) and across event days on which four separate types of macroeconomic news are released relative to: central bank meetings on interest rate decisions, inflation, unemployment and the gross national product (GDP). We use a three-day event window with the announcement day being the last day in the event window (days −2 to 0) in order to capture the effects of pre-announcement portfolio rebalancing on market liquidity. We measure the daily liquidity co-movement by first counting the number of benchmark bonds with positive and negative changes in their liquidity measure for each trading day, then dividing the larger of these two numbers by their sum. The liquidity co-movement measures are averaged across all sample days and over the three-day event window with the announcement day being the last day in the window. We present two panels in this table across the whole market, periphery markets, and core markets in order to evaluate the differential impact of macroeconomic news announcement on commonality in liquidity. Panel A and B show the impact of Euro Area macroeconomic announcements on proportional quoted spreads and average quoted depth. We calculate announcement surprises as the difference between the actual announcement (α_t) and the market expectation of the announcement ($E(\alpha_t)$) scaled by the cross-sectional standard deviation of the forecast error ($\alpha_t - E(\alpha_t)$). We extent our event-window to include two days after the announcement day (i.e. days −2 to 0 and to +2), in order to additionally capture the effects of post-announcement portfolio rebalancing on market liquidity. Here, *, **, and *** indicate that the test statistic is significant at the 10%, 5%, and 1% confidence levels, respectively, in a Welch's two-tailed, *t*-test for differences in means between the unconditional sample average and the average of the co-movement measure on macroeconomic announcement days for the Euro Area.

explanatory variable to the dependent variable. For at least several of the explanatory variables used, we cannot rule out the possibility that the causality may in fact run in the opposite direction. We need to be cautious with the extent to which we can make strong statements about the causal direction of the relations among these variables. However, simple OLS time-series regressions have strong statistical power. If the possibility of endogeneity due to simultaneity does not have a significant effect on our estimated coefficients, the simple OLS regression model may be preferable due to increased precision (Comerton-Forde and Putniņš 2015).

A potential solution to the problem of endogeneity due to simultaneity could be the use of two-stage least squares (2SLS) instrumental variables regressions (see, for example, Hasbrouck and Saar 2013; Comerton-Forde and Putniņš 2015; Ibikunle 2018). However, there are no clear or evident variables to be used as instruments. It would require an exogenous institutional change across sovereign bond markets from different countries and such an exogenous market structure is hard to identify. In addition with weak instruments, especially with many instruments, and even in large samples two-stage OLS inference is not efficient as estimates may be biased and confidence intervals too narrow (Hahn and Hausman 2002; Hausman, Stock, and Yogo 2005). Thus, we proceed by considering the best next alternative which is the use of a vector autoregressive model.

For a better understanding of the joint dynamics of commonality in liquidity and between the variables that control for the general market conditions as well as the variables that proxy for the supply and demand-side determinants we estimate a vector autoregressive (VAR) model. In this approach, commonality in liquidity responds to innovations on lags of itself and on lags of all the other explanatory variables. For both commonality in spreads and depths, we estimate an eleven-equation VAR model with commonality in liquidity, market returns, volatility,

Table 10. Granger causality wald tests (supply-side).

	$R^2_{COM,t}$	Market Return	Trading Volume	Market Liquidity	Credit Risk	Market Volatility	EONIA Rate	TED Spread	LOIS Rate	ECB's Excess Liq.	Dealer's Stock Returns
$R^2_{COM,t}$ in Spreads		5.64					6.33	5.47		5.33	
		(0.06)					(0.04)	(0.07)		(0.07)	
Market Return							8.43				
							(0.02)				
Trading Volume		5.71						8.76			
		(0.06)						(0.01)			
Market Liquidity		11.24				12.46	33.82	11.64			
		(0.00)				(0.00)	(0.00)	(0.00)			
Credit Risk				7.44			27.78	6.14		9.98	13.98
				(0.02)			(0.00)	(0.05)		(0.01)	(0.00)
Market Volatility				11.00				8.95			
				(0.00)				(0.01)			
EONIA Rate				12.30		4.84				11.18	8.04
				(0.00)		(0.09)				(0.00)	(0.02)
TED Spread							5.22	23.29			
							(0.07)	(0.00)			
LOIS Spread								15.17			
								(0.00)			
ECB's Excess Liquidity				10.46			7.15				
				(0.01)			(0.03)				
Dealer's Stock Returns			11.92	5.11				9.24			
			(0.00)	(0.08)				(0.01)			
$R^2_{COM,t}$ in Depths				6.06			6.52				8.33
				(0.05)			(0.04)				(0.02)
Market Return							8.50				
							(0.01)				
Trading Volume		4.92		6.77			6.10				
		(0.09)		(0.03)			(0.05)				
Market Liquidity		5.76					5.38	5.93	23.34		10.44
		(0.06)					(0.07)	(0.05)	(0.00)		(0.01)
Credit Risk						5.08	23.56			14.83	12.03
						(0.08)	(0.00)			(0.00)	(0.00)
Market Volatility				8.50					9.94		
				(0.01)					(0.01)		
EONIA Rate				4.96						8.75	
				(0.08)						(0.01)	
TED Spread				7.38			9.45		9.50	5.47	4.84
				(0.03)			(0.01)		(0.01)	(0.07)	(0.09)
LOIS Spread	5.84			6.00							
	(0.05)			(0.05)							
ECB's Excess Liquidity			5.20				5.02				
			(0.07)				(0.08)				
Dealer's Stock Returns		5.14	7.15							5.67	
		(0.08)	(0.03)							(0.06)	

Notes: This table presents χ^2 statistics and *p*-values (in parentheses) of pairwise Granger causality Wald tests between endogenous VAR variables, estimated at monthly frequency. The null hypothesis is that the row variable does not Granger-cause the column variable. The sample is from June 2011 to June 2018 (85 months). To facilitate interpretation, we leave the entry blank if *p*-values are statistically insignificant at the 10% significance level.

Table 11. Granger causality wald tests (demand-side).

	$R^2_{COM,t}$	Market Return	Trading Volume	Market Liquidity	Credit Risk	Market Volatility	Sentix EA	Sentix US	EPU Europe	EPU US	Stoxx50 RV
$R^2_{COM,t}$ in Spreads		5.46 (0.07)									
Market Return									4.93 (0.09)		
Trading Volume		12.54 (0.00)					8.90 (0.01)	11.72 (0.00)			4.88 (0.09)
Market Liquidity		8.86 (0.01)			13.58 (0.00)	14.63 (0.00)		5.06 (0.08)	11.53 (0.00)		25.99 (0.00)
Credit Risk		8.28 (0.02)		7.97 (0.02)			5.58 (0.06)			5.44 (0.07)	7.46 (0.02)
Market Volatility				15.65 (0.00)	6.12 (0.05)						11.88 (0.00)
Sentix Euro-Area						5.25 (0.07)			8.04 (0.02)		
Sentix USA											
EPU Europe			6.30 (0.04)								7.39 (0.03)
EPU USA			6.49 (0.04)								
Stoxx50 RV								6.36 (0.04)			
$R^2_{COM,t}$ in Depths				3.14 (0.08)			2.72 (0.10)				
Market Return				4.33 (0.04)					4.40 (0.04)		
Trading Volume				4.65 (0.03)					5.15 (0.02)		
Market Liquidity											
Credit Risk		3.97 (0.05)					4.73 (0.03)				6.48 (0.01)
Market Volatility		4.12 (0.04)			2.85 (0.09)						
Sentix Euro-Area											
Sentix USA					3.38 (0.07)		3.10 (0.08)				
EPU Europe											7.47 (0.01)
EPU USA	7.88 (0.01)		10.23 (0.00)				3.22 (0.07)				
Stoxx50 RV							2.99 (0.08)				

Notes: This table presents χ^2 statistics and p-values (in parentheses) of pairwise Granger causality Wald tests between endogenous VAR variables, estimated at monthly frequency. The null hypothesis is that the row variable does not Granger-cause the column variable. The sample is from June 2011 to June 2018 (85 months). To facilitate interpretation, we leave the entry blank if p-values are statistically insignificant at the 10% significance level.

and market-wide liquidity as endogenous variables. We further expand the model by adding each time a different set of endogenous variables that proxy for various demand and supply-side determinants. We estimate the model up to two monthly lags. We further estimate Granger causality Wald tests in an attempt to establish the direction of causation. For the null hypothesis that variable i does not Granger cause variable j, we test whether the lag coefficients of i are jointly zero when j is the dependent variable in the VAR. The results for the supply and demand-side models are reported in Tables 10 and 11, respectively.

Relative to the supply-side, the results suggest that our main conclusions are still valid even after controlling for the joint dynamics of the variables. Market volatility seems to Granger cause commonality in quoted spreads and, again, three out of the five proxies for the funding conditions of financial intermediaries are found to Granger cause commonality in quoted spreads, and the reverse is not supported by the empirical results. It is also important to note that commonality in quoted spreads is not found to Granger cause any of the remaining explanatory variables we used in our regression and VAR models. Market liquidity, as opposed to market volatility, is found to Granger cause commonality in depths and, again, two out of the five proxies for funding conditions are found to Granger cause commonality in depths. Regarding the demand-side, our VAR results are very similar to the results we obtain from the OLS time-series regressions in the sense that they also suggest that proxy variables used do not help to explain time-series variation of commonality in both quoted spreads and depths. Overall, our key findings survive even after an attempt to address the endogeneity of the variables we use in this study.

8. Summary

In this study we test for a common component in liquidity variation across sovereign benchmark bonds, within as well as across countries and maturities, issued from 10 large Euro-area economies, over a 7-year period of 2011–2018 using tick-by-tick data from MTS, the largest Euro-area inter-dealer fixed income market. We find strong evidence of commonality in liquidity in quoted spreads and depths within countries or maturities and across countries and maturities. Particularly, at the pan-European level, approximately 40% and 23% of the variation of spreads and depths, respectively, is explained by the variation of market-wide liquidity.

We then empirically examine which underlying economic sources generate time-series variation in the pan-European, common liquidity factor we extracted. We derive testable hypotheses that stem either from supply-side forces related to the funding costs of financial intermediaries or from demand-side forces related to investor sentiment, a government's economic policy uncertainty and the cross-market linkages with the equity market. Our overall evidence is more reliably consistent with supply-side explanations for commonality in liquidity. Our demand side proxies do not help explain time-variation of commonality in liquidity. We also examine whether commonality intensifies around days in which announcements of key macroeconomic indicators are taking place. We find that commonality in liquidity intensifies around ECB policy meetings.

Finally, policy makers may be able to draw policy-relevant implications from this study. Central banks concerned about potential liquidity dry-ups across many fixed-income securities may be able to minimize the risk of liquidity crises by lowering the funding cost of financial intermediaries and/or increasing liquidity provision in periods of market stress.

Notes

1. Studies on the US fixed-income market have examined commonality in liquidity in either US Treasury markets in isolation (Fleming 2003) or liquidity dynamics between US equities and bonds (Chordia, Sarkar, and Subrahmanyam 2005; Goyenko and Ukhov 2009) and across the corporate bond and credit default swap markets (Pu 2009).
2. The maturities are 2-year, 3-year, 5-year, 7-year, 10-year, 15-year, 20-year and 30-year.
3. All sovereign benchmark bonds included in our data set are based on the actions of the European Central Bank and are denominated in the same currency, thereby isolating the liquidity differences across countries (Beber, Brandt, and Kavajecz 2009).
4. Germany does not operate any primary dealership system per se but limits access to the primary market to financial institutions domiciled in an EU member state and fulfilling certain conditions. The institutions entitled to operate in German primary markets are known as the Bund Issues Auction Group.
5. Primary dealers, by being willing to hold inventories of government bonds and allowing investors to swap between various outstanding issues of government bonds on a continuous basis, help bring liquidity to primary and secondary markets.
6. AFME, Government Bond Data Report, 2018Q2.
7. The use of alternative funding instruments is largely a function of overall borrowing needs. For example, if public deficits increase suddenly, sovereign issuers initially tend to diversify into other funding sources to avoid large fluctuations in the volume of conventional issuance.
8. Including debt issued by supranational institutions.
9. ECB Statistical Data Warehouse and Haver Analytics.
10. BIS (2016), Electronic Trading in Fixed Income Markets, Markets Committee Report.
11. AFME, Government Bond Data Report, 2017Q4.

12. Sentix Indices is a comprehensive capital markets survey designed to identify sentiment and expectations of private and institutional investors. From the survey results, various indices and indicators are calculated such as Sentix Euro Break-up Index, which shows the likelihood, from the perspective of investors, for a breakup of the Euro Area within the next 12 months. These are collected by 'Sentix - Behavioral Indices' and are available on the internet via www.sentix.de to frequent participants in the survey. They are also obtainable inter alia via Bloomberg or Thomson Reuters.
13. Across markets, inventory carrying costs should co-move as these costs depend on market interest rates.
14. Realized volatility variables were obtained from Oxford-Man Institute of Quantitative Finance.
15. Sovereign bond trading is not centralized in any particular location, thus information on aggregated, actual traded volumes and market shares is not available even to the banks collecting price data with the various competing trading platforms not publicly revealing their actual trading volumes for business reputation purposes. The incompleteness of the data can cause estimated liquidity measures to be biased measures of liquidity in the inter-dealer market as a whole, and to become more biased over time. To alleviate such concerns, we compare the time series of end of day prices in Bloomberg and in MTS. The results show that quoted prices (bid, ask and mid) nearly perfectly co-move (the correlation coefficient ranges from 96.5% to 99.5%) between two electronic platforms, suggesting prices in the MTS are representative of market activities. In addition, although the level of the MTS coverage ratio in terms of trading volume is incomplete and varies across countries it is, however, fairly accurate in capturing trends in the overall market size. By collecting information on traded volumes from various sources and for the main trading platforms over our sample period, we attempted to most accurately calculate traded volumes per country as well as the Euro-area. We compared the estimated traded volumes with the traded volumes in our MTS dataset. The correlation coefficient from this comparison ranges from 65% to 90% across countries.
16. While we also have information on Greek securities, given the loss of market access that Greece experienced during our sample period the data are too sparse for inclusion in our analysis.
17. The market share is calculated based on the outstanding amounts of debt securities issued by central governments in August 2018 from the ECB's Statistical Data Warehouse.
18. International Security Identification Number.
19. For instance, new traders may come in, executing orders inside the publicized spread, or the spread may widen if the size of an order is large. Moreover, in some electronic markets traders may post hidden limit orders that are not reflected in quoted spreads.
20. While trading volume and order flow are certainly distinct concepts, they are likely to be correlated as days after larger order flows may well be the days with high trading volume.
21. Germany, France, Spain and Italy maintained the benchmark yield curve consisting of the above-mentioned eight maturities in the whole sample period of our study. However, for example, Portugal does not have a 20-year benchmark bond during June 2011 and January 2014 and Ireland does not have a 30-year benchmark bond until February 2015 due to loss of market access.
22. For example, Austria does not have a benchmark 20-year bond during February 2012 and March 2013. We compensated for the missing data by using observations from another Austrian bond (ISIN:AT0000A04967) which has about 25 years of remaining maturity and thus lies in the bucket between 20 and 30 years.
23. Missing benchmark bond series are: 15-year for Ireland and Portugal, 20-year for Finland, Ireland and Portugal and 30-year for Ireland and Portugal. Please note that the 73 balanced benchmark bond series per each liquidity measure are formed from a set of 625 sovereign bonds and making use of all 625 bonds. In each benchmark bond series, an observation represents a liquidity measurement from the respective benchmark bond at a specific day. Given that benchmark status is attained by the most recently issued and traded sovereign bond in each maturity, at the cross-section, this implies liquidity measurements from the respective benchmark bond from each country and maturity for every date in our sample period.
24. Following Chordia, Roll, and Subrahmanyam (2000), we examine percentage changes rather than levels for two reasons: first, our interest is in discovering whether liquidity co-moves, and second, time series of liquidity level are more likely to be non-stationary.
25. This, however, is more relevant for the effective spread which is a function of trade prices and is thus significantly correlated with market returns.
26. Bloomberg Barclays Pan-European Aggregate Bond Index is a widely used and cited index by market participants when referring to European government bonds. It is a subset of the Bloomberg Barclays Global Aggregate Bond Index and is calculated with the same methodology. It includes only bonds issued in a European currency. In addition, we perform the same analysis using as a proxy for the market the Bloomberg Barclays Euro Aggregate Bond Index which includes only Euro-denominated bonds. The results are very similar in either case and thus not reported separately.
27. In order for market-wide liquidity to be less influenced by extreme values, a common practice is to rely on a trimmed mean. We also calculate market-wide liquidities using trimmed mean, rather than simple mean by excluding the benchmark bond series with the highest and lowest value. As expected, these market-wide liquidities are somewhat less volatile but share the same pattern as market-wide liquidities based on a simple mean.
28. The market return is computed as the average over the month of the daily logarithmic return of the Bloomberg-Barclays Pan-European Aggregate Bond Index. Market liquidity for each liquidity measure, is defined as the first extracted principal component. Trading volume is computed as the Euro daily mean of traded volume of all benchmark bond series included in our data set. We use two different proxies for market volatility: the equally-weighted absolute intraday log return of the benchmark bonds used in this study (noted as MTS Volatility), and the standard deviation of the daily percentage changes of the Bloomberg-Barclays Pan-European Aggregate Bond Index. We use the iTraxx SovX Western Europe Index as proxy variable for

credit risk. This index measures the credit default risk of European sovereign debt covering the sovereign CDS of 15 European countries (Hui, Lo, and Lau 2013; Kallestrup, Lando, and Murgoci 2016). The results of unit-root tests can be found in Table A2 in the Appendix.

29. Previous work suggests that the number of trades, and not the volume of trading, is a better indicator of an individual's security asymmetric information. The propensity of traders to hide their information by order splitting, is viewed as a possible explanation for this result. Given that the sovereign bonds market is characterized by infrequent trading, we consider the total trading volume and we do not differentiate between the number and the size of the trades.
30. The impact of one one-standard-deviation (σ) increase in the value of a time-series variable (relative to its mean) on $R^2_{COM,t}$ can be computed using the following expression: $\Delta R^2_{COM,t} = \exp^{\alpha+\beta\times(\mu+\sigma)+\gamma\times\lambda} / (1+\exp^{\alpha+\beta\times(\mu+\sigma)+\gamma\times\lambda}) - \exp^{\alpha+\beta\times\mu+\gamma\times\lambda} / (1+\exp^{\alpha+\beta\times\mu+\gamma\times\lambda})$, where α, β, and γ are the intercept, the estimated coefficient on the time-series variable of interest, and the vector of coefficients on the other time-series variables in the model, respectively; μ and λ are the mean of the time-series variable of interest and the vector of means of the other time-series variables, respectively. For σ, we take the time-series standard deviation of the variable of interest. To express the economic significance as a fraction of one standard deviation of the commonality measures, we compute the time-series standard deviation of $R^2_{COM,t}$.
31. The correlation coefficient between the $R^2_{COM,t}$ measure and the monthly average of the synchronicity measure is estimated to be 91% for spreads and 83% for depths.
32. We did robustness checks with both 10% and 20%. The qualitative results do not change.
33. Periphery markets include Spain, Portugal, Ireland and Italy in our sample and core markets encompass Austria, Belgium, Finland, France, Germany, and Netherlands in our sample.
34. As a robustness test, we have estimated the same regressions using the cross-sectional average as the measure of market liquidity. The results are similar and reported in Tables A4, A5, A6 in the Appendix.
35. The cross-sectional t-statistic for the average β when using the PCA method to extract market-wide liquidity, is calculated under the assumption that the estimation errors in β_j are independent across regressions. To check whether the equations are related through the correlation in the errors, we conduct a simple investigation of the residuals in (1). The results suggest little cross-equation dependence. Test details and results can be found in Table A1 in the Appendix.
36. Here the VIX index is viewed as a volatility indicator, although it could also be considered as a proxy for investor sentiment.
37. We use the returns of the Bloomberg-Barclays Pan-European Aggregate Bond Index as market returns.
38. Note that the results for model (1) in Table 6 are consistent with the results in model (3) in Table 5.
39. More specifically, excess reserves are measured as the difference between the current accounts held by financial institutions at the central bank (available at the end of each day) and their required reserves (defined on a monthly basis). The net deposit facility corresponds to the difference between the deposit facility and the marginal lending facility of the ECB, both available at a daily frequency. Source: Recent Developments in Excess Liquidity and Money Market Rates, ECB, Monthly Bulletin, January 2014.
40. 'Actions to Restore Financial Stability', Federal Reserve Bank of Minneapolis, December 2008.
41. Similarly, we obtain a positive and statistically significant coefficient when using the monthly standard deviation of Stoxx50 daily returns as proxy variable.
42. In unreported regression results, since the FX market is in the crossroad of any international portfolio allocation, we also include in our time-series regressions exchange rate changes. We use the nominal as well as the real effective exchange rate of the Euro against a group of 19 partner countries. We expect that commonality is greater when the local currency depreciates (as this may attract foreign investors). The results are not statistically significant and thus not reported here.
43. Periphery markets include Spain, Portugal, Ireland and Italy in our sample and core markets encompass Austria, Belgium, Finland, France, Germany, and Netherlands in our sample.

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Appendix. Additional empirical results

Table A1. Test for cross-equation dependence in estimation error.

Liquidity measure	Average correlation	Mean $\gamma_{j,1}$	Mean t	Median t	$\mid t \mid > 1.645$ (%)	$\mid t \mid > 1.96$ (%)
L^{PQS}	−0.007	−0.011	−0.210	−0.242	15.45	9.80
L^{PES}	0.002	−0.007	0.016	0.013	8.22	4.32
L^{AQD}	−0.004	−0.009	−0.123	−0.140	7.25	4.94
L^{AIR}	0.002	−0.007	0.095	0.038	5.18	3.73

Notes: After estimating 73 time series regressions of individual liquidity measures on equal-weighted market liquidity, Equation (1), residuals for benchmark bond series $j+1$ are compared with residuals for benchmark bond series j, after assigning to each j a unique number generated by a random number generating function and subsequently assigned based on the value of this randomly assigned number, from the lowest to the largest value. We run 72 time series regressions between adjacent residuals, i.e.

$$\epsilon_{j+1,t} = \gamma_{j,0} + \gamma_{j,1}\epsilon_{j,t} + \xi_{j,t}, \tag{A1}$$

where $\gamma_{j,0}$ and $\gamma_{j,1}$ are estimated coefficients and $\xi_{j,t}$, is an estimated disturbance. The t-statistics for $\gamma_{j,1}$ provide evidence about cross-equation dependence. From these 72 pairs, the table reports the average correlation coefficient after 1,000 repetitions of the exercise. Also reported from pair-wise regressions, Equation (A1), are the average slope coefficient as well as the sample mean t-statistic of the regression slope coefficient and the frequency of absolute t-statistics (for the slope) exceeding typical critical levels, 5% and 2.5%. Because there are two tails, double these critical percentages (i.e. 10% and 5%, respectively), should be found just by chance if, in fact, there is no dependence. The results suggest little cross-equation dependence as the mean and median slope coefficients from Equation (A1) as well as the correlation coefficients are virtually zero on average with relative few observations concentrated at the tails of the distribution.

Table A2. Unit root testing.

	Levels			First differences		
Series	ADF	PP	DF-GLS	ADF	PP	DF-GLS
Commonality in Spreads	−7.57	−9.06	−5.28	−10.81	−14.46	−9.35
Commonality in Depths	−7.69	−9.51	−7.68	−11.21	−15.17	−9.39
Market Return	−6.15	−9.25	−5.06	−10.11	−16.84	−5.51
Trading Volume	−3.14	−3.77	−3.03	−8.85	−11.81	−6.64
Market Liquidity (Spreads)	−2.37	−1.76	−2.05	−7.79	−9.32	−3.74
Market Liquidity (Depths)	−2.07	−1.80	−2.02	−7.53	−8.94	−4.56
Bond Index Volatility	−3.91	−5.25	−3.17	−9.37	−13.38	−8.91
MTS Volatility	−2.33	−2.62	−1.94	−8.15	−12.43	−5.29
MOVE Index	−2.75	−2.56	−2.18	−7.65	−8.77	−6.59
VIX Index	−3.21	−3.15	−2.80	−8.63	−8.93	−8.61
VSTOXX Index	−2.62	−2.68	−2.22	−8.87	−9.41	−8.52
EONIA	−3.11	−4.16	−1.15	−5.96	−6.21	−5.20
TED Spread	−2.53	−2.22	−2.62	−7.18	−7.59	−7.14
E−OIS Spread	−2.53	−1.52	−2.14	−7.60	−5.02	−5.83
L−OIS Spread	−3.16	−1.95	−3.06	−5.89	−5.49	−5.77
ECB's Excess Liquidity	−0.22	−0.73	−0.83	−3.57	−5.77	−3.54
Dealer's Stock Returns	−6.68	−8.64	−6.71	−12.37	−15.27	−8.21
Sentix Euro−Area	−1.88	−1.55	−2.65	−5.59	−6.57	−5.55
Sentix USA	−2.58	−2.49	−2.51	−6.36	−7.59	−6.67
EPU Europe	−3.77	−4.54	−3.77	−9.08	−11.58	−8.93
EPU USA	−3.39	−3.49	−3.90	−10.18	−11.13	−6.19
Stoxx50 StDev	−3.39	−4.23	−3.91	−8.73	−12.18	−8.70
Stoxx50 RV	−3.80	−4.37	−4.12	−12.52	−11.32	−10.65
S&P500 StDev	−4.03	−5.14	−4.46	−10.76	−12.82	−10.49
S&P500 RV	−4.01	−4.64	−4.40	−11.48	−11.39	−11.43

Notes: This table reports the results of three unit root tests on the liquidity variables and low-frequency proxies related to various demand- and supply-side explanations of commonality in liquidity for the period from June 2011 to June 2018 at monthly frequency (i.e. 85 observation). ADF, PP and DF-GLS are Augmented Dickey–Fuller, Phillips–Perron and Elliott–Rothenberg–Stock DF-GLS test statistics, respectively. In each test, the null hypothesis is that the series contains a unit root, and the alternative is that the variable was generated by a stationary process. The critical values for ADF and PP are −3.44 (1%), −2.87 (5%) and −2.57 (10%). Test critical values for DF-GLS are −2.58 (1%), −1.95 (5%) and −1.62 (10%).

Table A3. Market-wide trading volume.

	Daily	Monthly
Mean	36.90	4,850
Std. Dev.	10.60	1,330
Min	8.33	2,010
Max	92.40	7,570
Skewness	0.91	0.09
Kurtosis	4.96	2.32
Observations	1,804	85

Notes: This table shows summary statistics for market-wide trading volume at daily and monthly frequency. Market-wide trading volume is computed as the Euro (in millions) mean of traded volume of all benchmark bond series included in our data set. The sample period is 2011:06–2018:6 and includes 1804 daily observations for 625 euro-denominated sovereign bonds.

Table A4. Changes in volatility and in commonality in liquidity (averaging).

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Changes in Commonality in Spreads							
Market Return	0.016	0.034	0.015	0.039	0.008	0.022	0.059∗
	(0.39)	(0.87)	(0.64)	(1.11)	(0.47)	(0.59)	(1.67)
ΔTrading Volume	0.016∗∗∗	0.015∗∗∗	0.014∗∗∗	0.014∗∗∗	0.016∗∗∗	0.016∗∗∗	0.011∗∗∗
	(3.39)	(3.57)	(2.99)	(2.97)	(3.16)	(3.29)	(2.61)
ΔMarket Liquidity	0.010∗∗∗	0.008∗∗∗	0.005∗	0.008∗∗∗	0.008∗∗∗	0.008∗∗∗	0.003∗
	(4.04)	(4.39)	(1.69)	(3.99)	(3.74)	(3.82)	(1.79)
ΔCredit Risk	0.001	0.000	0.001	−0.010	0.007	0.001	−0.001
	(0.43)	(0.23)	(0.49)	(−0.24)	(0.26)	(0.11)	(−0.29)
ΔBond Index Volatility		0.014∗∗					0.010
		(2.21)					(1.47)
ΔMTS Volatility			0.071∗∗∗				0.064∗∗∗
			(2.81)				(2.70)
ΔMOVE				0.009∗∗			0.003∗
				(2.01)			(1.65)
ΔVIX					0.007		−0.010
					(0.59)		(−0.49)
ΔVSTOXX						0.010	0.010
						(0.99)	(0.33)
Constant	−0.021	−0.021	−0.021	−0.021	−0.021	−0.021	−0.021
	(−0.39)	(−0.41)	(−0.39)	(−0.41)	(−0.39)	(−0.40)	(−0.40)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.09	0.12	0.11	0.12	0.10	0.10	0.14
Panel B: Changes in Commonality in Depth							
Market Return	0.007	0.011	0.015	0.038	0.008	0.011	0.031∗
	(0.33)	(0.48)	(0.73)	(1.30)	(0.35)	(0.42)	(1.66)
ΔTrading Volume	−0.021	−0.020	−0.026	−0.045	−0.021	−0.026	−0.055
	(−0.47)	(−0.39)	(−0.65)	(−1.09)	(−0.69)	(−0.70)	(−1.20)
ΔMarket Liquidity	−0.158∗∗	−0.157∗∗	−0.102∗	−0.119∗	−0.157∗∗	−0.149∗∗	−0.099
	(−2.20)	(−2.04)	(−1.67)	(−1.73)	(−2.01)	(−2.12)	(−0.25)
ΔCredit Risk	0.001	0.001	−0.007	−0.001	−0.000	−0.000	−0.002
	(0.07)	(0.03)	(−0.12)	(−0.39)	(−0.31)	(−0.30)	(−0.87)
ΔBond Index Volatility		0.401					0.440
		(0.71)					(0.35)
ΔMTS Volatility			0.037∗				0.004∗
			(1.78)				(1.73)
ΔMOVE				0.014∗∗∗			0.014∗∗∗
				(2.97)			(2.65)
ΔVIX					−0.000		−0.001
					(−1.10)		(−0.81)
ΔVSTOXX						0.005	0.003
						(0.43)	(0.66)
Constant	−0.030	−0.031	−0.031	−0.031	−0.031	−0.031	−0.030
	(−0.77)	(−0.84)	(−0.90)	(−0.81)	(−0.71)	(−0.75)	(−0.73)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.02	0.02	0.09	0.10	0.02	0.03	0.10

Notes: This table reports results of time-series regressions of the change in monthly average commonality in liquidity among 73 benchmark bond series – denoted by $R^2_{COM,t}$, computed as the logistic transformation of commonality in liquidity in month t – over the period 2011:06–2018:06 on changes of various aggregate volatility proxies. The reported regressions are in monthly changes. All equations are estimated using OLS with Newey–West standard errors, with lag length $T^{1/3}$, where T is the indicated sample size. t-statistics are given in parentheses below coefficient estimates. ∗∗∗$p < 0.01$, ∗∗$p < 0.05$, ∗$p < 0.1$.

Table A5. What drives time-series variation in commonality? (Supply-side, Averaging).

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Changes in Commonality in Spreads							
Market Return	0.020	0.018	0.029	0.027	0.019	0.021	0.010
	(0.69)	(0.59)	(0.78)	(0.81)	(0.36)	(0.50)	(0.44)
ΔTrading Volume	0.016∗∗∗	0.016∗∗∗	0.015∗∗∗	0.015∗∗∗	0.015∗∗∗	0.014∗∗∗	0.026∗∗∗
	(2.97)	(3.20)	(3.67)	(3.29)	(3.31)	(2.31)	(2.69)
ΔMarket Liquidity	0.005∗	0.005∗	0.006∗	0.006∗∗	0.006∗∗	0.003	0.004
	(1.67)	(1.65)	(1.70)	(1.98)	(1.98)	(1.22)	(0.46)
ΔCredit Risk	0.002	0.002	0.004	−0.003	−0.000	−0.006	−0.022
	(0.40)	(0.43)	(0.01)	(−0.01)	(−0.04)	(−0.13)	(−0.20)
ΔMarket Volatility	0.050∗∗∗	0.051∗∗	0.048∗∗	0.049∗∗	0.049∗∗	0.055∗∗∗	0.099∗∗
	(2.73)	(1.99)	(2.13)	(2.05)	(2.09)	(2.51)	(2.23)
ΔEONIA Rate		0.099					0.126
		(1.11)					(1.41)
ΔTED Spread			0.005∗				−0.001
			(1.89)				(−1.63)
ΔLOIS				0.003∗∗			0.004∗∗
				(1.78)			(1.83)
ΔECB's Excess Liquidity					0.003∗∗∗		0.005∗∗∗
					(1.99)		(2.25)
Dealer's Stock Returns						−0.013∗∗	−0.011∗
						(−1.97)	(−1.75)
Constant	−0.021	−0.021	−0.021	−0.021	−0.021	−0.021	−0.020
	(−0.44)	(−0.41)	(−0.47)	(−0.47)	(−0.33)	(−0.39)	(−0.29)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.10	0.09	0.11	0.11	0.11	0.12	0.16
Panel B: Changes in Commonality in Depth							
Market Return	0.019	0.027	0.018	0.015	0.017	0.016	0.031
	(0.75)	(1.11)	(0.79)	(0.70)	(0.71)	(0.68)	(1.00)
ΔTrading Volume	−0.020	−0.030	−0.020	−0.021	−0.019	−0.029	−0.040
	(−0.33)	(−0.40)	(−0.35)	(−0.36)	(−0.41)	(−0.75)	(−0.99)
ΔMarket Liquidity	−0.121	−0.111	−0.101	−0.117	−0.101	−0.091	−0.109
	(−1.14)	(−1.06)	(−1.13)	(−1.09)	(−1.12)	(−1.11)	(−0.88)
ΔCredit Risk	−0.009	−0.012	−0.009	−0.004	−0.011	−0.004	−0.004
	(−0.01)	(−0.01)	(−0.11)	(−0.11)	(−0.36)	(−0.43)	(−0.45)
ΔMarket Volatility	0.037∗	0.045∗∗	0.0328	0.036∗	0.037∗	0.035∗∗	0.039∗∗
	(1.80)	(2.19)	(1.77)	(1.81)	(1.75)	(1.81)	(2.31)
ΔEONIA Rate		0.099∗∗					0.102∗∗
		(1.99)					(2.05)
ΔTED Spread			0.000				−0.001
			(0.01)				(−0.01)
ΔLOIS				0.001			0.003
				0.10			0.51
ΔECB's Excess Liquidity					0.011		0.013
					(0.35)		(0.53)
Dealer's Stock Returns						−0.034∗	−0.029
						(−1.69)	(−1.61)
Constant	−0.047	−0.046	−0.047	−0.045	−0.046	−0.047	−0.046
	(−0.67)	(−0.88)	(−0.91)	(−0.89)	(−0.68)	(−0.74)	(−0.97)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.05	0.08	0.09	0.09	0.09	0.10	0.09

Notes: This table reports results of time-series regressions of the change in monthly average commonality in liquidity among 73 benchmark bond series – denoted by $R^2_{avg,t}$, computed as the logistic transformation of the average commonality in liquidity in month t – over the period 2011:06–2018:06 on changes of various proxies for funding conditions. All equations are estimated using OLS with Newey-West standard errors, with lag length $T^{1/3}$, where T is the indicated sample size. t-statistics are given in parentheses below coefficient estimates. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.

Table A6. What drives time-series variation in commonality? (Demand-side, Averaging).

Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Changes in Commonality in Spreads							
Market Return	0.047	0.049	0.048	0.039	0.055	0.060	0.050
	(0.34)	(0.67)	(0.70)	(0.81)	(0.39)	(0.89)	(0.71)
ΔTrading Volume	0.010***	0.011***	0.010***	0.008**	0.008***	0.009***	0.012**
	(2.99)	(2.87)	(3.01)	(2.01)	(2.20)	(3.01)	(2.15)
ΔMarket Liquidity	0.005*	0.005*	0.005*	0.004	0.003	0.005*	0.004
	(1.75)	(1.74)	(1.76)	(1.57)	(1.36)	(1.68)	(1.60)
ΔCredit Risk	0.001	0.001	0.000	0.010	0.001	0.000	−0.001
	(0.14)	(0.20)	(0.30)	(0.21)	(0.20)	(0.08)	(−0.37)
ΔMarket Volatility	0.075***	0.074***	0.080***	0.075***	0.074***	0.073***	0.075***
	(2.89)	(2.87)	(2.92)	(2.86)	(2.71)	(2.87)	(2.40)
ΔSentix Euro−Area		0.010					0.011
		0.90					0.81
ΔSentix USA			−0.021				−0.019
			(−0.69)				(−0.87)
ΔEPU Europe				0.036			0.041
				(1.49)			(1.11)
ΔEPU USA					−0.003		−0.007
					(−1.31)		(−0.89)
ΔStoxx50 RV						0.236***	0.0192*
						(2.51)	(1.90)
Constant	−0.040	−0.040	−0.038	−0.039	−0.020	−0.029	−0.033
	(−0.53)	(−0.52)	(−0.53)	(−0.51)	(−0.52)	(−0.50)	(−0.51)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.09	0.10	0.10	0.11	0.11	0.14	0.11
Panel B: Changes in Commonality in Depth							
Market Return	0.022	0.022	0.023	0.028	0.022	0.026	0.020
	(0.49)	(0.65)	(0.71)	(0.79)	(0.57)	(0.59)	(0.61)
ΔTrading Volume	−0.025	−0.033	−0.026	−0.053	−0.035	−0.030	−0.060
	(−0.62)	(−0.81)	(−0.63)	(−1.45)	(−0.87)	(−0.72)	(−1.42)
ΔMarket Liquidity	−0.122	−0.125	−0.122	−0.085	−0.105	−0.113	−0.129*
	(−1.44)	(−1.45)	(−1.42)	(−1.13)	(−1.33)	(−1.43)	(−1.79)
ΔCredit Risk	−0.009	−0.001	−0.009	−0.002	−0.002	−0.002	−0.002
	(−0.22)	(−0.13)	(−0.20)	(−0.46)	(−0.37)	(−0.44)	(−0.28)
ΔMarket Volatility	0.055*	0.052*	0.052*	0.069*	0.057*	0.059*	0.045*
	(1.78)	(1.77)	(1.77)	(1.91)	(1.79)	(1.82)	(1.68)
ΔSentix Euro−Area		0.001					0.001
		(0.77)					(0.77)
ΔSentix USA			−0.001				−0.001
			(0.46)				(0.40)
ΔEPU Europe				0.017			0.015
				(1.02)			(0.99)
ΔEPU USA					−0.011		−0.007
					(0.60)		(0.11)
ΔStoxx50 RV						0.141	0.0119
						(1.03)	(0.79)
Constant	−0.047	−0.047	−0.047	−0.047	−0.047	−0.045	−0.041
	(−0.61)	(−0.89)	(−0.85)	(−0.70)	(−0.72)	(−0.73)	(−0.69)
Observations	84	84	84	84	84	84	84
Adjusted R^2	0.05	0.09	0.09	0.10	0.10	0.10	0.05

Notes: This table reports results of time-series regressions of the change in monthly average commonality in liquidity among 73 benchmark bond series – denoted by $R^2_{avg,t}$, computed as the logistic transformation of the average commonality in liquidity in month t – over the period 2011:06–2018:06 on changes of various proxies on demand-side determinants. All equations are estimated using OLS with Newey–West standard errors, with lag length $T^{1/3}$, where T is the indicated sample size. t-statistics are given in parentheses below coefficient estimates. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$.