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On the term structure of liquidity in the European sovereign bond market*



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ABSTRACT

The paper provides a high-frequency analysis of liquidity dynamics in the eurozone sovereign bond market over tranquil and crisis periods. We study time series of liquidity across the yield curve using high-frequency data from MTS, one of Europe's leading electronic fixed-income trading platforms. We document flight-to-liquidity effects as investors prefer to trade on shorter-term benchmarks during liquidity dry-ups. We provide evidence of significant commonalities in spread and depth liquidity proxies which are weaker during the crisis period for both core and periphery economies although periphery countries display higher commonality than core countries during the crisis. We show that illiquidity of the periphery countries plays an important role in market dynamics and Granger causes illiquidity, volatility, returns, and CDS spreads across the maturity spectrum in both calm and crisis periods. Liquidity is priced both as a characteristic and as a risk factor even when controlling for credit risk, pointing to liquidity's systematic dimension and importance.

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1. Introduction

Market liquidity is important both as a characteristic and as a risk factor in international financial markets, especially during periods of increased market uncertainty. The events of 2007/8 revealed that liquidity should not be taken for granted and can completely evaporate leading to episodes of systemic financial distress. In this study we undertake an in-depth analysis of liquidity com-

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monality, liquidity dynamics, and liquidity pricing across the term structure of returns in the eurozone sovereign bond market using microstructure-based measures of liquidity. We employ a comprehensive dataset provided by MTS (Mercato dei Titoli di Stato), Europe's premier electronic fixed-income trading market for eurodenominated government bonds. The European sovereign debt crisis offers a unique opportunity to study the behaviour of bond market liquidity over both crisis and tranquil periods and its interrelations with market volatility, returns, and sovereign credit risk.

We are motivated by the role liquidity plays during economic recessions and expansions. In particular, liquidity deterioration during periods of stress can exacerbate investors' perceptions about future liquidity, as required rates of return must increase to compensate for additional amounts of risk they undertake in the form of a risk premium (Amihud and Mendelson, 1986). Moreover, covariation in liquidity poses significant challenges to traders, investors and policymakers as it raises the prospect of market-wide, systematic breakdowns in liquidity during market crises (Hasbrouck and Seppi, 2001). It is also often suggested that liquidity premia widen dramatically during extreme market episodes in tandem with flight-to-liquidity effects, suggesting that investors' preferences shift toward possessing more liquid assets (Vayanos, 2004).

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Generally speaking, the term structure of liquidity is positively sloped as investors demand progressively higher premiums on assets with long term maturities, that is, they will not agree to tie-up their funds for a longer period of time unless they receive compensation in the form of a higher rate of return. This is in line with the predictions of the Liquidity Preference Theory popularized by John Maynard Keynes in his book *The general theory of employment, interest, and money*. Recent research by Dick-Nielsen et al. (2012) has shown that the general pattern of the term structure of liquidity across ratings and regime is that the liquidity component increases as maturity increases. In fact, the premium is twice as high for long maturity bonds compared to short maturity bonds.

Regarding the role played by sovereign credit risk at the term structure level, it has been shown by Remolona et al. (2008) that market liquidity explains market participants' perception of sovereign risk in addition to country-specific economic fundamentals. The authors conclude that liquidity influences sovereign risk and risk premia and their finding that global risk aversion primarily determines the pricing of risk remains robust to the effects of market liquidity. A discussion on the importance of market liquidity as a determinant of sovereign risk and risk premia is also provided by Augustin (2018). We acknowledge the strong link between liquidity and sovereign credit risk and study their interrelationships in the empirical analysis that follows.

Earlier studies have mainly focused on lower frequency datasets (i.e. daily) or on countries in isolation. Thus, there are significant gaps in the literature on the liquidity dynamics of the eurozone government bond market in its entirety. To the best of our knowledge, no previous study has examined the European bond market liquidity across different segments of the yield curve, during both tranquil and crisis periods. Also, the bulk of previous studies on liquidity have focused on the equity markets while research on bond markets is scarce. There are differences between the sovereign bond market and the equity market which lead to differences in liquidity and price discovery. Generally speaking, bonds are inherently less liquid than equities as they have many outstanding issues of various types and can be held to redemption - so called buy and hold bonds. Moreover, equities are mainly exchange-traded despite competition from Multilateral Trading Facilities that have become quite popular in recent years, whereas bonds trade over-the-counter and have a much more decentralized structure than equities. Thus, any conclusions drawn from the equity market will not necessarily carry over to the bond market.

We examine liquidity dynamics and its interrelations with volatility, returns, and sovereign credit risk across the maturity spectrum. We partition benchmark securities into four representative maturity categories that reflect the distinct characteristics of short, medium, and longer-term liquidity, that is, 2-, 5-, 10-, and 30-year maturities. In doing so, we seek to identify important trends in these measures over both tranquil and crisis periods across non-GIIPS countries and periphery GIIPS countries.¹ We document a deterioration of liquidity and an intensification of volatility as we move from the pre-crisis to the crisis period, with the exception of the 30-year benchmark which proves to be less vulnerable than its shorter-term counterparts to liquidity episodes. Pelizzon et al. (2016) also find a deterioration of bond market liquidity during the crisis. The authors, although they study the European sovereign debt crisis period using MTS high-frequency data, focus on the liquidity of the Italian bond market. Moreover, they only study the crisis period and do not provide comparisons with the calm period that preceded it. Our analysis provides greater insights on the term structure of liquidity as it employs a comprehensive high-frequency dataset from the MTS platforms that includes 11 countries from both core and periphery regions and covers both calm and crisis periods.

We also show that the bond markets of non-GIIPS countries exhibit higher liquidity and lower volatility than those of GIIPS countries pointing to the potential for the occurrence of flights towards bonds of lower credit risk in periods of financial distress. Beber et al. (2009) have already discussed the occurrence of flights in the European sovereign bond market. Although the authors provide evidence for flight-to-liquidity for euro-area bonds, they employ a relatively short sample period which spans the dates from April 2003 to December 2004 and does not include the European sovereign debt crisis period. Our contribution in this regard is that we offer new insights on flights-to-liquidity and on the behaviour of eurozone bond markets during both calm and turbulent periods.

We also add to the almost non-existent literature on liquidity commonality in the context of bond markets. We would expect the liquidity of different bond markets to comove, as the Association for Financial Markets in Europe (AFME) reports that the same institutions make markets for sovereign bonds of different countries, leading us to believe that the arguments that Coughenour and Saad (2004) make for stocks with common dealers apply to the bond market as well. Coughenour and Saad (2004) argue that commonality in liquidity can materialize as a result of common variation in the supply of liquidity which can be induced by the actions of market makers who employ shared capital and information. Additional supporting evidence on the role market makers play in influencing liquidity co-variation is provided by Ho and Stoll (1983), Gehrig and Jackson (1998), and Coughenour and Deli (2002). It remains to be seen whether results from the equity market can be generalized to the case of the sovereign bond market.

We apply principal components analysis (PCA) to the GIIPS and non-GIIPS regions and extract common factors from relative spreads and quoted depths. Our results indicate that commonality in liquidity is weaker in the crisis period for both GIIPS and non-GIIPS countries; however, commonality is stronger in the GI-IPS region relative to the non-GIIPS region commonality and is more pronounced for spread than it is for depth liquidity proxies. During the crisis liquidity commonality decreases slightly whilst volatility increases in the GIIPS region whereas liquidity commonality decreases with decreasing volatility in the non-GIIPS region. In the crisis period both liquidity commonality and volatility are higher in the GIIPS region relative to the non-GIIPS region confirming previous findings from equity markets documented by Karolyi et al. (2012).

We examine Granger causalities among short, medium and long-term liquidity, returns, volatility, and credit risk in order to identify the direction and magnitude of market shocks transmitted during pre-crisis and crisis periods. In the pre-crisis period we document causality flowing from GIIPS volatility to GIIPS illiquidity as well as information impounded first into the 10-year GI-IPS and non-GIIPS benchmark bond returns before getting reflected into the other bond returns in both regions. Moreover, GIIPS illiquidity (measured by quoted depths) plays a significant role in market dynamics as it Granger causes not only GIIPS and non-GIIPS quoted depths, but also most maturity GIIPS returns and most maturity non-GIIPS returns, providing informal evidence of liquidity being a priced factor. In the crisis period we find, on the one hand, short-term non-GIIPS returns causing both short and long maturity own-returns and, on the other hand, we find returns impacted by both own-market and cross-market illiquidity (measured by relative spreads). Furthermore, similar to the pre-crisis period the 10year GIIPS return seems to be an important benchmark bond, as it Granger causes other maturity returns, relative spreads and volatility in both regions.

¹ We use the acronym GIIPS in reference to the financially distressed economies of Greece, Ireland, Italy, Portugal and Spain during the European debt crisis and the acronym non-GIIPS in reference to the more creditworthy economies of Austria, Belgium, Finland, France, Netherlands and Germany.

The pricing implications of liquidity have not been examined in detail in global bond markets, in particular over crisis periods, with even less consideration given to European bond market liquidity pricing. We investigate whether liquidity is priced across maturities using Impulse Response Functions from a multivariate vector autoregression (VAR) where we simultaneously model illiquidity, volatility, bond returns, and credit default swap (CDS) spreads across four maturities. Our results are consistent with the view that liquidity as a characteristic is priced in the non-GIIPS region pre-crisis, with own-market illiquidity shocks decreasing non-GIIPS returns at the short end of the maturity spectrum. Liquidity as a characteristic is priced in the GIIPS region as well, with bond returns initially increasing and subsequently decreasing in response to own-market liquidity shocks. The longer maturity benchmark bonds are more sensitive to liquidity shocks than the shorter maturity bonds. In the crisis period own-market illiquidity shocks initially result in returns falling in both regions, however, returns subsequently rise. Cross-market illiquidity shocks appear to be more important for both GIIPS and non-GIIPS returns. We document substantial cross-market effects as GIIPS illiquidity shocks impact non-GIIPS returns positively across the maturity spectrum, while non-GIIPS illiquidity shocks impact GIIPS returns negatively across the maturity spectrum.

Overall, our results indicate that the response of bond returns to illiquidity shocks increase in magnitude in the crisis period especially to cross-market illiquidity shocks. The bond return responses to illiquidity shocks decay more slowly for the periphery countries and during the crisis. These results are consistent with those of Schuster and Uhrig-Homburg (2013) who analyse the term structure of illiquidity premiums conditional on the economic environment for German government and guaranteed bonds. Moreover, we use a variant liquidity-adjusted CAPM model of Acharya and Pedersen (2005) to estimate market and liquidity risk premia and demonstrate that liquidity risk is priced, even after controlling for liquidity as a characteristic and sovereign credit risk.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 describes our data and the variable construction procedures. Section 4 reports our empirical results. Section 5 concludes the paper.

2. Literature review

Our study is related to separate strands of the literature on bond markets and the term structure of their liquidity. It also draws upon the extant literature on the dynamic interactions of liquidity with returns and volatility across different asset classes and time periods. Univariate or bivariate dynamic relationships between liquidity and returns have been examined by Amihud and Mendelson (1986) and Hasbrouck (1991) among others, whereas Benston and Hagerman (1974) and Subrahmanyam (1994) discussed volatility and liquidity univariate interactions, focusing on the U.S. stock market. Their evidence suggests that there are bidirectional causalities between liquidity and returns, as well as between liquidity and volatility, and that these causalities are as a result of future trading and a compensation for higher trading costs. Additionally, they show that bid-ask spreads increase as volatility increases, due to heightened inventory risk and that liquidity deterioration leads to volatility intensification. Examples of studies that have dealt with the time-varying liquidity modelling in Treasury bond markets and the joint dynamics of liquidity, volumes, returns, and volatility in U.S. stock and Treasury markets, include those of Krishnamurthy (2002), Chordia et al. (2005), and Goyenko et al. (2011) among others.

Second, our study relates to the literature on the microstructure of the European sovereign bond markets. The majority of stud-

ies refer to periods prior to the sovereign debt crisis or to markets in isolation, while only a few have employed high-frequency data from the MTS platform (e.g., Cheung et al., 2005; Dunne et al., 2007; Beber et al., 2009; Favero et al., 2010; Dufour and Nguyen, 2012; Caporale and Girardi, 2013; Paiardini, 2014; Pelizzon et al., 2016; O'Sullivan and Papavassiliou, 2019). Our study differs from the earlier literature in that it provides a detailed analysis of liquidity dynamics over calm and crisis periods, offering important insights on liquidity commonality and the pricing implications of liquidity.

Our analysis is also related to the literature on commonality in liquidity. The seminal empirical papers in this area are those of Chordia et al. (2000), Huberman and Halka (2001), and Hasbrouck and Seppi (2001). All three studies find evidence of commonality in liquidity for U.S. listed stocks. Coughenour and Saad (2004) argue that commonality in liquidity is higher among stocks that have the same dealer that facilitates trades on the NYSE exchange and such commonality is positively related to the risk of liquidity provision. Kamara et al. (2008) study the evolution of commonality in liquidity across U.S. firms over time and conclude that commonality has increased for large firms, whilst declining for smaller firms. This is mainly due to changes in the investor base, the growth of institutional investing and ETF trading strategies. Brunnermeier and Pedersen (2009) provide a model which links funding and market liquidity and explains the comovement of market liquidity and fragility across assets. Brockman et al. (2009) examine commonality within and across exchanges from around the world while Hameed et al. (2010) show a dramatic increase in common factors in liquidity after large market downturns. Karolyi et al. (2012) relate liquidity comovements to demand and supply determinants of liquidity across countries and show that comovements increase in times of high volatility and a higher proportion of foreign investors.

Apart from stock markets, commonality in liquidity has also been documented in foreign exchange and bond markets. Fleming (2003) finds considerable commonality in liquidity in the U.S. Treasury market across securities as well as measures. Chordia et al. (2005) analyse liquidity comovements across stocks and bonds and suggest that liquidity shocks are often systemic in nature, and Mancini et al. (2013) find strong commonality in liquidity across currencies and with equity and bond markets. Evidence of commonality in liquidity in the eurozone government bond market is scarce and has been provided by Coluzzi et al. (2008) and Schneider et al. (2016). Coluzzi et al. (2008) focus on the Italian sovereign bond market and employ data for the period January 2004 to December 2006 which does not include the European sovereign debt crisis. Moreover, their evidence on commonality is based on standard correlation coefficients across liquidity measures and not on any factor model. Schneider et al. (2016) also focus on the Italian bond market in isolation and use a dataset which covers the eurozone crisis period only, thus their analysis does not provide any useful comparisons with the calm period and between and within core and periphery countries. Our study circumvents the aforementioned problems and offers new insights vis-a-vis the existing literature.

Finally, our study is also related to the literature on the pricing of liquidity. Pástor and Stambaugh (2003) show that expected stock returns are related cross-sectionally to innovations in aggregate liquidity, and stocks that are more sensitive to liquidity exhibit higher expected returns. Acharya and Pedersen (2005) derive a liquidity-adjusted CAPM model which incorporates multiple forms of liquidity risk and provide evidence that liquidity is priced and the effects of liquidity level and liquidity risk are separate, as they affect asset prices via different channels. Goldreich et al. (2005) distinguish between current liquidity and

expected future liquidity in the U.S. Treasury market and find that the price premium for liquid securities depends strongly on expected future liquidity rather than on current liquidity. Gallmeyer et al. (2005) propose a rational expectations model in which heterogeneous investors exhibit asymmetries in their information about each others' preferences and conclude that liquidity is a priced risk factor as a forward-looking measure of preference generated risk. Goyenko et al. (2011) investigate the pricing implications of on-the-run and off-the-run illiquidity in the U.S. Treasury market and find that off-the-run illiquidity is the primary source of return predictability, whereas bond returns of onthe-run securities across maturities do not contain a liquidity premium. Lee (2011) uses Acharya and Pedersen's liquidity-adjusted CAPM to study liquidity risk at the global level and shows that liquidity risk is priced and arises from the covariation of individual stocks' return and liquidity with domestic and global market factors. To the best of our knowledge no previous study has employed the Acharya and Pedersen (2005) liquidity-adjusted CAPM model or a variant model to analyse the pricing of liquidity in sovereign bond markets.

There remain gaps in the literature on bond market liquidity and its behaviour during periods of stress. We provide a deeper understanding of liquidity dynamics by analyzing the interactions of liquidity with returns, volatility, and credit risk across a spectrum of benchmark bond maturities in the yield curve. We also add to the limited literature on liquidity commonality in the context of sovereign bond markets. Our study provides support to the notion that liquidity contributes to systematic risk and that its shocks transmitted across securities can cause market-wide effects. Moreover, the pricing implications of bond liquidity across the term structure are still unexplored especially in the case of the European sovereign bond market and we aim at filling this gap by linking liquidity conditions with the state of the economy.

3. Data and variable construction

3.1. Data

We employ a rich and comprehensive high-frequency dataset provided by MTS (Mercato dei Titoli di Stato), Europe's premier interdealer electronic fixed-income market for euro-denominated government bonds. MTS is majority owned by the London Stock Exchange Group since October 2007 and has recently been expanded to include U.S. bond markets, allowing for global coverage and harmonization in trading.² MTS market supports pre- and post-trade capabilities as well as trade execution across cash and repo markets, which takes place based on the principle of pricetime priority.

Our high-frequency dataset spans the dates from January 2008 to December 2013 and includes both tranquil and crisis periods. It consists of the following 11 countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. It contains: (a) all government bonds across the MTS market, and (b) the three best bid and ask quotations throughout the trading day, time-stamped to the nearest second. We consider November 2009 as the beginning of the European sovereign debt crisis, in line with previous studies such as Dellas and Tavlas (2013), Claeys and Vašíček (2014), and De Santis (2014), due to Greece's sovereign debt downgrade by Fitch in October 2009. The global financial crisis that started in August 2007 following the collapse of the U.S. subprime mortgage market had a small impact on Euro-

pean sovereign bond markets, as spreads remained in the vicinity of 30 basis points for 2007 and the first months of 2008 and only widened by a small amount after the collapse of Bear Stearns in March 2008, where they remained until the collapse of Lehman Brothers in September of 2008 (see Dellas and Tavlas (2013) for a detailed discussion). This justifies our selection to use the period January 2008 until October 2009 as the pre-crisis sample.³

Our analysis is based solely on benchmark fixed coupon-bearing government bonds from the domestic MTS markets which are divided into four time-to-maturity segments: 2-, 5-, 10-, and 30-year. We have selected to work with the most heavily traded benchmark for each country and maturity category. Our dataset has been further filtered to consider quotes recorded during regular trading hours, i.e. from 8:15 am to 5:30 pm CET, and excludes presessional and end-of-day quotations as well as quotes with zero and negative bid-ask spreads.

We obtain sovereign credit default swap (CDS) spreads for all countries in our sample at all four maturities from Markit.

3.2. Variable construction

Liquidity is an elusive concept and many different liquidity proxies have been proposed. To address this issue, we consider the following spread and depth based measures to capture the liquidity of benchmark securities in our sample:

- Relative spread: defined as the best bid-ask spread divided by the midpoint of the bid and ask quotes, i.e. $100((A_{it} B_{it})/M_{it})$ where A_{it} denotes the best ask price of security i at time t, B_{it} denotes the best bid price of security i at time t, and the midpoint is calculated as the mean of the best bid and ask price as follows: $M_{it} = (A_{it} + B_{it})/2$
- Quoted depth: defined as best bid size plus best ask size (where size is the quantity of securities bid or offered for sale at the posted bid and offer prices)
- Quote slope: defined as best bid-ask spread divided by the logarithm of quoted depth
- Market quality index: defined as half of quoted depth divided by the relative spread

These liquidity measures are constructed using intraday 5minute intervals and are then averaged on a daily basis per country and maturity bucket to obtain daily measures. We use midpoints of bid-ask quotes instead of transaction prices as they are less noisy measures of the efficient price and they do not suffer from bid-ask bounce effects (Bandi and Russell, 2006). Moreover, as we need a sufficiently large number of intraday observations to efficiently construct 5-minute returns and subsequently realized volatility and liquidity measures, we have relied on quotes that may be updated even if there is no trading. It is a fact that MTS transaction data is not as rich as quotation data. Focusing on a large number of observations reduces parameter estimation errors and leads to more accurate return and volatility estimators (see Gargano et al., 2019; Barndorff-Nielsen and Shephard, 2002 for a discussion). For all the aforementioned reasons an analysis using regularly spaced quotes is preferable. We construct 5-minute returns from the midpoint of the continuously recorded bid and ask quotes.⁴ Daily bond returns are also estimated as the summation

² Euro benchmark bonds with an outstanding value of at least 5 billion are allowed to trade on both the domestic MTS platforms and the EuroMTS platform - a platform for trading benchmark securities only - thus, liquidity is fragmented between the benchmark and the domestic markets.

³ We acknowledge the fact that the period from January 2008 to October 2009 was not perfectly calm due to the collapse of Bear Stearns and Lehman Brothers, however, it cannot be characterized as crisis period for eurozone bond markets.

⁴ In total, we use 171,024 5-minute sovereign bond midquote prices for each benchmark bond in our dataset (number of 5-minute prices per trading day (112) times dates in the sample (1527)). This number of observations is sufficiently large to ensure adequate power in our computations.

Table 1Summary statistics of tightness, depth, and multidimensional liquidity measures along with volatility and returns over the pre-crisis and crisis periods. Mean values are reported for relative spread, quoted depth, quote slope, market quality index, realized volatility and 5-minute returns across the 2-, 5-, 10-, and 30-year maturity segments. The summary statistics are measured at a daily frequency and span the period from January 2008 to December 2013. The pre-crisis refers to the period from January 2008 to October 2009 whilst the crisis refers to the period from November 2009 to December 2013.

| Period | Relative spread (bps) | Quoted depth | Quote slope | MQI (€ Bil) | RV (%) | Returns |
|------------|-----------------------|--------------|-------------|-------------|--------|---------|
| 2-Year | | | | | | |
| Pre-crisis | 11.96 | 25.11 | 0.004 | 26.04 | 0.12 | 0.012 |
| Crisis | 21.66 | 23.20 | 0.007 | 24.19 | 0.24 | 0.000 |
| 5-Year | | | | | | |
| Pre-crisis | 18.91 | 28.67 | 0.006 | 22.21 | 0.21 | 0.020 |
| Crisis | 23.69 | 24.90 | 0.015 | 31.67 | 0.23 | 0.000 |
| 10-Year | | | | | | |
| Pre-crisis | 30.79 | 27.16 | 0.010 | 14.41 | 0.36 | 0.029 |
| Crisis | 37.54 | 23.54 | 0.018 | 10.89 | 0.40 | 0.000 |
| 30-Year | | | | | | |
| Pre-crisis | 64.77 | 10.85 | 0.021 | 1.37 | 0.77 | 0.064 |
| Crisis | 52.32 | 10.75 | 0.031 | 1.60 | 0.64 | 0.001 |

of the 5-minute intraday returns for each security.⁵ Additionally, we construct daily realized volatility measures for each benchmark security by the summation of squared 5-minute intraday returns, following recent advances in the non-parametric realized volatility approach (Andersen and Bollerslev, 1998).

Table 1 provides descriptive statistics on liquidity and volatility measures across the 2-, 5-, 10-, and 30-year maturity category. There is a widening of relative spreads for bonds with longer maturities in both pre-crisis and crisis periods consistent with the findings of Pasquariello and Vega (2009), who show that shorter maturity bonds enjoy greater liquidity. Other things being equal, investors will normally ask for compensation for holding longer-term bonds in the form of a higher return. As shown in Table 1, the returns of the 30-year benchmark are much higher than those of shorter maturity bonds in the non-crisis period. As we move from the tranquil period to the turbulent, liquidity worsens as relative spreads increase sharply for the 2-, 5-, and 10-year benchmark securities, while they improve for the 30-year bonds. This finding indicates that longer maturity government bonds have been less vulnerable to liquidity dry-ups during crisis periods than shorter-term sovereign bonds due to lower selling pressure - see Friewald et al. (2012) for comparable evidence from the U.S. corporate bond market during the subprime crisis. This translates into a buy-and-forget strategy where investors do not actively manage their portfolios and prefer to hold bonds for the long term, allowing them to ride out periods where those bonds underperform and transaction costs increase.

The inverse relationship between spreads and depth is confirmed as the 30-year benchmarks exhibit a much lower quoted depth than the medium and shorter-term bonds. The average quoted depth declines during the crisis period indicating a deterioration of liquidity across the term structure. The quote slope liquidity proxy is lower for shorter maturities and takes on higher values during the crisis indicating a flight-to-liquidity effect towards shorter-term and more liquid bonds. The mean value of the market quality index declines between the pre-crisis and crisis periods for the 2- and 10-year benchmarks suggesting a deterioration in market quality has occurred due to smaller depths and wider

spreads. Finally, the table shows that volatility intensified during the crisis, except for the 30-year bond which behaves differently from the other benchmarks, as investors prefer to trade on the more liquid shorter-term benchmarks. To sum up, shorter maturity bonds are more adversely affected than their longer-term counterparts by liquidity dry-ups and higher volatility during the crisis period.

Table 2 presents descriptive statistics of liquidity and volatility measures across the GIIPS and non-GIIPS countries. The bond markets of core eurozone countries are more liquid than those of the periphery countries as evidenced by lower transaction costs and higher values for quoted depth and market quality index, in both tranquil and crisis periods. Volatility has intensified for GIIPS countries during the crisis (with the exception of the 30-year bond) but has declined for the non-GIIPS countries across all maturity buckets due to lowered trading intensity for non-GIIPS bonds, as evidenced by the smaller quoted depths for those benchmarks. Relative spreads of non-GIIPS countries narrowed during the crisis period. The market quality index of non-GIIPS countries declines from its pre-crisis levels across the 2-, 5- and 10-year maturity segment and increases across the longest maturity benchmarks. The quote slope liquidity proxy consistently increases in the crisis period for GIIPS countries, whereas it declines for the 10- and 30-year non-GIIPS instrument showing that the effect of smaller spreads dominates the decline of quoted depths.6

⁵ As the 5-minute returns are continuously compounded the summation of the 5-minute returns over the 5-minute intervals is equivalent to the daily return. We also experimented with daily bond excess returns, in line with Gargano et al. (2019), in place of raw returns. We used a daily risk-free return estimated from daily data on the 1-month German bond yield. Subsequent results do not depend on whether we use bond returns or bond excess returns (given we are using daily data this is not surprising) so we elect to rely on raw bond returns estimated from the high-frequency MTS dataset.

⁶ We have experimented with pair-wise correlations of bond returns across the term-structure for representative countries within the GIIPS and non-GIIPS markets. We have documented a large drop in correlations across returns measures, however, the term structure of bond return correlations remains upward sloping in the crisis period, as longer-term bonds exhibit higher correlations than shorter-terms bonds. This finding is in line with the predictions and findings in Jotikasthira et al. (2015) whose model predicts two main channels will contribute to the comovement of international yield curves. The first channel, referred to as a monetary policy channel, stems from the factors that drive the yield curves and has a larger contribution to the short end of the yield curve. The second main channel, referred to as a risk premium channel, stems from the risk premia that connect the pricing of bonds to the real world dynamics of the factors that drive yield curves and makes a larger contribution to the long end of the yield curve. As eurozone countries follow a common monetary policy but have country dependent liquidity and credit components, it seems plausible to conclude that the risk premium channel is more relevant in our analysis. The fact that return correlations drop during the crisis can be largely attributed to large drops in the liquidity factor as explained by Acharya and Schaefer (2006). Liquidity shocks during periods of market distress coincide with negative asset value shocks, as market illiquidity covaries with negative shocks to market returns. That is, the decline in return correlations during the crisis period can be largely attributed to large drops in the liquidity factor. Our findings are in line with those of Longin and Solnik (2001) who show that return correlations between markets and between assets are higher in crisis periods, that is, correlation increases in bear markets but not in bull markets. Drops in correla-

Table 2 Summary statistics of tightness, depth, and multidimensional liquidity measures along with volatility over the pre-crisis and crisis periods and in both non-GIIPS and GIIPS countries. Mean values are reported for relative spread, quoted depth, quote slope, market quality index and realized volatility across the 2-, 5-, 10-, and 30-year maturity segments. The summary statistics are measured at a daily frequency and span the period from January 2008 to December 2013. The pre-crisis refers to the period from January 2008 to October 2009 whilst the crisis refers to the period from November 2009 to December 2013.

| Period | Region | Relative spread (bps) | Quoted depth | Quote slope | MQI (€ Bil) | RV (%) |
|------------|-----------|-----------------------|--------------|-------------|-------------|--------|
| 2-Year | | | | | | |
| Pre-crisis | Non-GIIPS | 9.17 | 27.31 | 0.003 | 28.17 | 0.11 |
| | GIIPS | 14.49 | 23.16 | 0.005 | 24.01 | 0.13 |
| Crisis | Non-GIIPS | 8.63 | 23.44 | 0.004 | 25.88 | 0.01 |
| | GIIPS | 33.02 | 21.50 | 0.009 | 19.66 | 0.44 |
| 5-Year | | | | | | |
| Pre-crisis | Non-GIIPS | 14.91 | 29.98 | 0.005 | 23.87 | 0.20 |
| | GIIPS | 23.18 | 27.34 | 0.007 | 20.53 | 0.22 |
| Crisis | Non-GIIPS | 13.88 | 24.95 | 0.007 | 20.50 | 0.16 |
| | GIIPS | 31.15 | 23.22 | 0.022 | 10.01 | 0.30 |
| 10-Year | | | | | | |
| Pre-crisis | Non-GIIPS | 27.76 | 28.64 | 0.009 | 16.91 | 0.36 |
| | GIIPS | 34.63 | 25.36 | 0.011 | 11.37 | 0.37 |
| Crisis | Non-GIIPS | 24.87 | 26.55 | 0.008 | 15.88 | 0.35 |
| | GIIPS | 50.21 | 20.54 | 0.026 | 5.88 | 0.46 |
| 30-Year | | | | | | |
| Pre-crisis | Non-GIIPS | 61.71 | 11.09 | 0.021 | 1.45 | 0.75 |
| | GIIPS | 68.71 | 10.52 | 0.021 | 1.26 | 0.79 |
| Crisis | Non-GIIPS | 33.25 | 10.99 | 0.019 | 2.01 | 0.67 |
| | GIIPS | 70.92 | 10.48 | 0.032 | 1.10 | 0.60 |

Fig. 1a and b present, respectively, the average relative spreads and quoted depths on 10-year benchmark bonds from non-GIIPS and GIIPS countries. The figure includes important macroeconomic events that impact liquidity in both regions. The events selected include the Bear Stearns and Lehman Brothers collapse, Greece's disclosure of the 2009 revised budget deficit, Dubai World's sixmonth debt moratorium, various downgrades on Greece's credit rating by Fitch, Moody's and Standard & Poor's, Greece's € 110 billion bailout package, the launch of the ECB's Securities Market Programme (SMP) and EU finance ministers agreeing on an additional € 750 billion in financial assistance available to vulnerable European countries, Ireland's € 85 billion bailout, Portugal's € 78 billion bailout, Greek debt restructuring referred to as private sector *involvement*, or PSI, Spain's € 100 billion bailout, Mario Draghi's "Whatever it takes" speech, Spain receiving an additional € 40 billion for its nationalised banks, and the Greek bond buyback programme.

Looking at Fig. 1a, relatives spreads are generally higher for GI-IPS bonds than for non-GIIPS bonds and this difference increases further in the crisis period as liquidity deteriorates in a more pronounced way for GIIPS bonds. We see an increase in relative spreads around the first set of credit rating downgrades in November 2009. The second set of credit rating downgrades in April 2010 are associated with further increases in relative spreads. Relative spreads fall after the EU bailout and Ireland bailout announcements. Late 2011 and early 2012 was perhaps the most volatile period of the sovereign bond crisis and the link between macroeconomic announcements and relative spreads attenuates however, there is a general decrease in relative spreads in 2012 and into 2013 as further bailout announcements are made along with Mario Draghi's "Whatever it takes" speech in July 2012 followed a week later by the ECB announcing a programme to buy the bonds of its distressed countries, known as Outright Monetary Transactions. In Fig. 1b we observe that non-GIIPS quoted depths are generally

tions can also be explained as evidence against contagion and in favour of a decoupling across sovereign bond markets during the crisis, consistent with results of Beirne and Fratzscher (2013), Claeys and Vašíček (2014), and O'Sullivan and Papavassiliou (2019). Along these lines, Blatt et al. (2015) find that Europe is heterogeneous and the diffusion of financial shocks is not uniform across the euro-area.

higher than GIPS quoted depths and this difference becomes larger as we move from the pre-crisis to the crisis period. Quoted depths fall after negative events and credit ratings downgrade announcements. Quoted depths tend to rise after interventions by the ECB in terms of bailouts or additional funding commitments.

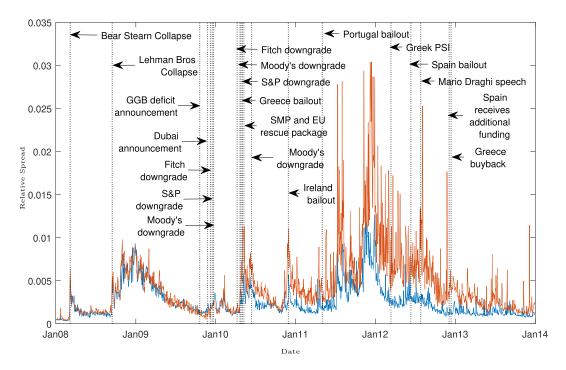
4. Empirical results

We divide our empirical findings into six main sections. The first section investigates commonality in liquidity across the yield curve during the pre-crisis and crisis periods. The second section discusses Granger causalities and the interlinkages between bond returns, volatility, liquidity and credit risk, whilst the third section provides some robustness tests on those causalities. The fourth and fifth sections examine Impulse Response Functions and the pricing of liquidity, and the sixth section refers to the pricing of systematic liquidity risk.

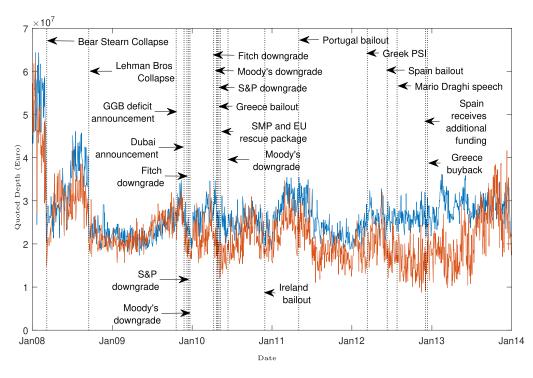
4.1. Commonality of liquidity measures

We use principal components analysis (PCA) to show that common factors exist in liquidity levels as measured by relative spreads and quoted depths. Prior to applying PCA we standardize our series to have zero mean and unit variance in order to prevent the first principal component from being overwhelmed by the most volatile variable. Generally speaking, longer maturity bond liquidity measures are more volatile than shorter maturity liquidity measures so more weight is given to the long bond liquidity measures if the data is not standardized. Subsequently, we apply PCA separately to the GIIPS and non-GIIPS regions to extract common liquidity factors from a cross-section of different maturities.

We use all countries within the GIIPS and non-GIIPS regions using two different sets of data. First we employ bond relative spread and quoted depth data for each individual country at four maturities (2-, 5-, 10-, and 30-year) (termed the 'full' set of data) and in a second step we construct relative spread and quoted depth measures at four maturities (2-, 5-, 10-, and 30-year) by equally weighting each individual bond liquidity measure (either relative spread or quoted depth) available at a given maturity (termed the 'index' data). The index data thereby focuses on the liquidity yield



(a) Relative Spreads: GIIPS (red) and non-GIIPS (blue)



(b) Quoted Depths: GIIPS (red) and non-GIIPS (blue)

Fig. 1. Plots of the 10-year mean relative spread for GIIPS and non-GIIPS countries (upper panel) and the 10-year mean quoted depth for GIIPS and non-GIIPS countries (lower panel) around important macroeconomic events. The sample period extends from January 2008 to December 2013.

curve by averaging away individual country effects. The initial preprocessed data in the index data contains the liquidity measures, averaged across countries in a given region, at the four different maturities. Whereas, the initial pre-processed data in the full dataset contains the individual country liquidity measures, at the four different maturities, for each country in a given region. Panel A of Table 3 depicts the PCA analysis for non-GIIPS bond relative spreads across the full data set and the index data, while Panel B reports the corresponding results for quoted depth measures. The amount of liquidity variation explained by the first two factors drops during the crisis period but still remains at high levels, although lower than the corresponding levels of commonality

Table 3

Principal component analysis (PCA) is applied to non-GIIPS relative spreads (Panel A) and non-GIIPS quoted depths (Panel B) using a full set of individual non-GIIPS sovereign bond relative spreads (quoted depths) and using non-GIIPS relative spread (quoted depth) index measures constructed at four maturities (2-, 5-, 10-, and 30-year) by equally weighting all available individual bond relative spreads (quoted depths) at a given maturity. The pre-crisis refers to the period from January 2008 to October 2009 whilst the crisis refers to the period from November 2009 to December 2013.

Panel A: Relative spreads % variation explained by PCA

| | Pre-crisis | | Crisis | |
|---------------------------------|------------------------------|------------------|------------------|------------------|
| | Full | Index | Full | Index |
| PCA 1 PCA 1+2 | 72.17% 77.73% | 89.39% 94.42% | 54.48% 60.81% | 81.22% 90.67% |
| Panel B: Quot % variation ex | ed depths aplained by PCA | | | |
| | Pre-crisis | | Crisis | |

| | Pre-crisis | | Crisis | |
|---------|------------|--------|--------|--------|
| PCA 1 | 53.62% | 81.50% | 20.68% | 40.06% |
| PCA 1+2 | 61.64% | 90.72% | 31.02% | 64.91% |

Table 4

PCA 1+2

Principal component analysis (PCA) is applied to GIIPS relative spreads (Panel A) and GIIPS quoted depths (Panel B) using a full set of individual GIIPS sovereign bond relative spreads (quoted depths) and using GIIPS relative spread (quoted depth) index measures constructed at four maturities (2-, 5-, 10-, and 30-year) by equally weighting all available individual bond relative spreads (quoted depths) at a given maturity. The pre-crisis refers to the period from January 2008 to October 2009 whilst the crisis refers to the period from November 2009 to December 2013.

Panel A: Relative spreads % variation explained by PCA

66.16%

| | Pre-crisis | | Crisis | |
|---------------------------------|------------------------------|------------------|------------------|------------------|
| | Full | Index | Full | Index |
| PCA 1 PCA 1+2 | 68.49% 77.54% | 91.91% 95.78% | 63.47% 76.15% | 70.09% 90.43% |
| Panel B: Quot % variation ex | ed depths eplained by PCA | | | |
| | Pre-crisis | | Crisis | |
| PCA 1 | 56.38% | 79.88% | 33.68% | 56.33% |

documented in the GIIPS region and shown in Table 4 (with the exception of spread commonality at the Index level).

92.30%

62.74%

78 16%

Panel A of Table 4 reports the proportion of variation in GIIPS relative spreads explained by the first and second principal components using the full set and the index relative spread values. In the pre-crisis period the first principal component explains 68.49 percent of the variation in the full cross-section of relative spreads considered whilst the first principal component from the index explains 91.91 percent of total variation. The proportion of variation explained by the first two principal components amounts to 77.54 percent for the full set and 95.78 percent for the index data, respectively. Although the first PCA factors extracted from the full and the index data are nearly identical, the explanatory power of the first PCA factor is lower in the full data relative to the index data due to larger presence of idiosyncratic liquidity components in the full data. In the index data these idiosyncratic liquidity components are reduced as the index liquidity measure at a given maturity is an average of individual liquidity measures. We note that the correlation of the full and index first PCA is very high indicating that the PCA is close to an equally weighted average of the individual bond liquidity measures.⁷

In the crisis period, the amount of variation in relative spreads explained by the first principal component drops to 63.47 percent for the full set of data and remains reasonably high at 70.09 percent for the index bond relative spreads. The amount of total variation explained by the first two principal components is also very high for both the full and index groups. These findings suggest that spread measures exhibit significant commonalities during both pre-crisis and crisis periods, providing evidence that variation in liquidity has a strong common component. It is also suggested that the evidence of liquidity commonality found in equity markets such as that documented by Coughenour and Saad (2004) can carry over to the context of bond markets.

Panel B of Table 4 reports the proportion of variation in GIIPS quoted depths explained by the first two principal components. Although the amount of variation in depths explained by PCA drops in the crisis period for both the full set and the index data, it is still reasonably high at 62.74 and 78.16 percent, respectively. However, commonality in depths appears to be lower than commonality in spreads, as shown in Panel A of the table. Comparing GIIPS and non-GIIPS commonality we can see that commonality in liquidity is more pronounced in the GIIPS region during the crisis where liquidity dry-ups are more apparent.

Commonality in liquidity is weaker during the crisis period for both GIIPS and non-GIIPS countries. In the crisis period GI-IPS bonds experience significant price declines whilst commonality in liquidity remains high whereas non-GIIPS experience price increases and a large drop in commonality. These results are in line with those of Karolyi et al. (2012) who examine commonality in liquidity in global equity markets and find that commonality is high in periods of price declines and weakens in periods of price increases. Thus, there appears to be an asymmetric volatility effect on commonality with GIIPS commonality weakening (albeit only slightly) when GIIPS volatility intensifies as we move from the calm to the turbulent period (see Table 2 column 7) whereas non-GIIPS commonality weakens (much more significantly than GIIPS commonality) whilst non-GIIPS realized volatility falls across all maturities as we move into the crisis period.

Overall our findings show that both spread and depth measures exhibit significant commonalities and this evidence is stronger for spread than depth liquidity proxies. Additionally, we show that the magnitude of liquidity commonality is higher in the GIIPS region where market-wide liquidity risk is higher.⁹ The following re-

 $^{^{7}}$ The first factor PCA weights (not reported in the interests of space) are very close to being equally weighted on both the individual bond relative spreads and the index relative spreads.

⁸ We have also experimented with liquidity innovations using residuals from fitted autoregressive AR models estimated with spread or depth time series data. Commonality in liquidity appears to be much weaker when innovations in liquidity are employed, as the first two principal components explain a lower proportion of liquidity variation. We prefer to work with liquidity levels instead of innovations, similar to Hasbrouck and Seppi (2001), as analysis of levels is more economically meaningful and more appropriate for inclusion in a PCA framework.

⁹ The primary dealer system is not uniformly applied across eurozone countries. It would be interesting to investigate whether there is commonality in liquidity among countries that impose similar restrictions to MTS market makers. We follow Dunne et al. (2006) and categorize countries on MTS with respect to their issuance techniques and the secondary market obligations they impose. The first group consists of Italy, Portugal, Austria, Belgium, and Finland. These countries exhibit similar characteristics in terms of their use of syndicated issuance and the imposition of secondary market obligations on primary dealers. The second group consists of Germany and France. Germany has a unique structure as it never issues by syndication and imposes no obligations on primary dealers. This affects the willingness of dealers to participate in the secondary market. France shares common features with Germany, such as very little syndication activity and no obligation for primary dealers to participate in the secondary market. The third group consists of Spain and Greece. Both countries do not impose secondary market obligations that are

marks are in order. The factor loadings on the first factor extracted from principal component analysis applied to the liquidity measures are positive across all countries within a non-GIIPS or GI-IPS region. For example, focusing on the non-GIIPS region, the first principal component extracted from individual relative spreads of non-GIIPS bonds is approximately equally weighted across the individual bond relative spread measures in the region. This holds for both non-crisis and crisis periods. We do not observe a negative weight on Germany and positive weights on the remaining non-GIIPS countries. A similar result is found in the GIIPS region. Thus, the first factors extracted from the liquidity measures can be thought of as a proxy for the level or average value of the liquidity measure across maturities. This is analogous to applying PCA to yield curves, using bond yields within a country or region, and where the first PCA factor is often interpreted as the level of the yield curve (see Litterman and Scheinkman, 1991).

4.2. Granger causality

To examine causality and interlinkages between volatility, bond returns across the term structure, liquidity measures, and CDS spreads between GIIPS and non-GIIPS regions we use the following VAR model:

$$X_{t} = \sum_{j=1}^{K} a_{1j} X_{t-j} + \sum_{j=1}^{K} b_{1j} Y_{t-j} + u_{t}$$
 (1)

$$Y_{t} = \sum_{i=1}^{K} a_{2j} X_{t-j} + \sum_{i=1}^{K} b_{2j} Y_{t-j} + \nu_{t}$$
 (2)

In this system the vectors X and Y are given by:

$$X = \left(RV_{10}^{NG}, RET_{2}^{NG}, RET_{5}^{NG}, RET_{10}^{NG}, RET_{30}^{NG}, RS^{NG}, QD^{NG}, CDS^{NG}\right)$$
(3)

$$Y = (RV_{10}^{G}, RET_{2}^{G}, RET_{5}^{G}, RET_{10}^{G}, RET_{30}^{G}, RS^{G}, QD^{G}, CDS^{G})$$
(4)

The first entry of the vector X(Y) consists of a single region-specific volatility measure, denoted as RV^{NG} and RV^G for the non-GIIPS and GIIPS regions. We use the 10-year bond return realized volatility for each region. To investigate term structure effects, the next four entries of X(Y) are non-GIIPS (GIIPS) bond returns, denoted as $RET_T^{NG}\left(RET_T^G\right)$, where T is one of the usual four maturities of 2-, 5-, 10- and 30-years. The next entries of X(Y) consist of two non-GIIPS (GIIPS) liquidity measures where $RS^{NG}(RS^G)$ denotes the first principal component extracted from non-GIIPS (GIIPS) bond relative spreads using maturities of 2-, 5-, 10- and 30-years and where $QD^{NG}(QD^G)$ denotes the first principal component extracted from non-GIIPS (GIIPS) quoted depths using quoted depths at the four maturities. The final entries consist of the mean premia for 5-year CDS contracts in each region denoted as $CDS^{NG}(CDS^G)$.

The previous section on liquidity commonality motivates the use of a single relative spread and quoted depth factor for each of non-GIIPS and GIIPS regions. This reduces the dimensionality of the VAR allowing us to focus on the impact of liquidity on the term structure of returns using information from within and

between each region. The ordering of the variables in the VAR is as follows: RV_{10}^{NG} , RV_{10}^{G} , RET_{20}^{NG} , RET_{5}^{NG} , RET_{10}^{NG} , RET_{30}^{G} , RET_{20}^{G} , RET_{5}^{NG} , RET_{10}^{NG} , RET_{30}^{G} , RET_{30}^{G} , RS^{NG} , QD^{NG} , RS^{G} , QD^{G} , CDS^{NG} , CDS^{G} . The ordering of volatility before returns with liquidity measures placed after returns is motivated by the VAR variable ordering used in Chordia et al. (2005) and in Goyenko et al. (2011). Non-GIIPS measures are placed before GIIPS measures given the higher liquidity and larger size of the non-GIIPS markets. The number of lags in the VAR are chosen using a log likelihood ratio test with Sims correction, Sims (1980), to test K lags versus K-1 lags and find that the model does not deteriorate in a statistically significant manner at the 1 percent significance level if we choose K to be 3 lags in both the pre-crisis and crisis periods.

Table 5 depicts Granger causality p-values (to ease the interpretation we leave the entry blank if p-values are statistically insignificant at 10%) with Panel A depicting the pre-crisis period results and Panel B depicting the crisis period results. In the precrisis period the 10-year GIIPS realized volatility Granger causes itself which is to be expected given the high persistence of volatility. There is evidence of causality flowing from GIIPS volatility to GIIPS relative spreads which is consistent with Benston and Hagerman (1974) and Duffie et al. (2007) who suggest an increase in volatility increases inventory risk leading to higher bid-ask spreads. Table 5 also provides evidence of 10-year non-GIIPS and GIIPS returns Granger causing 30-year non-GIIPS and GIIPS returns. This suggests that information gets reflected into 10-year benchmark returns first in both regions before flowing into the 30-year ownmarket and cross-market returns which is consistent with the 10year return being a benchmark return.

One of the most striking results in Table 5 is of GIIPS quoted depth (and to a lesser extent non-GIIPS quoted depth) Granger causing GIIPS and non-GIIPS 2-, 5-, and 10-year returns, as well as own market and cross-market quoted depth illiquidity. We investigate these dynamics further in the next section on Impulse Response Functions but the evidence points to liquidity being a priced factor with GIIPS illiquidity playing a larger role than non-GIIPS illiquidity in the pre-crisis period.

In the crisis period, depicted in Panel B of Table 5, realized volatility Granger causes future own-market realized volatility in both markets. It also exerts significant influence on all maturities GIIPS returns (and almost all non-GIIPS returns), and on non-GIIPS and GIIPS relative spreads and CDS spreads. The 2-year non-GIIPS and GIIPS return Granger causes various maturities of ownmarket and cross-market returns, suggesting that information is reflected first into the 2-year bond return before propagating up the yield curve to affect longer maturity returns, indicating that the 2-year benchmark bonds reflect crisis period information before longer maturity bonds. Nevertheless, the 10-year GIIPS return is the most influential in the crisis as it Granger causes non-GIIPS and GIIPS volatility, returns, and illiquidity. There is also evidence of non-GIIPS and GIIPS returns Granger causing relative spreads in both regions. These results are in agreement with Chordia et al. (2005) where return and liquidity comovements across U.S. stocks and bonds are analysed and evidence of bidirectional causalities between returns and liquidity is found, with returns causing liquidity through their influence on future trading behaviour. The authors also show that there is a bidirectional causality between quoted spreads and volatility as we found.

Our results on GIIPS and non-GIIPS illiquidity Granger causing cross-market returns at most maturities are also analogous to the results in Goyenko et al. (2011) in their study of U.S. Treasury bonds where off-the-run illiquidity is found to Granger cause both on-the-run and off-the-run bond returns of all maturities. That is, the class of bonds more sensitive to illiquidity (GIIPS in our case, off-the-run issues in Goyenko et al., 2011) are the first to respond to a deterioration in liquidity which subsequently impacts

specific to the MTS platforms. We then apply principal components analysis (PCA) to identify whether there is commonality in liquidity in each group of countries. We document positive liquidity factor loadings across all countries in each group and find that commonality drops as we move from pre-crisis to crisis. We also ran PCA on the three combined groups to see if the factor loadings might be positive on one group and negative on another, that is, if different signs appeared on the factor loading we might interpret this as different liquidity responses across the three groups. However, the results showed this is not the case. Conclusively, whilst the primary dealer system is not uniformly applied across eurozone countries, this does not seem to affect the secondary market spread and depth liquidity measures.

10 The results are very similar if we use the first principal component extracted from realized volatilities at 2-, 5-, 10- and 30-years for each region.

Table 5

This table presents p-values of pairwise Granger causality tests between endogenous VAR variables using non-GIIPS (NG) and (GIIPS) G data over the pre-crisis period (Panel A) and the crisis period (Panel B). The null hypothesis is that the column variable does not Granger-cause the row variable. Bond illiquidity estimates are based on relative spreads (RS-(N)G) and quoted depths (QD-(N)G) extracted from a PCA on four maturities $T \in \{2-, 5-, 10-, \text{ and } 30-\text{years}\}$. R-(N)G-T is the return on a T-year bond with $T \in \{2-, 5-, 10-, \text{ and } 30-\text{years}\}$. V-(N)G-10 is the daily realized volatility of returns on a 10-year bond and is estimated as the summation of squared 5-minute returns. CDS-(N)G is the mean premia for 5-year credit default swaps (CDS) contracts in each region. The pre-crisis refers to the period from January 2008 to October 2009 whilst the crisis refers to the period from November 2009 to December 2013.

| | <i>p</i> -values: 1 | Do column | factors G | ranger caus | se the row | factors? | | | | | | | | | | |
|------------|---------------------|-----------|-----------|-------------|------------|----------|-------|-------|--------|--------|-------|------|-------|------|--------|-------|
| Panel A: P | re-crisis | | | | | | | | | | | | | | | |
| | V-NG-10 | V-G-10 | R-NG-2 | R-NG-5 | R-NG-10 | R-NG-30 | R-G-2 | R-G-5 | R-G-10 | R-G-30 | RS-NG | RS-G | QD-NG | QD-G | CDS-NG | CDS- |
| V-NG-10 | | | | | | | | | | | | | | | | |
| V-G-10 | | 0.07 | | | | | | | | | | | | | | |
| R-NG-2 | 0.09 | | | | | | | | | | 0.07 | | | 0.06 | | |
| R-NG-5 | 0.09 | | | | | | | | | | | | 0.05 | 0.01 | | |
| R-NG-10 | 0.03 | | | | | | | | | | | | 0.04 | 0.02 | | |
| R-NG-30 | 0.01 | 0.09 | | | 0.00 | | | | 0.00 | | | | | | | |
| R-G-2 | | | | | | | | | | | | | | 0.02 | | 0.06 |
| R-G-5 | | | | | | | | | 0.03 | 0.08 | | | | 0.01 | | |
| R-G-10 | | | | | | 0.02 | | | 0.03 | | | | | 0.02 | | 0.01 |
| R-G-30 | 0.00 | 0.05 | | | 0.00 | 0.02 | | | 0.00 | | | | | | 0.00 | 0.06 |
| RS-NG | | | | | | | | | | | 0.00 | 0.00 | | | | |
| RS-G | | 0.07 | | | | | | | | | | 0.00 | | | | |
| QD-NG | | | | | | | | | | | | | 0.00 | 0.00 | | |
| QD-G | | | | | | | | | | | | | 0.00 | 0.00 | | |
| CDS-NG | 0.01 | 0.07 | | | | | | 0.07 | | | 0.04 | 0.08 | | 0.00 | 0.00 | 0.00 |
| CDS-G | 0.01 | 0.07 | | | | | | 0.10 | | | 0.01 | 0.00 | | | 0.09 | 0.00 |
| Panel B: C | Crisis | | | | | | | | | | | | | | | |
| | V-NG-10 | V-G-10 | R-NG-2 | R-NG-5 | R-NG-10 | R-NG-30 | R-G-2 | R-G-5 | R-G-10 | R-G-30 | RS-NG | RS-G | QD-NG | QD-G | CDS-NG | CDS-0 |
| V NC 10 | | | | | | | | | | | | | | | | |
| V-NG-10 | 0.00 | 0.03 | 0.00 | 0.04 | | | 0.04 | 0.08 | 0.09 | 0.08 | 0.01 | 0.00 | | | 0.00 | 0.01 |
| V-G-10 | | 0.00 | 0.00 | 0.04 | | | 0.04 | | 0.02 | 0.01 | | 0.00 | | | 0.02 | 0.00 |
| R-NG-2 | | 0.05 | | 0.06 | | | | 0.07 | 0.07 | | | 0.04 | | | 0.07 | |
| R-NG-5 | 0.04 | 0.04 | | | | | 0.04 | 0.07 | 0.00 | | | 0.01 | | | 0.07 | |
| R-NG-10 | 0.04 | 0.00 | 0.00 | | | | 0.04 | | 0.06 | | | 0.02 | | | 0.01 | |
| R-NG-30 | | 0.06 | 0.06 | | | | 0.08 | | 0.00 | | | 0.00 | | | | |
| R-G-2 | 0.01 | 0.01 | | | | | 0.00 | 0.01 | | | | | | | | |
| R-G-5 | 0.04 | 0.03 | 0.07 | | 0.04 | | | 0.09 | | | 0.08 | | | | | |
| R-G-10 | 0.01 | 0.10 | | | | | | | 0.05 | 0.05 | | | | | | |
| R-G-30 | 0.04 | 0.06 | 0.05 | 0.08 | | | 0.05 | | 0.00 | | 0.02 | | | | | |
| RS-NG | 0.07 | | 0.01 | 0.00 | 0.08 | | | | 0.07 | | 0.00 | 0.00 | | | | 0.00 |
| RS-G | 0.00 | | 0.01 | | 0.02 | 0.05 | | | 0.00 | | | 0.00 | | | | |
| QD-NG | | | | | | | | | | | 0.05 | | 0.00 | | | |
| QD-G | | | | | | | | | | | | | | 0.00 | | |
| CDS-NG | 0.01 | 0.00 | | | | | | | | | 0.04 | 0.00 | | | 0.00 | |
| CDS-G | 0.00 | 0.03 | | | | | | 0.02 | | | | | | | 0.04 | 0.00 |

both own-market and cross-market returns and volatilities. Quoted depth measures manage to Granger cause only their own-market illiquidity in the crisis period, whereas relative spreads do a better job in Granger causing non-GIIPS and GIIPS volatility, returns, illiquidity and credit risk. Thus, GIIPS and non-GIIPS returns are impacted by cross-market illiquidity in the crisis period as measured by relative spreads, whereas quoted depth-based illiquidity is stronger in the pre-crisis period. Quoted depths and relative spreads are inversely related but both are related to a common latent liquidity component. In the pre-crisis period quoted depths tend to knock out the significance of relative spreads however, in the crisis period quoted depths fall to very low levels and become less informative than relative spreads (see for example Coluzzi et al., 2008; Beber et al., 2009 for a discussion on this documented inverse relation between spreads and depths).

To sum up, the most important variables in the Granger sense are liquidity proxies and realized volatility in both regions. Non-GIIPS and GIIPS returns have equal importance in terms of causing other variables in the pre-crisis but GIIPS returns are more dominant in the crisis. CDS spreads do not Granger cause realized volatility in the pre-crisis but do in the crisis whereas volatility Granger causes volatility in both periods. CDS spreads exert no impact on liquidity pre-crisis, whilst they impact minimally on liquidity in the crisis period (GIIPS CDS Granger causes non-GIIPS rela-

tive spread). However, relative spreads Granger cause CDS spreads significantly in both the pre-crisis and crisis periods. This finding shows that although we have accounted for sovereign credit risk, the effect credit risk has on liquidity and commonality in liquidity is negligible. Thus, the Granger causality analysis further reinforces the previous results on commonality in liquidity confirming the fact that we actually measure common liquidity factors and not common credit risk factors.

4.3. Robustness tests on Granger causality

The previous section motivates the use of a single relative spread and quoted depth PCA factor for each of the non-GIIPS and GIIPS regions. This keeps the dimensionality of the VAR reasonably low allowing us to focus on the level of liquidity and the impact this has on the term structure of returns using information from within and between each region. By focusing our attention on the first PCA factor extracted from the regional liquidity measures at the four different maturities, we aim to capture the first order effects of liquidity and how it impacts volatility, returns, and credit spreads. However, the fact that the analysis is concentrated on the first liquidity factor may leave out important second order effects, in particular for the crisis period.

Table 6

This table presents p-values of pairwise Granger causality tests between endogenous VAR variables using non-GIIPS (NG) and (GIIPS) G data over the pre-crisis period (Panel A) and the crisis period (Panel B). The null hypothesis is that the column variable does not Granger-cause the row variable. Bond illiquidity estimates are based on relative spreads (RS-(N)G-1, RS-(N)G-2) and quoted depths (QD-(N)G-1, QD-(N)G-2) extracted from the first two PCA components applied to 4 maturities $T \in \{2-, 5-, 10-, \text{ and } 30-\text{ years}\}$. R-(N)G-10 is the return on a 10-year maturity bond. V-(N)G-10 is the daily realized volatility of returns on a 10-year bond and is estimated as the summation of squared 5-minute returns. CDS-(N)G is the mean premia for 5-year credit default swaps (CDS) contracts in each region. The pre-crisis refers to the period from January 2008 to October 2009 whilst the crisis refers to the period from November 2009 to December 2013.

| | p-values: I | Do column | factors Gran | nger cause | the row fact | ors? | | | | | | | | |
|-------------|-------------|-----------|--------------|------------|--------------|---------|--------|--------|---------|---------|--------|--------|--------|-------|
| Panel A: Pi | re-crisis | | | | | | | | | | | | | |
| | V-NG-10 | V-G-10 | R-NG-10 | R-G-10 | RS-NG-1 | RS-NG-2 | RS-G-1 | RS-G-2 | QD-NG-1 | QD-NG-2 | QD-G-1 | QD-G-2 | CDS-NG | CDS-G |
| V-NG-10 | | | | | | | | | | | | | | |
| V-G-10 | | 0.08 | | | 0.08 | | 0.07 | | | 0.08 | | | | |
| R-NG-10 | 0.04 | | | | | | | | | | 0.05 | | | |
| R-G-10 | | | 0.00 | 0.01 | | | | | | | 0.10 | | | 0.01 |
| RS-NG-1 | | | | | 0.00 | | 0.00 | 0.03 | | 0.07 | | | | 0.09 |
| RS-NG-2 | | | | | | 0.00 | | 0.00 | | | | | | |
| RS-G-1 | | | 0.07 | 0.06 | | | 0.00 | | | | | | | |
| RS-G-2 | 0.08 | 0.01 | | | | | | 0.00 | | | | | 0.07 | |
| QD-NG-1 | | | | | | | | | 0.00 | 0.00 | 0.00 | | | |
| QD-NG-2 | | | | | 0.01 | | | | 0.00 | 0.00 | 0.00 | | | |
| QD-G-1 | | | | | | | | | | 0.03 | 0.00 | 0.05 | | |
| QD-G-2 | | | | | 0.09 | | | | | 0.00 | | 0.00 | | |
| CDS-NG | 0.01 | 0.02 | | | 0.10 | 0.02 | 0.06 | 0.03 | | | | | 0.00 | 0.00 |
| CDS-G | | | 0.00 | 0.02 | | 0.02 | | | | | | | | 0.00 |
| Panel B: C | risis | | | | | | | | | | | | | |
| | V-NG-10 | V-G-10 | R-NG-10 | R-G-10 | RS-NG-1 | RS-NG-2 | RS-G-1 | RS-G-2 | QD-NG-1 | QD-NG-2 | QD-G-1 | QD-G-2 | CDS-NG | CDS-G |
| | V-NG-10 | V-G-10 | K-NG-10 | K-G-10 | K3-NG-1 | N3-NG-2 | K3-G-1 | N3-G-2 | QD-NG-1 | QD-NG-2 | QD-G-1 | QD-G-2 | CD3-NG | CD3-G |
| V-NG-10 | 0.00 | | | 0.06 | 0.00 | | 0.00 | 0.04 | | | | | | 0.04 |
| V-G-10 | 0.02 | 0.00 | | 0.03 | 0.00 | | 0.02 | 0.00 | | | | | 0.02 | 0.00 |
| R-NG-10 | 0.01 | | | | | 0.05 | 0.02 | | | | | | 0.00 | |
| R-G-10 | | 0.03 | | 0.00 | 0.04 | | | 0.04 | | | | | | 0.05 |
| RS-NG-1 | | | 0.10 | | 0.00 | 0.00 | 0.00 | | | | | | 0.10 | 0.00 |
| RS-NG-2 | 0.01 | | | | 0.00 | 0.00 | 0.05 | | | | 0.07 | 0.09 | 0.07 | 0.01 |
| RS-G-1 | 0.00 | 0.01 | 0.01 | | 0.01 | 0.09 | 0.00 | 0.10 | | | | | | 0.03 |
| RS-G-2 | 0.01 | 0.02 | 0.01 | | | | 0.00 | 0.00 | | | | | | |
| QD-NG-1 | | | | | 0.03 | | | | 0.00 | 0.02 | 0.08 | | | |
| QD-NG-2 | | | 0.07 | | | | | | | 0.00 | | | 0.03 | |
| OD-G-1 | | | | | | | | | | | 0.00 | 0.07 | | |
| QD-G-2 | | | | 0.07 | | | | | | | | 0.00 | | |
| CDS-NG | 0.01 | | | | 0.00 | 0.00 | 0.02 | 0.00 | | 0.06 | | 0.09 | 0.00 | |
| | 0.01 | | 0.02 | 0.07 | | 0.03 | | 0.01 | | | | | 0.02 | 0.00 |

To address this issue we include a second PCA liquidity factor for each liquidity measure (relative spreads and quoted depth) and for each region. This amounts to adding an additional four factors to the VAR model. The second PCA liquidity factor captures variation in the slope of the term structure of liquidity, a likely second order liquidity factor, but one that could provide important contributions to the VAR model. To keep the dimensionality of the VAR similar to the main VAR presented in Eqs. (3) and (4), we focus our attention on the 10-year bond return and leave out bond returns at other maturities. We also include the realized volatility and CDS spreads. In this alternative VAR model, there are eight PCA liquidity factors which include the first two PCA factors from relative spreads and quoted depths across both regions.

Table 6 presents Granger causality results from an estimate of the VAR model in Eqs. (1) and (2) but where the X and Y variables are given by:

$$X = (RV_{10}^{NG}, RET_{10}^{NG}, RS - PCA_1^{NG}, RS - PCA_2^{NG}, QD - PCA_1^{NG}, QD - PCA_2^{NG}, CDS^{NG})$$
(5)

$$Y = (RV_{10}^{G}, RET_{10}^{G}, RS - PCA_{1}^{G}, RS - PCA_{2}^{G}, QD - PCA_{1}^{G}, QD - PCA_{2}^{G}, CDS^{G})$$
(6)

To simplify the analysis we ignore the impact a liquidity measure has on itself and other liquidity measures and focus on the causal links from the liquidity measures to the other factors in the VAR. In the pre-crisis period, the majority of the Granger causal links that were present when using the first principal component for each liquidity measure, are also present when using the first

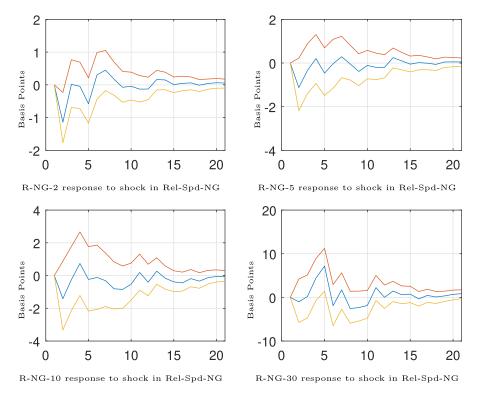
two principal components. Additional Granger causal links are also present when using two principal components.

In the crisis period, relative spread dominates quoted depth in its Granger causal impact on volatility, returns, and CDS premia. However, the addition of the second principal component for each liquidity measure in Table 6 does not contribute very much above what is already captured by the VAR using the four first principal component factors as presented in Table 5. We conclude that, whilst second order liquidity effects are certainly important, we do not bias our results by examining first order liquidity effects. Still, an analysis of the interaction between returns, volatility, and the slope of liquidity is certainly a very interesting topic for future research.

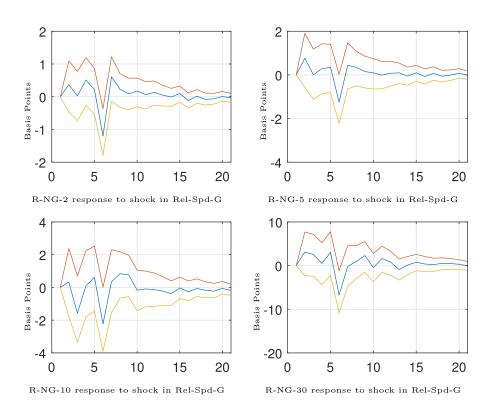
4.4. Impulse Response Functions: returns, volatility, and CDS spreads

In this and the following section we use Impulse Respone Functions (IRFs) to examine the impact of illiquidity on the term structure of bond returns and on volatility and credit risk. We also consider the reverse direction and examine the impact returns, volatility and credit risk have on illiquidity. We use IRFs from the VAR to account for the joint dynamics in the VAR system, unlike Granger causality that focuses on a single equation from the VAR.

Figs. 2–5 plot bond return IRFs at 2-, 5-, 10- and 30-year maturities to a one standard deviation shock to either non-GIIPS or GI-IPS relative spreads. In all plots the centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. Fig. 2a plots IRFs for the re-

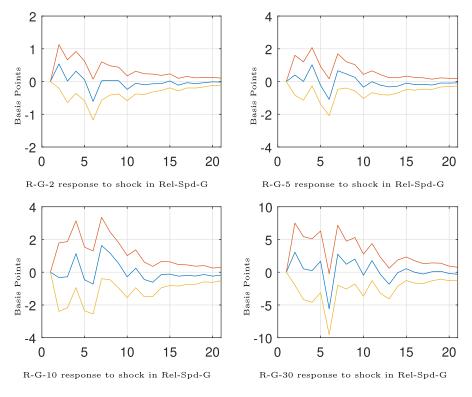


(a) Non-GIIPS Returns IRFs to shocks in non-GIIPS illiquidity

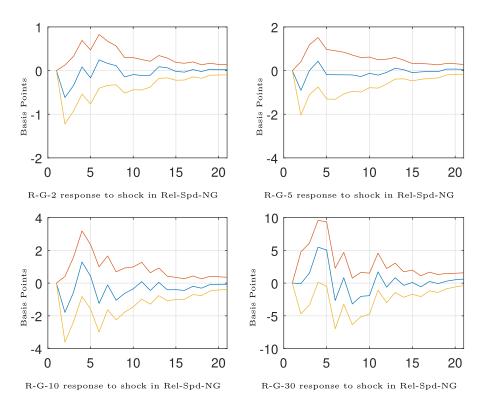


(b) Non-GIIPS Returns IRFs to shocks in GIIPS illiquidity

Fig. 2. Pre-crisis period non-GIIPS (NG) returns Impulse Response Functions (IRFs) to a one standard deviation shock to own-market NG relative spreads (upper panel (a)) or to cross-market GIIPS (G) relative spreads (lower panel (b)). The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The pre-crisis period extends from January 2008 to October 2009.

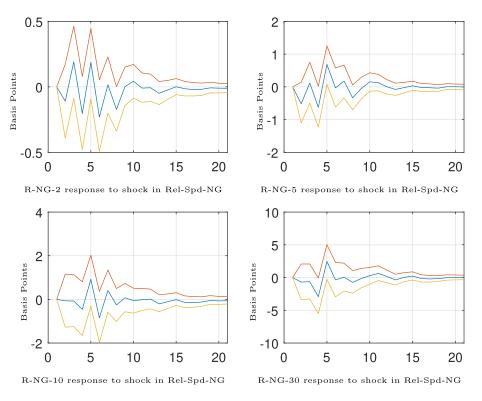


(a) GIIPS Returns IRFs to shocks in GIIPS illiquidity

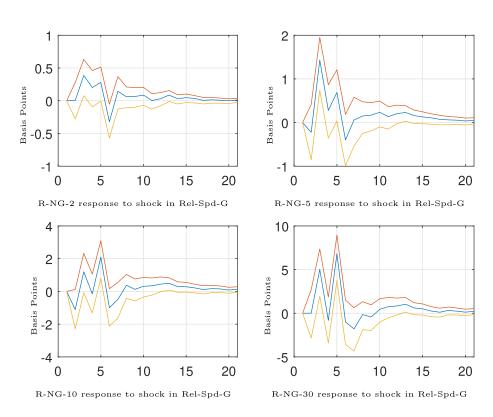


(b) GIIPS Returns IRFs to shocks in non-GIIPS illiquidity

Fig. 3. Pre-crisis period GIIPS (G) returns Impulse Response Functions (IRFs) to a one standard deviation shock to either own-market G relative spreads (upper panel (a)) or cross-market NG relative spreads (lower panel (b)). The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The pre-crisis period extends from January 2008 to October 2009.

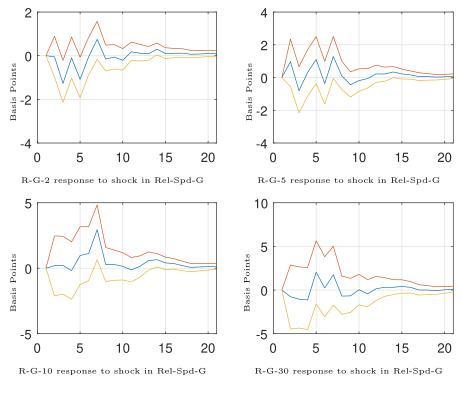


(a) Non-GIIPS Returns IRFs to shocks in non-GIIPS illiquidity

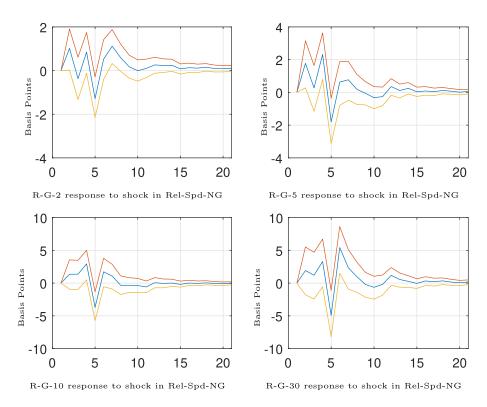


(b) Non-GIIPS Returns IRFs to shocks in GIIPS illiquidity

Fig. 4. Crisis period non-GIIPS (NG) returns Impulse Response Functions (IRFs) to a one standard deviation shock to either own-market NG relative spreads (upper panel (a)) or cross-market G relative spreads (lower panel (b)). The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The crisis period extends from November 2009 to December 2013.



(a) GIIPS Returns IRFs to shocks in GIIPS illiquidity



(b) GIIPS Returns IRFs to shocks in non-GIIPS illiquidity

Fig. 5. Crisis period GIIPS (G) returns Impulse Response Functions (IRFs) to a one standard deviation shock to either own-market G relative spreads (upper panel (a)) or cross-market NG relative spreads (lower panel (b)). The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The crisis period extends from November 2009 to December 2013.

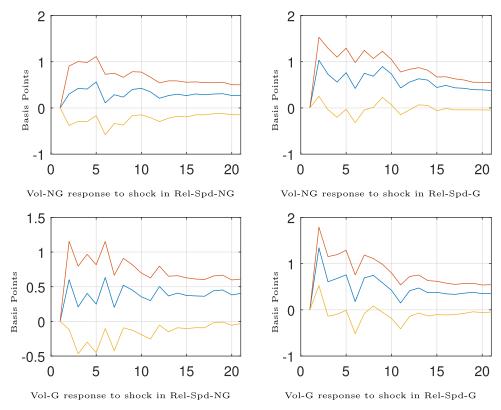


Fig. 6. Pre-crisis period non-GIIPS (NG) (upper panel) and GIIPS (G) (lower panel) volatility Impulse Response Functions (IRF) to a one standard deviation shock to either NG or G relative spreads. The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The pre-crisis period extends from January 2008 to October 2009.

turn on the four maturity non-GIIPS bonds to shocks in non-GIIPS relative spread in the pre-crisis period. A shock to own-market illiquidity statistically significantly decreases non-GIIPS returns at the 2-year maturity in the day following the shock, however, the effect on 5-, 10- and 30-year returns is not significant. The drop in returns in response to an illiquidity shock is consistent with results in Amihud (2002) where stock returns are shown to initially drop in response to an illiquidity shock.

Fig. 2b plots IRFs for the return on the four maturity non-GIIPS bonds to cross-market shocks in the relative spread of the GIIPS region bonds in the pre-crisis period. Here a shock to GIIPS illiquidity increases non-GIIPS returns at all maturities but this is followed by a subsequent decrease in returns at a lag of 5 to 6 days. The delayed decrease in returns, and not the initial increase, in non-GIIPS returns is statistically significant for the 2- and 30-year maturities and marginally statistically significant for the 5 and 10-year maturities.

Fig. 3a and b plots IRFs for the return on the four maturity GI-IPS bonds to shocks in own-market GIIPS (or cross-market non-GIIPS) relative spreads in the pre-crisis period. Shocks to own-market illiquidity increase GIIPS returns for the few days after the shock but subsequently, at around 5 to 6 days after the shock, returns decrease. The initial increase in returns is not significant and only the 30-year maturity has a decrease in return that is statistically significant. Shocks to cross-market illiquidity decrease GIIPS returns but not with any statistical significance. Thus, in the precrisis period there is weak evidence of liquidity having an impact on returns in the GIIPS region with returns generally decreasing in response to own-market and cross-market illiquidity shocks.

Fig. 4a and b plots IRFs for the return on the four maturity non-GIIPS bonds to shocks in non-GIIPS (GIIPS) relative spreads in the crisis period. Own market illiquidity shocks weakly impact non-GIIPS returns with relatively small decreases in returns

that are marginally statistically significant at the 5- and 30-year maturities. Cross-market illiquidity shocks have a stronger effect on non-GIIPS bonds. Returns on non-GIIPS bonds increase in a statistically significant manner, at lags of 3 to 5 days, across all maturities in response to shocks in cross-market illiquidity. Price pressure in the GIIPS markets, as a result of increased illiquidity, results in the non-GIIPS bonds appearing more attractive resulting in investors switching into non-GIIPS bonds causing increases in non-GIIPS returns initially. These results are consistent with Subrahmanyam (2007) where investors buy into REITS and sell out of the stock market in response to illiquidity shocks in the stock market.

Fig. 5a and b plots IRFs for the return on the four maturity GIIPS bonds to shocks in GIIPS (non-GIIPS) relative spreads in the crisis period. Own market illiquidity shocks result in GIIPS returns falling significantly for the 2-year maturity with insignificant responses for the other maturities. Cross-market shocks to illiquidity result in GIIPS returns initially increasing and subsequently decreasing with significance in both the initial increase and subsequent decrease for the 5- and 10-year maturities and significant decreases for the 2- and 30-year. Thus, the cross-market illiquidity shock initially makes the GIIPS bonds seem more attractive, relatively speaking, to the non-GIIPS bonds, but the factors that caused the illiquidity shock eventually spillover into the GIIPS market, some days later, reducing significantly GIIPS returns.

Figs. 6 and 7 plot Impulse Response Functions (IRFs) for realized volatility to a one standard deviation shock to either non-GIIPS or GIIPS relative spreads in the pre-crisis and crisis period. Fig. 6 demonstrates that pre-crisis period shocks to both own-market and cross-market illiquidity increases realized volatility by approximately 1 basis point in both non-GIIPS and GIIPS markets. Pre-crisis period shocks to non-GIIPS illiquidity increases realized volatility in both markets but not in a significant manner. The im-

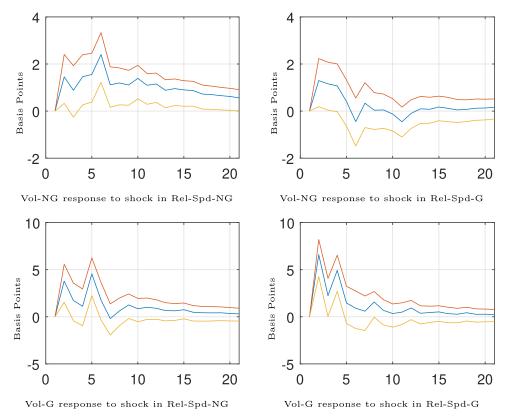


Fig. 7. Crisis period non-GIIPS (NG) (upper panel) and GIIPS (G) (lower panel) volatility Impulse Response Functions (IRF) to a one standard deviation shock to either NG or G relative spreads. The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The crisis period extends from November 2009 to December 2013.

pact of a GIIPS shock to illiquidity on volatility dies away very slowly. Thus, a deterioration in GIIPS liquidity subsequently impacts both own-market and cross-market volatilities. In the precrisis period, GIIPS illiquidity provides a more reliable forecast of future market turbulence in both regions than non-GIIPS illiquidity in line with Goyenko et al. (2011) who find that off-the-run treasury bond illiquidity (bonds that are more sensitive to illiquidity) forecast off-the-run and on-the-run treasury bond volatility.

Fig. 7 plot IRFs for realized volatility to a one standard deviation shock to either non-GIIPS or GIIPS relative spreads in the crisis period. As in the pre-crisis, shocks to GIIPS illiquidity causes GIIPS volatility and non-GIIPS volatility to rise with the shock persisting for a number of days. However, unlike in the pre-crisis period, shocks to non-GIIPS illiquidity also result in increased non-GIIPS and GIIPS volatility that take over 20 days to die out in the case of a non-GIIPS volatility response to a non-GIIPS illiquidity shock.

Next, we consider the IRFs of credit default swap (CDS) spreads in response to own market and cross-market shocks to illiquidity with Fig. 8 depicting pre-crisis IRFs and Fig. 9 depicting crisis IRFs. In the pre-crisis period, shocks to illiquidity in both regions impact 1-day ahead non-GIIPS CDS spreads but these quickly become insignificant at longer horizons. GIIPS CDS spreads are not impacted significantly by shocks to illiquidity in either region.

In the crisis, non-GIPS CDS spreads respond significantly to shocks in own-market illiquidity whereas, they are not affected by cross-market illiquidity shocks. GIIPS CDS spreads increase in a significant manner in response to both own-market and cross-market illiquidity shocks although, the response to cross market illiquidity shocks is more persistent in terms of statistical significance. Thus, own-market liquidity shocks are already priced into GIIPS CDS risk premia but this is not the case for cross-market liquidity shocks.

We also consider the reverse direction in terms of how shocks to CDS spread impact illiquidity. We plot the IRFs of relative

spreads in response to own market and cross-market shocks to CDS spreads with Fig. 10 depicting pre-crisis IRFs and Fig. 11 depicting crisis IRFs. Non-GIIPS illiquidity is not sensitive to ownmarket or cross-market shocks in CDS spreads in the pre-crisis period. However, GIIPS illiquidity initially falls but subsequently rises, with both decreases and increases statistically significant, in response to own-market and cross-market shocks to CDS spreads. In the period before the crisis, non-GIIPS illiquidity is not impacted by CDS spreads whereas, GIIPS illiquidity is significantly impacted by CDS spreads. In the crisis period, non-GIIPS illiquidity increases in a statistically significant manner in response to own-market CDS spread shocks. Non-GIIPS illiquidity rises, then falls and finally rises again in response to cross-market CDS spread shocks but these changes are insignificant at the 95 percent level. GIIPS illiquidity increases in response to own-market CDS spread shocks in a marginally significant manner. GIIPS illiquidity also increases with statistical significance in response to cross-market CDS spread shocks. GIIPS CDS spread shocks generally have a larger impact on illiquidity than non-GIPS CDS spread shocks, with the former increasing relative spreads by approximately 2 basis points whereas, the latter increases relative spreads by approximately 1 basis point.

4.5. Impulse Response Functions: illiquidity

Finally we consider the Impulse Response Functions (IRFs) of relative spreads in response to own market and cross-market shocks to volatility with Fig. 12 depicting pre-crisis IRFs and Fig. 13 depicting crisis IRFs. In most plots shocks to own market and cross-market volatility increase relative spreads, usually by between 2 and 3 basis points in the pre-crisis period but by as much as 10 basis points in the crisis period. The finding that shocks to volatility increase illiquidity is in line with the microstructure models of Ho and Stoll (1983) and Hara and Oldfield (1986) where

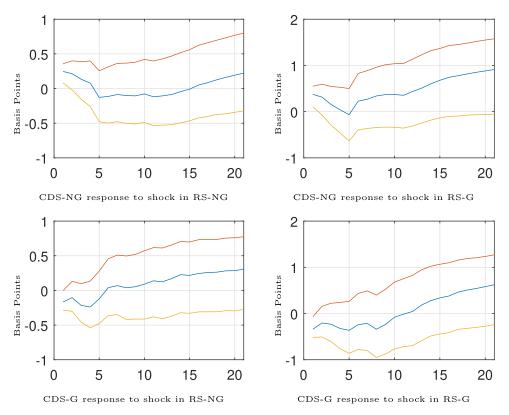


Fig. 8. Pre-crisis period non-GIIPS (NG) (upper panel) and GIIPS (G) (lower panel) credit default swap (CDS) premia Impulse Response Functions (IRF) to a one standard deviation shock to either NG or G relative spreads. The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The pre-crisis period extends from January 2008 to October 2009.

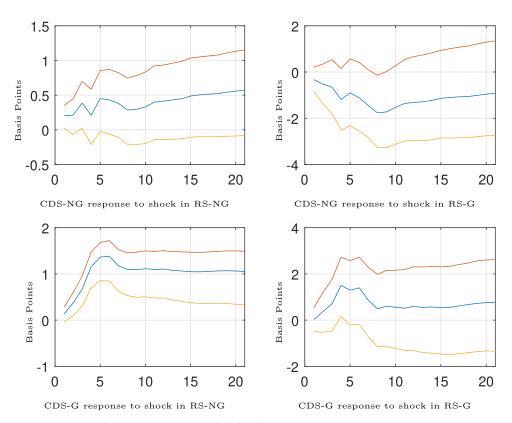


Fig. 9. Crisis period non-GIIPS (NG) (upper panel) and GIIPS (G) (lower panel) credit default swap (CDS) premia Impulse Response Functions (IRF) to a one standard deviation shock to either NG or G relative spreads. The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The crisis period extends from November 2009 to December 2013.

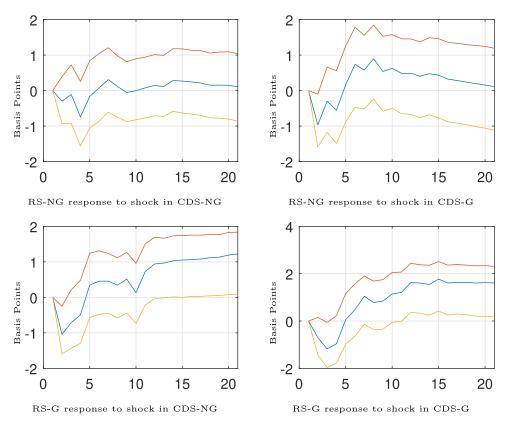


Fig. 10. Pre-crisis period non-GIIPS (NG) (upper panel) and GIIPS (G) (lower panel) relative spread (RS) Impulse Response Functions (IRF) to a one standard deviation shock to either NG or G CDS spreads. The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The pre-crisis period extends from January 2008 to October 2009.

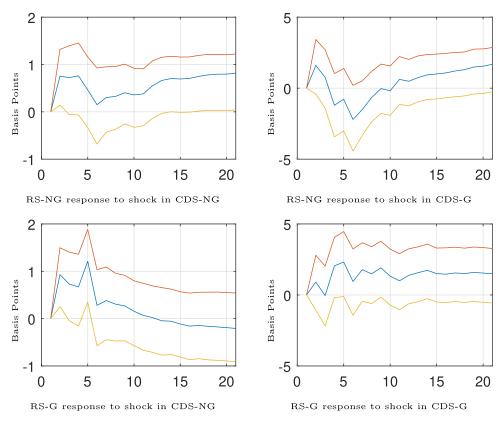


Fig. 11. Crisis period non-GIIPS (NG) (upper panel) and GIIPS (G) (lower panel) relative spread (RS) Impulse Response Functions (IRF) to a one standard deviation shock to either NG or G CDS spreads. The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The crisis period extends from November 2009 to December 2013.

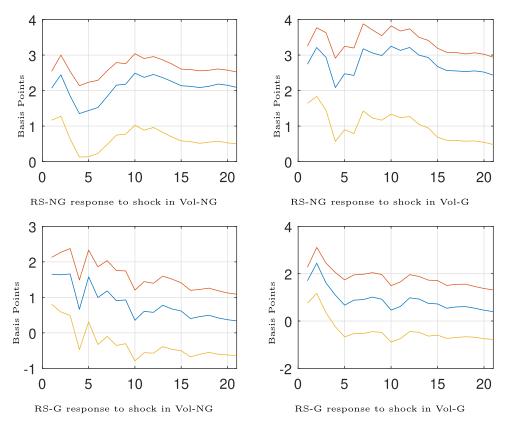


Fig. 12. Pre-crisis period non-GIIPS (NG) (upper panel) and GIIPS (G) (lower panel) relative spread (RS) Impulse Response Functions (IRF) to a one standard deviation shock to either NG or G volatility. The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The pre-crisis period extends from January 2008 to October 2009.

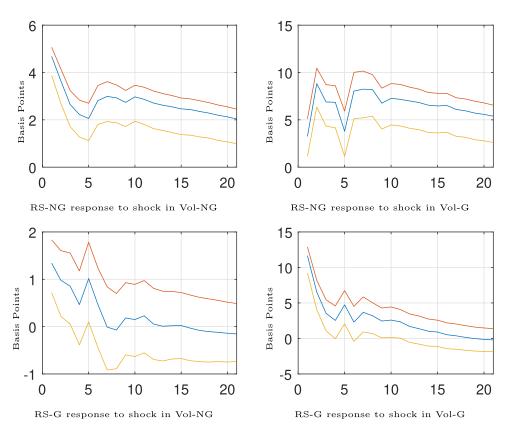


Fig. 13. Crisis period non-GIIPS (NG) (upper panel) and GIIPS (G) (lower panel) relative spread (RS) Impulse Response Functions (IRF) to a one standard deviation shock to either NG or G volatility. The centre line is the IRF whilst the outer lines are the 95 percent bootstrapped confidence intervals using 2500 bootstrapped simulations. The crisis period extends from November 2009 to December 2013.

Table 7

This table depicts the variance decompositions of illiquidity computed from a VAR with endogenous variables V-NG-10, V-G-10, R-NG-2, R-NG-5, R-NG-10, R-NG-30, R-G-2, R-G-5, R-G-10, R-G-30, RS-NG, QD-NG, RS-G, QD-G, CDS-NG, and CDS-G. V-NG-10 and V-G-10 stand for realized volatility of the 10-year benchmark for non-GIIPS and GIIPS countries, respectively, and are computed using 5-minute squared intraday returns. R-NG-2, R-NG-5, R-NG-10, and R-NG-30 are the daily returns for the 2-, 5-, 10-, and 30-year benchmark respectively, for non-GIIPS countries and are calculated as the summation of 5-minute intraday returns. R-G-2, R-G-5, R-G-10, and R-G-30 denote the corresponding daily returns for the GIIPS countries. RS-NG (RS-G) denote the first principal component extracted from non-GIIPS (GIIPS) bond relative spreads using 2-, 5-, 10-, and 30-year benchmark securities. QD-NG (QD-G) denote the first principal component extracted from non-GIIPS (GIIPS) quoted depths using all four maturities. CDS-NG (CDS-G) denote the 5-year daily average non-GIIPS (GIIPS) credit default swaps (CDS) spreads. The full sample period spans the dates from January 2008 to December 2013.

| Panel A | : Pre-crisis | | | | | | | | | | | | | | | | |
|---------|-----------------|---------|--------|--------|--------|---------|---------|-------|-------|--------|--------|-------|-------|-------|-------|--------|-------|
| | Variance period | V-NG-10 | V-G-10 | R-NG-2 | R-NG-5 | R-NG-10 | R-NG-30 | R-G-2 | R-G-5 | R-G-10 | R-G-30 | RS-NG | QD-NG | RS-G | QD-G | CDS-NG | CDS-0 |
| RS-NG | 1 | 8.43 | 2.12 | 0.23 | 0.28 | 0.04 | 1.38 | 0.91 | 0.38 | 0.56 | 1.02 | 84.65 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 10 | 14.28 | 4.42 | 0.21 | 1.77 | 0.18 | 1.06 | 0.95 | 2.38 | 1.96 | 0.69 | 52.28 | 2.29 | 14.76 | 0.15 | 0.22 | 2.40 |
| QD-NG | 1 | 2.52 | 1.01 | 0.61 | 0.60 | 0.00 | 0.00 | 0.42 | 0.02 | 0.02 | 0.02 | 5.98 | 88.80 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 10 | 1.89 | 0.41 | 0.20 | 0.67 | 0.55 | 0.02 | 1.10 | 0.12 | 0.05 | 0.06 | 13.17 | 65.88 | 0.99 | 14.70 | 0.09 | 0.10 |
| RS-G | 1 | 8.81 | 3.18 | 0.41 | 0.07 | 0.08 | 0.70 | 0.17 | 0.57 | 0.73 | 0.05 | 39.47 | 0.29 | 45.47 | 0.00 | 0.00 | 0.00 |
| | 10 | 15.26 | 5.46 | 0.29 | 2.25 | 0.10 | 1.31 | 0.93 | 2.88 | 1.99 | 0.53 | 33.87 | 1.23 | 29.69 | 0.01 | 0.39 | 3.81 |
| QD-G | 1 | 4.81 | 0.55 | 0.21 | 0.55 | 0.10 | 0.11 | 1.35 | 0.03 | 0.00 | 0.20 | 7.90 | 30.52 | 0.28 | 53.39 | 0.00 | 0.00 |
| | 10 | 3.08 | 0.14 | 0.07 | 0.72 | 0.92 | 0.04 | 2.34 | 0.16 | 0.11 | 0.14 | 9.36 | 40.94 | 0.48 | 40.03 | 0.13 | 1.34 |
| Panel B | : Crisis | | | | | | | | | | | | | | | | |
| | Variance period | V-NG-10 | V-G-10 | R-NG-2 | R-NG-5 | R-NG-10 | R-NG-30 | R-G-2 | R-G-5 | R-G-10 | R-G-30 | RS-NG | QD-NG | RS-G | QD-G | CDS-NG | CDS- |
| RS-NG | 1 | 15.99 | 1.34 | 0.07 | 0.03 | 0.00 | 0.80 | 0.34 | 0.03 | 0.15 | 0.72 | 80.53 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 10 | 21.46 | 3.22 | 0.40 | 1.02 | 0.05 | 0.41 | 0.94 | 1.88 | 0.10 | 0.32 | 65.41 | 0.03 | 3.36 | 0.04 | 1.31 | 0.05 |
| QD-NG | 1 | 0.32 | 0.18 | 0.03 | 0.01 | 0.13 | 0.60 | 0.01 | 0.24 | 0.16 | 0.05 | 1.03 | 97.24 | 0.00 | 0.00 | 0.00 | 0.00 |
| | 10 | 0.28 | 0.15 | 0.00 | 0.02 | 0.09 | 0.09 | 0.16 | 0.25 | 0.10 | 0.03 | 0.44 | 88.76 | 0.43 | 9.07 | 0.00 | 0.13 |
| RS-G | 1 | 0.39 | 7.41 | 0.14 | 0.12 | 0.03 | 0.03 | 0.12 | 0.09 | 0.21 | 0.00 | 18.88 | 0.19 | 72.39 | 0.00 | 0.00 | 0.00 |
| | 10 | 10.13 | 7.89 | 0.61 | 1.57 | 0.12 | 0.39 | 0.32 | 3.02 | 0.18 | 0.34 | 26.69 | 2.49 | 43.98 | 0.63 | 1.32 | 0.33 |
| QD-G | 1 | 0.21 | 0.04 | 0.02 | 0.06 | 0.00 | 0.01 | 0.02 | 0.00 | 0.01 | 0.01 | 0.39 | 15.16 | 0.20 | 83.87 | 0.00 | 0.00 |
| | 10 | 0.23 | 0.06 | 0.01 | 0.03 | 0.02 | 0.08 | 0.16 | 0.64 | 0.14 | 0.04 | 0.12 | 43.27 | 0.35 | 54.67 | 0.01 | 0.17 |

increases in volatility lead to higher inventory risk thus adversely impacting liquidity. It is interesting to note that non-GIIPS relative spreads increase by a larger amount in response to cross-market volatility shocks relative to own market volatility shocks. However, GIIPS relative spreads are more sensitive to own market shocks than to cross-market shocks. Hence GIIPS volatility has a larger effect on both markets illiquidity both prior to and during the eurozone bond market crisis.

As an alternative way of describing liquidity dynamics, we estimate variance decompositions which give the proportion of the movements in the dependent variables that are due to their own shocks, versus shocks to the other variables. For the sake of space we report results for forecast horizons of one day and ten days only. Table 7 provides a variance decomposition of illiquidity (both relative spreads and quoted depths) in both pre-crisis and crisis periods. Non-GIIPS realized volatility explains nearly 9 percent and 3 percent (9 percent and 5 percent), respectively, of non-GIIPS (GIIPS) relative spreads and quoted depth total variance in the pre-crisis period (Panel A) at the one day horizon. GIIPS realized volatility explains 2 percent and 1 percent), respectively, of non-GIIPS (GIIPS) relative spreads and quoted depths. Thus, in the pre-crisis period, GIIPS realized volatility has a lower explanatory power than non-GIIPS realized volatility.

Relative spreads and quoted depths of non-GIIPS countries explain a larger percentage of their own variance than the corresponding GIIPS illiquidity measures. Moreover, quoted depths explain a significant amount of variation in relative spreads in both short horizon and longer horizon variance periods, whereas it seems that relative spreads are only able to explain properly their own variance. Variation in quoted depths of GIIPS countries can be explained by relative spreads of non-GIIPS countries at a higher percentage than that explaining variation of non-GIIPS quoted depths at short horizons.

Panel B reports the variance decomposition results for the crisis period. Bond volatility of non-GIIPS countries explains about 16 percent of non-GIIPS relative spread forecast error variance at short horizons, increasing to almost 22 percent after 10 days. The im-

portance of volatility of GIIPS countries increases during the crisis as it explains a higher percentage of the forecast error variance of relative spreads of the GIIPS region than in the pre-crisis period. Innovations in own-market illiquidity explain most of the liquidity dynamics especially at shorter horizons, and this finding is magnified in the case of GIIPS illiquidity which gains importance in the crisis period.

Own market or cross-market shocks to bond returns usually contribute little to both illiquidity measures in both regions with the 5-year GIIPS benchmark contributing more than the rest. CDS spreads are not important factors in explaining the variance of illiquidity before or during the crisis. It can be deduced that GI-IPS CDS spreads are more informative pre-crisis and at longer horizons, whilst non-GIIPS CDS spreads become more important in the crisis as they can explain own market and cross-market relative spreads more effectively.

4.6. Liquidity pricing

It has been shown that liquidity not only affects asset returns as a characteristic but also as a risk factor (e.g., Pástor and Stambaugh, 2003; Acharya and Pedersen, 2005; Liu, 2006; Watanabe and Watanabe, 2007). Acharya and Pedersen (2005) propose the liquidity-adjusted capital asset pricing model (L-CAPM) which uses three different forms of liquidity risk that are independent of traditional market risk: the first due to covariation between a security's liquidity and the market liquidity, the second due to covariation between a security's return and the market liquidity, and the third due to covariation between a security's liquidity and the market return. Acharya and Pedersen (2005) form illiquidity portfolios using return data from CRSP from 1962 until 1999 for all common shares listed on NYSE and AMEX and find weak evidence that liquidity risk is important over and above the effects of traditional market risk and liquidity as a characteristic. In the following analysis we show that bond market liquidity risk is priced and is distinct from bond market risk. Our results are consistent with those of Liu (2006) who examine all NYSE, AMEX and NASDAQ common stocks over the period 1960 to 2003 and document a significant and robust liquidity premium which is distinct from systematic market risk and the Fama-French three-factor risks.

We model bond returns using a factor model similar in spirit to Fama and French (1993) and Houweling et al. (2005) as opposed to using a term structure model that links bond yields across maturities by no-arbitrage restrictions. An advantage of using bond returns over yields is that returns exhibit a much lower degree of autocorrelation relative to bond yields, as pointed out in Goliński and Spencer (2017) and references therein. We model eurozone sovereign bond returns using a variant of L-CAPM framework in Acharya and Pedersen (2005) in which we include liquidity as a characteristic. However, we also augment the model with a credit risk factor using individual bond credit default swap (CDS) spreads as a proxy for credit risk. Thus, analogous to the model for corporate bond returns in Fama and French (1993), the model we use includes a market risk component that proxies for interest rate risk and includes a credit risk factor. Moreover, we also include liquidity risk factors that are discussed in more detail below. The proxy for the eurozone government bond market return index, ret_m, is taken to be the cross-sectional average of all the bonds in our sample across both regions and all maturities of 2-,5-,10-, and 30-years. Similarly, the proxy for the market liquidity index, liq_m , is taken to be the cross-sectional average of all the bond relative spreads at the usual four maturities. To remove the persistence in liquidity a market liquidity innovation factor, denoted Δliq_i , is constructed from the residuals of an AR(1) model estimated on the market liquidity level.

To obtain risk factor loadings the return of bond i, ret_i , is regressed on the market return, ret_m , and the market liquidity innovation, Δliq_m , to obtain two betas for each bond, $\beta_1=\beta(ret_i,ret_m)$ and $\beta_3=\beta(ret_i,\Delta liq_m)$. Similarly, individual bond liquidity innovations, Δliq_i , are regressed on market liquidity innovations, Δliq_m , and market returns, ret_m , to obtain another two betas for each bond, $\beta_2=\beta(\Delta liq_i,\Delta liq_m)$ and $\beta_4=\beta(\Delta liq_i,ret_m)$. These first pass regressions use data from day 1 to day t. In each second pass Fama and MacBeth (1973) regression, the average return of each bond over the subsequent 20-day period, from day t+1 to t+20, are regressed on the four betas to determine the risk premia, λ 's, associated with each liquidity risk factor. We also include liquidity as a characteristic and CDS spreads as controls. The full regression is as follows:

$$E[r_{i}] = \lambda_{0} + \kappa E[liq_{i}] + \delta E[CDS_{i}] + \lambda_{1}\beta(ret_{i}, ret_{m}) + \lambda_{2}\beta(\Delta liq_{i}, \Delta liq_{m}) + \lambda_{3}\beta(ret_{i}, \Delta liq_{m}) + \lambda_{4}\beta(\Delta liq_{i}, ret_{m}),$$
(7)

where $E[r_i]$ denotes the mean return on bond i from day t+1 to t + 20, $E[liq_i]$ is the relative spread of bond i averaged over day 1 to t, and where $E[CDS_i]$ is the CDS spread of bond i averaged over day 1 to t. We roll the window on the procedure by extending the time period from day 1 to day t + 20, to update the estimates of the first pass betas and controls. The average return of each bond over the subsequent 20-day period, from day t + 21 to t + 40, are regressed on these updated betas and controls. We repeat this process by rolling forward the regressions in this manner using each subsequent non-overlapping 20-day average returns, ensuring that the second pass regressions embed no foresight bias by using betas and controls estimated using data that precede the return measurement period. Finally, we take the average of the risk premia (the lambdas) and control coefficients estimated using all the 20-day intervals in the sample and calculate Fama and Mac-Beth (1973) standard errors using the sample of 20-day risk premia.¹¹ In subsequent tables we analyse the contribution of each control and risk factor to expected bond returns.

As in Lee (2011) we also consider subsets of the liquidityadjusted CAPM in Eq. (7) by adding a single additional liquidity risk factor, λ_i , to the market risk factor, λ_1 , for $i \in \{2, 3, 4\}$, in order to avoid multicollinearity problems that may arise when all betas are included in a single regression model. In each of these sub-models we also include controls and adjust the first pass regressions accordingly to only take account of a single additional liquidity risk factor in the estimation of the first pass β 's. It must be noted that there can also be significant correlation between the liquidity risk factors and liquidity as a characteristic, as discussed in Acharya and Pedersen (2005). To mitigate this potential problem, we orthogonalise all betas with respect to liquidity as a characteristic before running the second pass regressions by regressing each liquidity risk factor as a dependent variable on liquidity as a characteristic as the independent variable, and using the residuals from this regression as the proxy for orthogonalised betas.¹² This ensures that the liquidity risk factors are capturing liquidity effects that are separate to the effects of liquidity as a characteristic.

The risk premium λ_1 associated with the covariance between a bond's return and the market's return should be positive to compensate investors for higher systematic return risk. Generally bonds with longer maturities have higher market return covariance and earn a higher return to compensate investors for this systematic risk. This is analogous to a duration or an interest rate risk factor. The risk premium λ_2 associated with the covariance between a bond's liquidity and the market's liquidity should also be positive to compensate for higher systematic liquidity risk. The risk premiums associated with the cross terms, λ_3 and λ_4 , should be negative. In the case of λ_3 , an individual bond whose returns are on average higher when the market is experiencing higher illiquidity is acting like insurance against shocks to systematic liquidity risk, hence the required return on such a bond should be decreasing in this covariance risk. Similarly in the case of λ_4 , an individual bond whose illiquidity is high when the market return is high experiences higher illiquidity in good states of the world when this illiquidity is less costly, hence the required rate of return on such a bond should be decreasing in this covariance risk.

We estimate this model separately on GIIPS and non-GIIPS bonds and divide the estimation sample into pre-crisis and crisis periods. Table 8 presents the results on the estimation of the risk premia where t-statistics, reported in parentheses, are estimated using Fama-MacBeth standard errors. All the λ risk premia are reported in terms of basis points (by multiplying by 1×10^4) however, the liquidity characteristic and credit spread control risk premia, κ , and δ , are left unchanged.

In the pre-crisis period for the non-GIIPS region, we observe in Panel A of Table 8 that all factors are significant when included as the only regressor in univariate regressions. Less liquid bonds and bonds with higher CDS spreads earn higher returns as evidenced by coefficients that are significant at the 1 percent level. Liquidity as a characteristic has an \bar{R}^2 of 40 percent which is significantly higher than the explanatory power of credit spreads, which have an \bar{R}^2 of 16 percent. The market risk factor λ_1 and the systematic liquidity risk factor are highly significant and have very high explanatory power with \bar{R}^2 's of 46 percent and 39 percent, respec-

Similar to Acharya and Pedersen (2005) we have also estimated the risk premia and their standard errors in a single cross-sectional regression set-up but using a Generalized Method of Moments (GMM) framework as a robustness test. The GMM estimated results are not dramatically different from those of the Fama-MacBeth methodology and are available from the authors upon request.

¹² This orthogonalisation is only used when liquidity as a characteristic is included as a control and is carried out using rolling windows to ensure no foresight bias in the second pass regressions.

Table 8

This table presents the coefficient estimates from a two-stage Fama-MacBeth regression of the following form: $E(r_i) = \lambda_0 + \kappa E[liq_i] + \delta E[CDS_i] + \lambda_1 \beta(ret_i, ret_m) + \lambda_2 \beta(\Delta liq_i, \Delta liq_m) + \lambda_3 \beta(ret_i, \Delta liq_m) + \lambda_4 \beta(\Delta liq_i, ret_m)$ where the cross-sectional expected returns are averaged over non-overlapping 20-day windows. In multivariate regressions, the liquidity risk factors, $\beta(ret_i, ret_m)$, $\beta(\Delta liq_i, \Delta liq_m)$, $\beta(ret_i, \Delta liq_m)$ and $\beta(\Delta liq_i, ret_m)$, have been orthogonalised with respect to liquidity as a characteristic, $E[liq_i]$, to purge the liquidity risk factors of components that are common to liquidity as a characteristic, $All \lambda$ estimates are reported in terms of basis points and t-statistics are reported in parentheses. The average adjusted- R^2 s from the cross-sectional regressions are also reported. The pre-crisis refers to the period from January 2008 to October 2009 and the crisis period refers to the period from November 2009 to December 2013. *, ** and *** denote significance at the 10%, 5% and 1% level, respectively.

| | κ on-GIIPS Pre- Fama-MacBe | | λ_1 | λ_2 | λ_3 | λ_4 | \bar{R}^2 |
|---|---|---|---|---------------------------|-----------------------------|-------------------------------------|--|
| 0.556** | 0.116*** | ii negressio | .1.5 | | | | 40.13% |
| (2.37) | (5.92) | | | | | | 40.15% |
| -0.273 | | 0.130*** | | | | | 16.43% |
| (-0.97) 0.380 | | (5.57) | 2.714*** | | | | 46.31% |
| (1.41) | | | (6.13) | | | | 40.51% |
| 0.561** | | | | 3.004*** | | | 39.25% |
| (2.30) 3.379*** | | | | (7.70) | 0.557*** | | 8.53% |
| 9.23) | | | | | (2.20) | | 0.33% |
| 2.220*** | | | | | | -73.063*** | 29.38% |
| 10.92) | | | | | | (-8.54) | |
| Multivariat | e Fama-Mac | Beth Regres | sions | | | | |
| 0.517** | 0.118*** | -0.014 | | | | | 47.21% |
| (2.23) 0.049 | (5.06) 0.112*** | (-1.02) 0.0003 | 2.198*** | | | | 59.30% |
| (0.22) | (4.93) | (0.02) | (4.49) | | | | 55.50% |
| 0.126 | 0.127*** | -0.006 | 2.252*** | 0.552** | | | 62.51% |
| (0.62) -0.048 | (5.14) 0.013 | (-0.36) 0.004 | (4.66) 2.552*** | (2.22) | 0.414** | | 59.58% |
| -0.048 (-0.22) | (0.55) | (0.30) | (5.02) | | (2.33) | | JJ.J0/0 |
| 0.343** | 0.092*** | 0.002 | 3.291*** | | . , | -8.133** | 58.15% |
| (2.16) 0.102 | (5.51) 0.019 | (0.16) -0.010 | (6.66) 2.774*** | 1.040*** | 0.212 | (-2.18) 12.225*** | 61.71% |
| 0.52) | (0.75) | (-0.56) | (5.18) | (3.80) | (1.11) | (3.97) | 01./1/6 |
| | IPS Pre-crisi | | | | | | |
| | | | | | | | |
| | | tii Kegiessii | 7113 | | | | |
| 0.144 | 0.133*** | tii Regressi | J113 | | | | 33.22% |
| 0.144 | | 0.090*** | JII5 | | | | 33.22% |
| 0.144 (0.86) -2.521*** | 0.133*** | | J113 | | | | |
| 0.144 (0.86) -2.521*** (-5.16) 0.983*** | 0.133*** | 0.090*** | 3.168*** | | | | |
| 0.144 (0.86) -2.521*** (-5.16) 0.983*** (6.19) | 0.133*** | 0.090*** | | 3.634*** | | | 21.51% |
| 0.144 (0.86) -2.521*** (-5.16) (0.983*** (6.19) -0.275 | 0.133*** | 0.090*** | 3.168*** | 3.634*** (9.00) | | | 21.51% 34.98% |
| 0.144 0.86) -2.521*** -5.16) 0.983*** 6.19) -0.275 -1.18) 2.462*** | 0.133*** | 0.090*** | 3.168*** | | -2.578*** | | 21.51% 34.98% |
| 0.144 0.86) -2.521*** -5.16) 0.983*** 6.19) -0.275 -1.18) 2.462*** 10.23) | 0.133*** | 0.090*** | 3.168*** | | -2.578*** (-6.67) | -75.104*** | 21.51% 34.98% 25.66% 24.26% |
| 0.144 0.86) -2.521*** -5.16) 0.983*** 6.19) -0.275 -1.18) 2.462*** 10.23) 1.406*** | 0.133*** | 0.090*** | 3.168*** | | | -75.104*** (-8.89) | 21.51% 34.98% 25.66% |
| 0.144 0.86) -2.521*** -5.16) 0.983*** 6.19) -0.275 -1.18) 2.462*** 10.23) 1.406*** 5.59) | 0.133*** | 0.090*** (7.32) | 3.168*** (9.07) | | | | 21.51% 34.98% 25.66% 24.26% |
| 0.144 0.86) -2.521*** -5.16) 0.983*** 6.19) -0.275 -1.18) 2.462*** 10.23) 1.406*** 5.59) Multivariat | 0.133*** (8.52) | 0.090*** (7.32) | 3.168*** (9.07) | | | | 21.51% 34.98% 25.66% 24.26% |
| 0.144 0.86) -2.521*** (-5.16) 0.983*** 6.19) -0.275 -1.18) 2.462*** (10.23) 1.406*** 5.59) Multivariat -2.223** (-4.73) | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) | 0.090*** (7.32) Beth Regres 0.038 (4.29) | 3.168*** (9.07) | | | | 21.51% 34.98% 25.66% 24.26% 16.19% |
| 0.144 0.86) -2.521*** (-5.16) 0.983*** 6.19) -0.275 -1.18) 2.462*** 10.23) 1.406*** 5.59) Multivariat -2.223** (-4.73) -1.940*** | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* | 3.168*** (9.07) | | | | 21.51% 34.98% 25.66% 24.26% 16.19% |
| 0.144 (0.86) -2.521*** (-5.16) 0.983*** (6.19) -0.275 (10.23) 1.406*** (5.59) Multivariati -2.223** (-4.73) -1.940*** (-3.82) | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) | 0.090*** (7.32) Beth Regres 0.038 (4.29) | 3.168*** (9.07) | | | | 21.51% 34.98% 25.66% 24.26% 16.19% |
| -2.223** (-4.73) -1.940*** (-3.82) -1.952*** (-4.05) | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) | (9.00) | (-6.67) | | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% 39.89% |
| 0.144 (0.86) -2.521*** (-5.16) 0.983*** (6.19) -0.275 (-1.18) 2.462*** (10.23) 1.406*** (5.59) Multivariat -2.223** (-4.73) -1.940*** (-3.82) -1.952*** (-4.05) -1.928*** | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) 0.123*** | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) 0.031*** | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) 2.635*** | 0.266 | 0.040 | | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% |
| 0.144 (0.86) -2.521*** (-5.16) 0.983*** (6.19) -0.275 (-1.18) 2.462*** (10.23) 1.406*** (5.59) Multivariat -2.223** (-4.73) -1.940*** (-3.82) -1.952*** (-4.05) -1.928*** (-4.39) | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) | 0.266 | (-6.67) | | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% 39.89% |
| 0.144 (0.86) -2.521*** (-5.16) 0.983*** (6.19) -0.275 (-1.18) 2.462*** (10.23) 1.406*** (5.59) Multivariat -2.223** (-4.73) -1.940*** (-3.82) -1.952*** (-4.05) -1.185** (-4.32) | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) 0.123*** (7.04) 0.140*** (7.01) | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) 0.031*** (4.30) 0.007 (0.55) | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) 2.635*** (3.70) 1.763** (3.10) | (9.00) 0.266 (0.46) | 0.040 (0.09) | (-8.89) -38.466*** (-5.46) | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% 39.89% 51.63% 45.14% |
| 0.144 0.86) -2.521*** (-5.16) 0.983*** 6.19) -0.275 -1.18) 2.462*** 10.23) 1.406*** 5.59) Multivariati -2.223** -4.73) -1.940*** (-3.82) -1.952*** -4.05) -1.185** (-2.32) -0.196 | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) 0.123*** (7.04) 0.140*** (7.01) 0.140*** | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) 0.031*** (4.30) 0.007 (0.55) -0.002 | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) 2.635*** (3.70) 1.763** (3.10) 1.749** | 0.266 (0.46) | 0.040 (0.09) -1.308** | -38.466*** (-5.46) -23.258*** | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% 39.89% 51.63% |
| 0.144 (0.86) -2.521*** (-5.16) 0.983*** (6.19) -0.275 (-1.18) 2.462*** (10.23) 1.406*** (5.59) Multivariat -2.223** (-4.73) -1.940*** (-3.82) -1.952*** (-4.05) -1.185** (-4.39) -1.185** (-2.32) -0.196 (-0.49) | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) 0.123*** (7.04) 0.140*** (7.01) 0.140*** (7.81) | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) 0.031*** (4.30) 0.007 (0.55) -0.002 (-0.26) | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) 2.635*** (3.70) 1.763** (3.10) | (9.00) 0.266 (0.46) | 0.040 (0.09) | (-8.89) -38.466*** (-5.46) | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% 39.89% 51.63% 45.14% |
| 0.144 0.86) -2.521*** (-5.16) 0.983*** (6.19) -0.275 -1.18) 2.462*** 10.23) 1.406*** (5.59) Multivariate -2.223** -4.73) -1.940*** [-4.05) -1.928*** [-4.39) -1.185** -2.32) 0.196 [-0.49) Panel C: No | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) 0.123*** (7.04) 0.140*** (7.01) 0.140*** | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) 0.031*** (4.30) 0.007 (0.55) -0.002 (-0.26) sis | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) 2.635*** (3.70) 1.763** (3.10) 1.749** (2.41) | 0.266 (0.46) | 0.040 (0.09) -1.308** | -38.466*** (-5.46) -23.258*** | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% 39.89% 51.63% 45.14% |
| 0.144 (0.86) -2.521*** (-5.16) 0.983*** (6.19) -0.275 (-1.18) 2.462*** (10.23) 1.406*** (5.59) Multivariat -2.223** (-4.73) -1.940*** (-3.82) -1.952*** (-4.05) -1.928*** (-4.39) -1.185** (-2.32) 0.196 (-0.49) Panel C: No | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) 0.123*** (7.04) 0.140*** (7.01) 0.140*** (7.81) on-GIIPS Cris | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) 0.031*** (4.30) 0.007 (0.55) -0.002 (-0.26) sis | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) 2.635*** (3.70) 1.763** (3.10) 1.749** (2.41) | 0.266 (0.46) | 0.040 (0.09) -1.308** | -38.466*** (-5.46) -23.258*** | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% 39.89% 51.63% 45.14% |
| 0.144 (0.86) (-2.521*** (-5.16) 0.983*** (6.19) (-0.275 (-1.18) 2.462*** (10.23) 1.406*** (5.59) Multivariate (-4.73) -1.940*** (-4.405) -1.928*** (-4.405) -1.185** (-4.39) -1.185** (-2.32) 0.196 (-0.49) Panel C: No | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) 0.123*** (7.04) 0.140*** (7.01) 0.140*** (7.81) on-GIIPS Cris | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) 0.031*** (4.30) 0.007 (0.55) -0.002 (-0.26) sis eth Regression | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) 2.635*** (3.70) 1.763** (3.10) 1.749** (2.41) | 0.266 (0.46) | 0.040 (0.09) -1.308** | -38.466*** (-5.46) -23.258*** | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% 39.89% 51.63% 45.14% 47.79% |
| 0.144 (0.86) -2.521*** (-5.16) 0.983*** (6.19) -0.275 (-1.18) 2.462*** (10.23) 1.406*** (5.59) Multivariat -2.223** (-4.73) -1.940*** (-3.82) -1.952*** (-4.05) -1.185** (-2.32) -0.196 (-0.49) Panel C: No Univariate 0.658*** (5.34) 0.346* | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) 0.123*** (7.04) 0.140*** (7.01) 0.140*** (7.81) on-GIIPS Cris Fama-MacBe 0.021*** | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) 0.031*** (4.30) 0.007 (0.55) -0.002 (-0.26) sis eth Regressio | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) 2.635*** (3.70) 1.763** (3.10) 1.749** (2.41) | 0.266 (0.46) | 0.040 (0.09) -1.308** | -38.466*** (-5.46) -23.258*** | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% 39.89% 51.63% 45.14% 47.79% |
| 0.144 (0.86) (-2.521*** (-5.16) 0.983*** (6.19) (-0.275 (-1.18) 2.462*** (10.23) 1.406*** (5.59) Multivariate (-4.73) -1.940*** (-4.405) -1.928*** (-4.405) -1.185** (-4.39) -1.185** (-2.32) 0.196 (-0.49) Panel C: No | 0.133*** (8.52) e Fama-Mac 0.118*** (8.17) 0.129*** (7.74) 0.127*** (6.92) 0.123*** (7.04) 0.140*** (7.01) 0.140*** (7.81) on-GIIPS Cris Fama-MacBe 0.021*** | 0.090*** (7.32) Beth Regres 0.038 (4.29) 0.023* (2.09) 0.026** (2.68) 0.031*** (4.30) 0.007 (0.55) -0.002 (-0.26) sis eth Regression | 3.168*** (9.07) sions 2.920*** (4.10) 2.778*** (3.57) 2.635*** (3.70) 1.763** (3.10) 1.749** (2.41) | 0.266 (0.46) | 0.040 (0.09) -1.308** | -38.466*** (-5.46) -23.258*** | 21.51% 34.98% 25.66% 24.26% 16.19% 38.63% 47.18% 39.89% 51.63% 45.14% 47.79% |

Table 8

| λ ₀ | K CHPC Coioir | δ | λ_1 | λ_2 | λ_3 | λ_4 | \bar{R}^2 |
|---|--|---|---|------------------------|-----------------------|----------------------|--|
| | n-GIIPS Crisis ama-MacBeth | Regressions | | | | | |
| 1.091*** (7.72) | | | | -0.310 (-0.10) | | | 14.27% |
| 0.513*** (3.35) | | | | (33 3) | 9.491*** (5.84) | | 16.65% |
| 1.353*** (5.48) | | | | | , , | 47.037*** (6.85) | 4.75% |
| Multivariate | Fama-MacBe | th Regression | ıs | | | | |
| 0.702*** (3.39) | 0.027** (2.90) | -0.009* (-2.03) | | | | | 25.05% |
| 0.882*** (3.88) | 0.030*** (3.06) | -0.012** (-2.61) | 7.023*** (5.47) | | | | 36.24% |
| 0.572** (2.52) | 0.019* (1.98) | $-0.0002 \\ (-0.04)$ | 7.625*** (6.29) | -34.433*** (-9.34) | | | 38.87% |
| 0.735*** (3.19) | 0.024** (2.58) | -0.005 (-1.00) | 3.083** (2.55) | | 7.986*** (6.03) | | 36.26% |
| 0.896*** (3.72) | 0.028** (2.78) | -0.010^* (-1.96) | 5.890*** (5.30) | 25.500*** | 4.020*** | 22.344*** (3.78) | 37.29% |
| 0.605** (2.43) | 0.020* (2.19) | -0.0007 (-0.14) | 4.270*** (3.72) | -35.598*** (-8.72) | 4.938*** (3.41) | -5.458 (-0.81) | 41.36% |
| Panel D: GI Univariate I | IPS Crisis Fama-MacBeth | Regressions | | | | | |
| 23.184*** (22.69) | -0.477*** (-24.37) | | | | | | 48.32% |
| | | | | | | | |
| | | -0.701*** (-25.55) | | | | | 45.05% |
| (24.74) 5.025*** (7.31) | | | -22.810*** (-20.15) | | | | 44.59% |
| (24.74) 5.025*** (7.31) 6.230*** (14.73) | | | | -20.907*** (-25.47) | | | 44.59% 49.85% |
| 138.048*** (24.74) 5.025*** (7.31) 6.230*** (14.73) -18.567*** (-17.68) | | | | | 217.124*** (19.68) | | 44.59% 49.85% 36.02% |
| (24.74) 5.025*** (7.31) 6.230*** (14.73) -18.567*** (-17.68) 1.947*** | | | | | | 96.404*** (16.48) | 44.59% 49.85% |
| (24.74) 5.025*** (7.31) 6.230*** (14.73) -18.567*** (-17.68) 1.947*** (4.39) Multivariate 97.448*** | ⊵ Fama-MacBe —0.127*** | (-25.55) th Regression -0.462*** | (-20.15) | | | | 44.59% 49.85% 36.02% |
| (24.74) 5.025*** (7.31) 6.230*** (14.73) -18.567*** (-17.68) 1.947*** (4.39) Multivariate 97.448*** (14.28) 80.436*** | $-0.127*** (-4.03) \\ -0.249***$ | (-25.55) th Regression -0.462*** (-11.84) -0.333*** | (-20.15) as -19.628*** | | | | 44.59% 49.85% 36.02% 43.92% |
| (24.74) 5.025*** (7.31) 6.230*** (14.73) -18.567*** (-17.68) 1.947*** (4.39) Multivariate 97.448*** (14.28) 80.436*** (12.07) 15.289*** | -0.127*** (-4.03) -0.249*** (-9.16) -0.504*** | (-25.55) th Regression -0.462*** (-11.84) -0.333*** (-9.33) 0.051*** | (-20.15) 15 -19.628*** (-8.80) 4.292 | (-25.47) -25.307*** | | | 44.59% 49.85% 36.02% 43.92% 59.88% |
| (24.74) 5.025*** (7.31) 6.230*** (14.73) -18.567*** (-17.68) 1.947*** (4.39) Multivariate 97.448*** (14.28) 80.436*** (12.07) 15.289*** (7.70) 51.039*** | -0.127*** (-4.03) -0.249*** (-9.16) -0.504*** (-20.57) -0.406*** | (-25.55) eth Regression -0.462*** (-11.84) -0.333*** (-9.33) 0.051*** (3.52) -0.146*** | (-20.15) -19.628*** (-8.80) 4.292 (1.20) -8.442*** | (-25.47) | 35.563*** | | 44.59% 49.85% 36.02% 43.92% 59.88% 75.35% |
| (24.74) 5.025*** (7.31) 6.230*** (14.73) -18.567*** (-17.68) 1.947*** (4.39) Multivariate 97.448*** (14.28) 80.436*** (12.07) | -0.127*** (-4.03) -0.249*** (-9.16) -0.504*** (-20.57) | (-25.55) oth Regression -0.462*** (-11.84) -0.333*** (-9.33) 0.051*** (3.52) | (-20.15) -19.628*** (-8.80) 4.292 (1.20) | (-25.47) -25.307*** | (19.68) | | 44.59% 49.85% 36.02% 43.92% 59.88% 75.35% 82.32% |

tively. We expect the first cross-term risk factor, λ_3 , to be negative from theory but it is significantly positive although, it has the lowest explanatory power with an \bar{R}^2 of 9 percent, relative to the other controls and risk factors. The second cross-term risk factor, λ_4 , is negative as expected from theory and has medium explanatory power relative to the other controls and risk factors. Considering a multifactor version of L-CAPM we find that in most cases liquidity as a characteristic remains significant at the 1 percent level, credit spreads become insignificant, and the liquidity risk factors are robust to the inclusion of the controls and market risk. Thus, there is strong evidence of liquidity being priced in non-GIIPS markets prior to the sovereign bond crisis and that liquidity risk factors, over and above liquidity as a characteristic, impact bond returns.

The results for the augmented L-CAPM applied to GIIPS bonds in the pre-crisis period are presented in Panel B of Table 8. Similar to univariate results for non-GIIPS, we find that higher illiquidity and CDS spreads are associated with higher subsequent GIIPS returns. Liquidity as a characteristic has higher explanatory power

than CDS spreads with an \bar{R}^2 of 33 percent versus 22 percent, respectively. The market risk factor and the liquidity risk factors are all significant with signs as expected from theory with λ_1 and λ_2 positive and λ_3 and λ_4 negative. In multifactor versions of the model, we see that liquidity as a characteristic and CDS spreads remain highly significant. The market risk factor is also highly significant in each model although the significance of the systematic liquidity risk factor λ_2 and the cross-term liquidity risk factor λ_3 are not robust to the inclusion of the controls. In the GI-IPS region the systematic liquidity risk factor is found to be highly correlated with the market risk factor hence λ_2 is not robust to the inclusion of λ_1 . However, the second cross-term liquidity risk factor λ_4 is robust to the controls and the sign remains negative as expected from theory. We also note that the adjusted \bar{R}^2 in both regions are high at 62 percent and 48 percent for non-GIIPS and GIIPS bonds, respectively, suggesting that the variation in individual bond mean returns in excess of contemporaneous liquidity costs is well explained by the variation in the four betas over the cross-section.

We now turn our attention to the crisis period and consider non-GIIPS bonds as presented in Panel C of Table 8. As in the pre-crisis, we find higher illiquidity as a characteristic and credit spreads are significantly associated with increases in returns. Illiquidity as a characteristic has higher explanatory power than CDS spreads. Market risk λ_1 is also significantly associated with increases in returns. However, in the multivariate regressions we observe a switch in sign on λ_2 relative to the pre-crisis, as bonds with higher systematic liquidity risk experience price declines in the crisis. Furthermore, the cross-term liquidity risk factors, λ_3 and λ_4 , are significantly positive, as investor demand increases for bonds whose returns increase on average when the market is experiencing higher illiquidity (λ_3) or bonds that are more liquid when market returns are decreasing (λ_4). In the crisis period, non-GIIPS bonds still earn a positive risk premium for exposure to liquidity as a characteristic and credit risk however, the evidence suggests investors are rebalancing their portfolios into bonds that have lower systematic liquidity risk and bonds that hedge against liquidity risk.

Panel D of Table 8 presents results for GIIPS bonds in the crisis period. The signs on liquidity as a characteristic and CDS spreads are now significantly negative as investors sell out of less liquid and lower credit quality bonds during the crisis. Similarly, the signs on market risk and systematic liquidity risk are also significantly negative as investors sell out of riskier assets (both market and liquidity risk). The signs associated with the cross-term liquidity risk factors are both significantly positive, as investors seek out bonds that hedge against liquidity risk. This indicates that liquidity risk was of primary importance in the crisis period. Thus, in the GIIPS region during the crisis, there is a general flight to safety as investors sell bonds that are less liquid and have higher liquidity risk along with bonds that are of lower credit quality. As we move from pre-crisis to crisis the adjusted \bar{R}^2 value in the multivariate regressions increases from its pre-crisis value of 48 percent to a crisis value of 89 percent indicating that there is a higher proportion of systematic¹ liquidity risk for GIIPS bonds in the crisis period relative to the pre-crisis period.

Overall, the findings suggest that liquidity risk is priced even when controlling for liquidity as a characteristic and credit spreads. In the pre-crisis period, the signs of the liquidity risk premia match up with expectations from theory, in the majority of cases, as bonds with higher liquidity risk earn positive liquidity risk premia and bonds that act as liquidity hedges are associated with negative risk premia. In the crisis period in the non-GIIPS region, bonds with high liquidity risk and bonds that do not act as liquidity risk hedges, experience price declines as investors sell out of these bonds. However, bonds with higher factor loadings on liquidity as a characteristic, credit risk and market risk still earn positive risk premia. The evidence suggests investors rebalance their portfolios into lower liquidity risk bonds and bonds that act as liquidity risk hedges but not necessarily into bonds that are more liquid and of higher credit quality. In the GIIPS region during the crisis, bonds with higher factor loadings on liquidity as a characteristic, credit risk, market risk, and liquidity risk experience steep price declines. Thus, in the GIIPS region there is evidence of flights to lower market risk bonds, flight to bonds with higher liquidity, flights to higher credit quality bonds, and flights away from bonds with liquidity risk. Judging from the magnitude of the liquidity beta coefficients, flights are more pronounced for GIIPS countries than non-GIPS countries due to liquidity's heightened importance for distressed eurozone economies.

5. Conclusion

Recent crises in financial markets have raised concerns about the state of market liquidity. During periods of stress and changing fundamentals in international financial markets arrangements to more efficient price discovery and faster resolution of uncertainty become extremely important. In this study we depart from single security settings and examine market liquidity across maturities in the eurozone government bond market. We aim to explore liquidity dynamics between and within core and periphery economies during tranquil and turbulent periods. We find that liquidity evaporates during the crisis for GIIPS countries suggesting that flights occur towards less risky and more liquid benchmarks.

We also explore commonality in liquidity, thereby raising the prospect of a liquidity risk premium. We provide unambiguous evidence for the existence of significant commonalities in spread and depth-based measures of liquidity confirming earlier findings from other markets that commonality is a wide-spread phenomenon and plays a pervasive role especially in markets with higher liquidity risk. Weakening of liquidity commonalities during the crisis period for both distressed and healthier economies within the eurozone suggests that the susceptibility of the financial system to liquidity dry-ups across securities is reduced. However, the magnitude of liquidity variation remains high pointing to the coexistence of inventory and asymmetric information risk that affect idiosyncratic liquidity (Chordia et al., 2000) and to the role played by local and regional sources of commonality as well as by macroeconomic announcements in increasing commonality levels across markets (Brockman et al., 2009).

We document GIIPS illiquidity's significant role across markets as it Granger causes illiquidity, volatility, returns, and CDS spreads both in its own region and the rest of the eurozone countries. Moreover, we study the pricing implications of liquidity during tranquil and crisis periods. Liquidity forecasts returns across the yield curve and it is priced in GIIPS and non-GIIPS countries, with GIIPS liquidity playing a particularly important role in the bond returns and volatilities of both regions in the crisis.

Finally, we demonstrate that liquidity is a priced risk factor in the GIIPS and non-GIIPS regions even when taking into account liquidity as a characteristic and sovereign credit risk. Bonds in both regions with high systematic liquidity risk experienced the largest price declines in the crisis whereas non-GIIPS bonds with high systematic market risk experienced increases in price.

CRediT authorship contribution statement

Conall O'Sullivan: Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing - original draft, Writing - review & editing. Vassilios G. Papavassiliou: Conceptualization, Data curation, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing - original draft, Writing - review & editing.

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