Sovereign Credit Risk, Liquidity, and ECB Intervention: *Deus ex Machina*? *

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Abstract

This paper examines the dynamic relationship between credit risk and liquidity in the sovereign bond market in the context of the European Central Bank (ECB) interventions. Using a comprehensive set of liquidity measures obtained from a detailed, quote-level dataset for the largest interdealer market for Italian government bonds, we show that changes in credit risk, as measured by the credit default swap (CDS) spread, generally drive the liquidity of the market. The relationship is stronger and tighter when the CDS spread is above 500 basis points. This threshold was estimated endogenously and can be ascribed mainly to changes in margins and collateral. Moreover, we show that the long-term refinancing operations (LTRO) intervention by the ECB weakened the sensitivity of the liquidity provision by the market makers to changes in the Italian government's credit risk, by providing them with vastly expanded funding liquidity. Finally, we document the importance of market-wide and dealer-specific funding liquidity measures in determining the market liquidity for Italian government bonds.

Keywords: Liquidity, government bonds, financial crisis, MTS bond market
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I Introduction

The challenges facing the governments of the GIIPS countries (Greece, Ireland, Italy, Portugal and Spain) in refinancing their debt marked the genesis of the Euro-zone sovereign debt crisis. Following a series of credit rating downgrades of three countries on the Euro-zone periphery, Greece, Ireland and Portugal, in the spring of 2010, the crisis spread throughout the Euro-zone, and even beyond. The instability in the Euro-zone sovereign bond market reached its apogee during the summer of 2011, when the credit ratings of two of the larger countries in the Euro-zone periphery, Italy and Spain, were downgraded. This culminated in serious hurdles being faced by several Euro-zone countries in placing their new sovereign bond issues, causing their bond yields to spike to unsustainable levels. The contagion soon spread into the European banking system through the sovereign debt holdings of the major European banks, converting the sovereign debt crisis into a full-fledged banking crisis. It even threatened countries at the core of the Euro-zone, such as France and Germany, due to the close linkages between *their* major banks and the sovereign debt of countries on the periphery. The crisis has abated to some extent, due in part to fiscal measures by the European Union (EU) and the International Monetary Fund (IMF) but, as we will show in this paper, mostly thanks to the intervention by the European Central Bank (ECB) through a series of policy actions, including the Long-Term Refinancing Operations (LTRO) and Outright Monetary Transactions (OMT) programs, starting in December 2011. Even so, the Euro-zone sovereign debt crisis remains a drag on the economic recovery of the global economy, leaving open the question of whether the crisis will resurface.

The discussion in the academic and policy-making literatures on the Euro-zone crisis has mainly focused on market aggregates such as bond yields, relative spreads, and credit default swap (CDS) spreads, at various points during the crisis, and the reaction of the market to intervention by the troika of the ECB, the EU and the IMF. Although the analysis of yields and spreads is useful, it is equally relevant for policy makers and market participants to understand the dynamics of market liquidity in the European sovereign debt markets, i.e., the drivers of market liquidity, particularly given the impact market liquidity has on bond yields, as documented in the previous literature on asset prices. In particular, it is important to analyze the inter-relationship between market liquidity and credit risk, as well as the effect of the funding liquidity of the market makers, and how this inter-relationship has changed thanks to the ECB interventions. An improvement in market liquidity moderates bond yields, and a deeper understanding of the determinants of market liquidity could help policy makers in their efforts to improve it. Consequently, such an understanding would allow policy makers to assess the efficacy of their interventions in these markets in terms of diminished risk perceptions.

Why is the linkage between credit risk and market liquidity of considerable interest to monetary economists and policy makers, such as central bankers and public debt managers? First, market liquidity and liquidity risk have an important influence on interest rates, variables that monetary policy actions, such as quantitative easing, attempt to control. Second, the major central banks of the world, including the Federal Reserve System, the Bank of Japan and the ECB, have employed unusually strong quantitative easing measures, which will ultimately have to be unwound, and a sound knowledge of the mechanisms affecting market liquidity in the sovereign bond market will be of paramount importance when this occurs. Third, monetary policy has a direct impact, not only on the level of short-term (and perhaps long-term) interest rates, but also on market liquidity and liquidity risk, as we demonstrate in this paper. Fourth, again as we show in this paper, monetary policy has an impact on market sentiment, and hence on credit risk, as well as on the interplay between credit risk and market liquidity.

The Euro-zone sovereign crisis provides us with an unusual laboratory in which to study how the interaction between credit risk and illiquidity played out, in a more comprehensive framework, compared to previous studies of corporate or other sovereign bond markets. Compared to corporate bonds, which are generally traded over-the-counter, we have the advantage of investigating an exchange-traded market, using a unique, tick-by-tick dataset obtained from the Mercato dei Titoli di Stato (MTS), the world's largest electronic trading platform for sovereign bonds. With respect to the US Treasury or other sovereign bonds markets, the presence of a common currency for sovereign issuers with different credit standings allows for the separate identification of the risk free rate and the credit spread dynamics. Further, unlike prior analyses that presume sovereign debt to be free of credit risk, our analysis addresses the issue of *sovereign* credit risk head on, in a setting where differential monetary policies and exchange rate dynamics do not confound the identification of sovereign credit risk. In fact, we are able to investigate the dynamic relationship between credit risk and market liquidity, measured by proxies constructed with intra-day data, on a daily basis. We also analyze other risk factors, such as those measuring global systemic risk, the counterparty risk of the primary dealers, and funding liquidity risk, during a period when several macro-economic shocks affected the sovereign risk of many countries in the Euro-zone. On top of this, we have also been able to directly investigate how the ECB programs affected both credit risk perceptions and market liquidity. It is difficult to imagine another setting where the confluence of these issues could be studied with such detailed data as are available in the context of the Euro-zone crisis.

Ours is the first paper to empirically investigate the dynamic relationship between market liquidity and credit risk in the sovereign bond market, particularly during a period of crisis. The existing literature has highlighted the theoretical relationship between credit risk and market liquidity, as well as that between funding liquidity and market liquidity (see Brunnermeier and Pedersen (2009)) in a generic sense. We focus here on such an analysis in the Italian sovereign bond market, particularly since the inception of the Euro-zone crisis in July 2011. Italy has the largest sovereign bond market in the Euro-zone (and the third largest in the world after the US and Japan), and is also a market that experienced substantial stress during the recent crisis. In addition, it has a large number of bond issues with a wide variety of characteristics. Hence, the Italian sovereign bond market is best suited to an in-depth analysis of the liquidity effects of the crisis, both in terms of the inter-linkages between sovereign credit risk and liquidity, and the credit risk and funding constraints of the market makers.

We perform our analysis focusing on the MTS Global Market bond trading system. Our dataset, obtained from MTS, is unique for several reasons. First, this market is the largest interdealer trading system for Euro-zone government bonds, largely based on electronic transactions, and is hence one of the most important financial markets in the world.[1] Second, Italy has the largest number of sovereign bonds outstanding and the largest trading volumes on the MTS trading platform, which permits an

[1] While it is difficult to precisely quantify the market share of the MTS in terms of trading in Italian sovereign bonds, estimates provided to us by leading market participants range between 80% and 85% of interdealer transactions.

examination of the link between credit risk and liquidity. Third, similarly to other countries in the Euro-zone, Italy is distinctive in that its central bank, the ECB, is completely independent of its government. Hence, the central bank's monetary policy has a qualitatively different impact on its sovereign credit risk, as well as on the market liquidity of its sovereign bonds, compared to countries whose central banks are somewhat within the control of the sovereign. Finaly, while one could consider extending our analysis to the other two countries with a large amount of bonds outstanding, France and Germany, Germany was not affected by the sovereign credit risk concerns but actually attracted investors in a flight to quality, and France was affected only marginally. Thus neither of the countries has the characteristics required for us to conduct our analysis.

The main focus of our research in this paper is to determine the dynamic relationship between market liquidity and credit risk, as well as other risk factors such as global systemic risks, primary dealers' credit risk, and the funding liquidity risk of market makers. We study the effects of the ECB measures in the context of this dynamic relationship. We employ a range of liquidity metrics, as well as the time series of CDS spreads, to analyze the liquidity of Italian sovereign bonds during the period from June 1, 2011 to December 31, 2012. We allow the data to help us uncover how the relationship between credit risk and liquidity depends on the endogenous level of the CDS spread, with the changes in the latter depending on particular break points in calendar time. In addition, we examine how these relationships were influenced by the interventions of the ECB, and whether those interventions were successful in ameliorating credit risk and illiquidity.

First, we test the hypothesis that the relationship between the credit risk of a sovereign bond and its liquidity is statistically significant and, specifically, that the credit risk, as measured by the CDS spread, leads the liquidity, and not the other way around. Given the data we have available, we are able to investigate this relationship on a daily basis to determine the quantitative impact of changes in credit risk on market liquidity. We find that a one-standard-deviation change in credit risk is followed by a change of 0.3 standard deviations in market liquidity. Further, we find that the coefficients of both contemporaneous and lagged changes in the CDS spread are statistically and economically significant in explaining the sovereign bonds' market liquidity, after controlling for the lagged liquidity variable.

Second, we examine whether the relationship between credit risk and market liquidity is non-linear, and specifically whether it is significantly altered when the CDS spread crosses a certain threshold. We let the data identify the presence of such a CDS threshold effect, and find that the relationship between market liquidity and credit liquidity is different depending on whether the Italian CDS spread is below or above 500 bp. We find not only that a change in the CDS spread has a larger impact on market liquidity when the CDS spread is above 500 bp, but that this relationship is instantaneous, while the lead-lag relationship is more marked for lower levels of CDS spread.

The threshold effect is present only until December 8, 2011. In fact, our test for a structural break indicates that, on December 8, 2011 (when the ECB formally announced the implementation of the LTRO program), the relationship between the two variables changes significantly. Thereafter, changes in market liquidity still respond to changes in credit risk, but with a lagged effect, and with a significantly lower intensity.

Third, we investigate other factors that may affect market liquidity and, in particular, whether global systemic risk and funding liquidity factors, or Italian sovereign-specific risk factors *per se*, affect market liquidity. We perform several additional analyses, and confirm that the dual relationships below and above the threshold in the CDS spread of 500 bp hold before 2011, while market liquidity is largely related to the global systemic risk factor, USVIX, and the market credit risk factor, the Euribor-Eonia spread, as well as the Italian sovereign-specific risk. During 2012, which is after the LTRO program was initiated, market liquidity responds only to the changes in market liquidity on the previous day, while the only contemporaneous variable that affects market liquidity significantly is the global funding liquidity variable proxied by the Euro-US Dollar cross-currency basis swap spread (CCBSS).[2]

Fourth, we analyze the effect of the funding liquidity of primary dealers on market liquidity through the potential funding liquidity channel strictly related to their own credit risk. We analyze the effects of changes in the differential funding rates of the primary dealers over the Euribor benchmark on changes in market liquidity, and find that market makers' own funding liquidity has an impact on the Italian government bonds' market liquidity, especially in periods of severe stress.

In Section II of the paper, we survey the literature on sovereign bonds, particularly the papers relating to liquidity issues. In the following section, Section III, we discuss the hypotheses to be tested in the paper and their economic motivation. In Section IV, we provide a description of the MTS market architecture, the features of our database, our data filtering procedures and our liquidity measures. In Section V, we present our descriptive statistics. Our analysis and results are presented in Section VI, and Section VII presents several robustness checks. Section VIII concludes.

II Literature Survey

The dynamic relationship between credit risk and the market liquidity of sovereign bond markets has received limited attention in the literature thus far. The extant literature on bond market liquidity seldom focuses on sovereign bond markets, with the exception of the US Treasury bond market; yet, even in this case, most papers cover periods before the current financial crisis and address limited issues related to the pricing of liquidity in the bond yields. It is hence fair to say that the relation between sovereign credit risk and market liquidity has not yet been investigated in the US Treasury market, possibly because US sovereign risk was not an issue until the recent credit downgrade by Standard & Poor's. Similarly, there is a handful of papers on the European sovereign bond markets, and again, these papers generally examine a limited time period, mostly prior to the global financial crisis, and largely focusing on the impact of market liquidity on bond yields. Hence, it is valid to conclude that the existing literature on the sovereign bond markets is fairly limited in depth and scope in the context of what we study in this paper: the relationship between credit risk and liquidity in the Euro-zone sovereign bond markets during the depths of the recent Euro-zone crisis. Nevertheless, we provide below a short summary of the existing literature so as to put our research in context.

We begin with a brief review of the papers on liquidity in the US Treasury bond market. Fleming and Remolona (1999) study the price and volume responses of the US Treasury markets to unantici-

[2]This spread represents the additional premium paid per period for a cross-currency swap between Euribor and US Dollar Libor. Market participants view it as a measure of the liquidity imbalances in currency flows between the Euro and the US Dollar, the global reserve currency.

pated macro-economic news announcements. Chakravarty and Sarkar (1999) study the determinants of the bid-ask spread in the corporate, municipal, and government bond markets in the US during 1995-1997, using data from the National Association of Insurance Commissioners. Fleming (2003) studies the realized (i.e., effective) bid-ask spread using GovPX data from 1996-2000, and finds that it is a better measure of liquidity than the quote size, trade size, on-the-run/off-the-run spread, and other competing metrics. Pasquariello and Vega (2006) analyze the announcement effects of macro news using daily data from GovPX on the US Treasury bond market. In a related paper, Pasquariello, Roush and Vega (2011) study the impact of outright (i.e., permanent) open-market operations (POMOs) by the Federal Reserve Bank of New York (FRBNY) on the microstructure of the secondary US Treasury market. Goyenko, Subrahmanyam and Ukhov (2011) use quoted bid and ask prices for Treasury bonds with standard maturities, obtained from the Center for Research in Security Prices (CRSP) database, for the period from November 1967 to December 2005, to study the determinants of liquidity in the US Treasury bond market. They document that order flow surprises are linked to macro-economic news announcements.

There are a few papers in the literature analyzing data from the electronic trading platform similar to MTS known as BrokerTec, which was introduced in 2000. Fleming and Mizrach (2009) provide a detailed description of this market and an analysis of its liquidity, showing the latter to be much greater than has been reported in prior studies using less detailed data from GovPX. Using more recent data from BrokerTec, Engle, Fleming, Ghysels and Nguyen (2011) propose a new class of dynamic order book models based on prior work by Engle (2002). They show that liquidity decreases with price volatility, but increases with liquidity volatility.

There is a vast literature on liquidity effects in the US corporate bond market, examining data from the Trade Reporting and Compliance Engine (TRACE) database maintained by the Financial Industry Regulatory Authority (FINRA) and using liquidity measures for different time periods, including the global financial crisis. This literature is relevant to our research both because it analyzes a variety of liquidity measures and because it deals with a relatively illiquid market with a vast array of securities. For example, Friewald, Jankowitsch and Subrahmanyam (2012a) show that liquidity effects are more pronounced in periods of financial crisis, especially for bonds with high credit risk, based on a sample of over 20,000 bonds and employing several measures including the Amihud measure, the price dispersion measure, and the Roll measure, as well as bond characteristics and transaction measures such as the bid-ask spread. Similar results have been obtained by Dick-Nielsen, Feldhütter and Lando (2012), who investigate the effect of credit risk (credit ratings) on the market liquidity of corporate bonds.[3]

In the context of European sovereign bond markets, Coluzzi, Ginebri and Turco (2008) use various liquidity measures to analyze Italian Treasury bonds, using data from the MTS market during the period 2004-2006. Dufour and Nguyen (2011) analyze data from 2003-2007 for the Euro-zone sovereign bond market to estimate the permanent price response to trades. Beber, Brandt and Kavajecz (2009) analyze the Euro-zone sovereign markets using MTS data between April 2003 and December 2004. They show that most of the yield spread differences are accounted for by differences in credit quality,

[3]Other recent papers quantifying liquidity in this market provide related evidence. See, for example, Edwards, Harris and Piwowar (2007), Mahanti, Nashikkar, Subrahmanyam, Chacko and Mallik (2008), Ronen and Zhou (2009), Jankowitsch, Nashikkar and Subrahmanyam (2011), Bao, Pan and Wang (2011), Nashikkar, Subrahmanyam and Mahanti (2011), Lin, Wang and Wu (2011), Feldhütter (2012), and Jankowitsch, Nagler and Subrahmanyam (2014).

although liquidity plays some role for the bonds of higher-rated countries. Similar results have been found for a more recent time period by Favero, Pagano and Von Thadden (2010). More recently, Bai, Julliard and Yuan (2012) have studied how liquidity and credit risks have evolved in the Euro-zone sovereign bond markets since 2006. They conclude that bond yield spread variations prior to the recent global financial crisis were mostly due to liquidity concerns but, since late 2009, have been more attributable to credit risk concerns, exacerbated by contagion effects.

He and Milbradt (2014) provide an important theoretical framework for the analysis of corporate bonds traded in over-the-counter (OTC) markets. Building on the search cost literature pioneered by Duffie, Garleânu and Pedersen (2007), they show that, in a combined dealer-to-dealer and dealer-to-customer OTC market where bond holders are hit by liquidity shocks, the liquidity of defaultable bonds is increasing in the distance to default of the company that issued them. Moreover, they show that, in their model, a thinner market liquidity, following a cash flow decline, feeds back into the shareholders' decision to default, making the company more likely to default.

The paper whose analysis is most closely related to ours is by Darbha and Dufour (2012), who use a range of liquidity proxies to analyze the liquidity component of Euro area sovereign bond yield spreads prior to the global financial crisis (2004-2007), and during the crisis period (2007-2010). They find that liquidity, particularly measured by the bid-ask spread of non-AAA bonds, explains the dynamics of corresponding yield spreads better during the crisis than prior to the crisis.

Recent works have highlighted the effects of ECB interventions on bond yields, market liquidity, and arbitrage relationships between fixed income securities. Ghysels, Idier, Manganelli and Vergote (2013) study the effect of the Security Markets Programme (SMP) intervention on the first and second moments of bond returns, using high-frequency data on ECB government bond purchases, and show that it was successful in reducing both bond yields and volatility. Corradin and Rodriguez-Moreno (2014) document the existence of unexploited arbitrage opportunities between European sovereign bonds denominated in Euros and in Dollars, as a consequence of the SMP. Finally, Eser and Schwaab (2014) show long- and short-term effects of the SMP on the European bond yields.

There are several important differences between the prior literature and the evidence we present in this paper. First, we are the first to focus on sovereign credit risk, which is a relatively recent concern among the G8 countries. Second, we focus on liquidity (rather than yield spreads), measured by a range of liquidity metrics, and investigate the relationship between market liquidity in the cash bond market and credit risk, measured by changes in the CDS spread on the Italian sovereign debt. We also examine the credit risk of the primary dealers, measured by their CDS spreads. Third, while most of the previous literature spans past, and thus more normal, time periods in the US and Euro-zone markets, the sample period we consider includes the most relevant period of the Euro-zone sovereign crisis, that since mid-2011, when both Italy and Spain experienced a series of rating downgrades that spread instability both to other European countries (including France, and later on even Germany) and to many European banks. Fourth, our focus is on the *interaction* between credit risk and liquidity, i.e., how credit risk affects illiquidity and vice versa, which has been of particular interest since the onset of the Euro-zone crisis. In particular, we examine the dynamics of the interaction between credit and liquidity, tracing these effects over time. We also explore how the effect of a macro-credit shock on liquidity is affected by the level of the credit risk. This is in contrast to the prior literature on both corporate bonds and, to a lesser extent, sovereign bonds, which focuses only on the static cross-sectional relationship between credit quality and liquidity rather than its time-series property. Last but not least, we define global macro-economic variables relating to credit, market liquidity and funding liquidity, which are important determinants of credit risk and liquidity in sovereign debt markets.

III Hypothesis Development

In this section, we provide an overview of the questions we pose and the hypotheses we test in our research. In motivating these hypotheses, we draw upon the results from the broad microstructure literature. We also take into account the specific institutional aspects of the Italian sovereign bond market, wherever appropriate.

H1 The Dynamics of Credit Risk and Liquidity: *Credit risk is a significant factor in the determination of the market liquidity of Italian sovereign bonds. The dynamic relationship between credit risk and market liquidity is non-linear in the creditworthiness of the government.*

The microstructure literature has extensively investigated the impact of market liquidity on the price of corporate bonds, and, to a limited extent, sovereign bonds.[4] However, to the best of our knowledge, ours is the first formal study to present empirical evidence on the *dynamic* relationship between credit risk and changes in market liquidity, exploiting the time-series evolution of credit risk, rather than cross-sectional differences in credit ratings.[5]

A hypothesis similar to ours is present in He and Milbradt (2014), who show that, in a market where bond holders are subjected to liquidity shocks, an increase in the credit risk of a company will cause the liquidity of its bonds to shrink. At the same time, a decrease in the bonds' market liquidity will cause the equity holders to make the company default earlier. While He and Milbradt's model is specifically developed under the assumptions that the bonds are issued by a corporation and traded by dealers in an OTC market, the intuition of the liquidity of an asset being adversely affected by its credit risk applies under broader conditions. The relation between the more generally defined risk of an asset and its liquidity has been addressed previously, specifically in the theoretical microstructure literature.

The literature pioneered by Bagehot (1971), Glosten and Milgrom (1985), Kyle (1985), and Easley and O'Hara (1987) argues that asymmetry of information about the value of an asset has a positive impact on liquidity, in particular the bid-ask spread, in a quote-driven equity market. The intuition is that, if the market maker anticipates that there is a higher probability of trading with a market participant with superior information, she will raise her bid-ask spread for all participants to compensate for this possibility. As argued by Kyle, this effect translates into other proxies for liquidity,

[4] In the discussion below, the term liquidity usually refers to *market* liquidity, except where defined otherwise.

[5] Specifically, the existing literature documents the *direct* impact of liquidity (e.g. Dick-Nielsen et al. (2012) among others) on bond yields and prices, but not the impact of credit risk on liquidity, or how credit risk affects the bond yields through bond liquidity. In this spirit, we need to establish the relation between credit risk and liquidity in order to then, in turn, quantify its effect on bond yields.

such as volume, market breadth, depth, and price impact. In this context, this asymmetry of information relates to the assessment of credit risk by various agents in the market, i.e. the probability of default and the defaulted bond's recovery value. Hence, the asymmetry of information will be most pronounced ahead of a credit event: the more likely is the occurrence of the credit event (i.e., the higher the credit risk), the more valuable will be the private information of the traders as opposed to the market makers, and therefore, the more the market maker will widen the asset's bid-ask spread. As argued in He and Milbradt (2014), the qualitative results of models based on search costs would not change if asymmetry of information was the driving force rather than search costs.

Similar implications are derived in inventory models of microstructure (such as Garbade and Silber (1976), Garman (1976), Amihud and Mendelson (1980), and Ho and Stoll (1980)), which also suggest that the greater is the risk of an asset, the greater will be the aversion of market makers to hold the asset (long or short), due to its opportunity costs, and hence the higher will be the bid-ask spread they post. To the extent that the asymmetry of information about an asset is correlated with its underlying risk, the two strands of the microstructure literature, based on inventory models and asymmetry of information, lead to the same conclusion: an increase in the risk of an asset adversely affects its liquidity.

Finally, a similar conclusion follows from the risk management practices based on value-at-risk (VaR) models used by market participants, particularly the market makers. A portfolio with an excessively large VaR, based on the assessment of credit risk, erodes the dealers' buffer risk capacity, implying a greater aversion of the dealer to holding the asset, which results in the dealer setting higher bid-ask spreads (lowering market liquidity).

The link between the practice of risk-management based on VaR models and our hypothesis also has also implications for the *dynamics* of the relationship between credit risk and market liquidity: risk constraints are typically based on the agent's risk exposure on the previous day. That is day t liquidity depends on the VaR calculated at the end of day $t-1$. In periods of market stress, however, the VaR is often monitored at an intraday frequency, implying that day t liquidity will depend on the contemporaneous day t credit risk. We address this practice-based implication in our analysis of the dynamic relation between Italian credit risk and market liquidity.

The prior literature has focused on the distinction between the two components of the bond yield spread: the liquidity component and the credit risk component.[6] We take a step back and argue that, although both market liquidity and credit risk are priced cross-sectionally in the bond yield spread so that more liquid and safer bonds trade at a premium, there are important dynamic elements closely linking market liquidity to credit risk. For example, the market's perception of credit risk could itself depend on market liquidity, especially under conditions of market stress, as posited by He and Milbradt (2014), which we explicitly address in this hypothesis.

Based on this theoretical background, we expect the change in credit risk to be a relevant variable in characterizing the *dynamics* of liquidity in the market through the inventory and risk concerns of the market makers. Hence, we investigate whether there is any lead-lag relationship between credit risk and illiquidity, and the directionality of this relationship. We test, for the first time, whether

[6] See Friewald et al. (2012a) and Dick-Nielsen et al. (2012) for a recent investigation of this argument in the context of corporate bonds.

the increase in credit risk drives the reduction of liquidity in the bond market or vice versa, i.e., whether the low liquidity in the bond market increases the CDS spread, or the other way around. We attempt to define, with a lead-lag analysis in a Granger causality setting, which of the two economic variables leads the other, albeit in a statistical manner. While it may be argued that there is a stronger theoretical basis for credit risk to influence liquidity than the other way around, we let the data inform us about this interaction.

The second part of the hypothesis is motivated by observations by market makers and policy pronouncements, which suggest that the credit risk-liquidity relationship shifted as the credit quality of the Italian sovereign eroded. In the period under consideration, several economic and political events occurred that caused the level of credit risk to increase more than threefold (the CDS spread shot up from 145 bp to 592 bp). Several conceptual arguments can be advanced for such a structural shift in the relationship. First, the adverse change in credit quality was generally accompanied by downgrades in the credit rating, altering the clientele of investors who were able to hold Italian sovereign bonds. Second, margins in the repo markets are generally increased in response to a decline in credit quality, which would have made it more expensive for investors to hold Italian sovereign bonds. Third, in the presence of a sharp decline in credit quality, internal (and external) models of risk-weighting and illiquidity used by banks, a major investor segment, would necessarily predict an increase in the capital required to support the higher level of risk.[7]

This structural break is likely to be particularly important when the worsening of creditworthiness suggests an upcoming credit rating downgrade to below the investment grade, at which point the clientele effects are exacerbated. The rule of thumb for traders is that this occurs when the CDS spread goes above 500 bp, when the structural shift is likely to fundamentally alter the relationship between credit risk and market liquidity.[8] It should be emphasized that this threshold should be distinguished from any potential credit downgrade of Italian sovereign bonds. Indeed, even though there were some credit downgrades for European governments, Italy maintained its investment grade rating throughout the period of our study, despite the sharp spike in its sovereign CDS spread.

Parallel arguments for these effects have been proposed in the literature based on the behavior of agents in a crisis. For example, Duffie, Garleanu and Pedersen (2007) argue that liquidity is more important in crisis periods, when inventory holding costs and search costs are higher, and asymmetric information is more significant.[9] Moreover, a greater proportion of investors could shorten their investment horizons in a period of crisis. For example, bond mutual funds and hedge funds could face the possibility of redemptions or be forced to meet VaR requirements and margin calls, and would therefore wish to hold more liquid assets to address these eventualities (see, e.g., Sadka (2010)). Individual investors could shift more of their portfolios from illiquid to liquid assets as they turn more risk averse, rendering already illiquid assets even more so, in a vicious cycle. Market makers may also face more severe funding constraints based on accentuated risk aversion, as well as a reduction in their

[7]A similar argument arises for the accounting classification of assets by liquidity into Levels 1, 2, and 3, the latter calling for more provisions.

[8]This threshold of 500 bp is also used by clearing houses, such as the Depository Trust and Clearing Corporation (DTCC) and LCH.Clearnet, to switch between the quotation of CDS contracts from a yield basis to a price basis, leading to more stringent margining.

[9]There is empirical support for this hypothesis in the context of the US corporate bond market in the work of Friewald et al. (2012a), Bao et al. (2011), Feldhütter (2012), and Dick-Nielsen et al. (2012).

risk limits in a crisis. In this vein, we investigate the second part of Hypothesis 1, letting the data inform us whether there is a level of CDS above which there is a statistically significant change in the relationship between changes in CDS spreads and changes in market liquidity variables.[10]

H2 Policy Intervention and Structural Breaks: *The monetary policy interventions of the central bank affect the dynamic relationship between credit risk and market liquidity.*

By virtue of its status as the central bank of the Euro-zone, the ECB has a major influence on its sovereign bond markets, while being virtually independent of the actions of the governments of individual countries. The ECB's monetary intervention takes many forms, ranging from jawboning and formal guidance by its board members, in particular its President, to the injection of liquidity into the major banks in the Euro-zone, which themselves hold these bonds, and even to direct purchases of sovereign bonds in the cash markets.[11] During the Euro-zone crisis, the policy interventions by the ECB consisted of (i) the SMP, initiated in May 2010, (ii) LTRO, announced in December 2011, (iii) policy guidance, and (iv) OMT, also announced in December 2011. A significant event, classified under (iii) in the judgment of several market observers we spoke to, was the speech by Mario Draghi, the ECB President, who unveiled the potential for new tools to ease the European sovereign debt crisis. Against the backdrop of each of these policy interventions, we next investigate whether the nature of the dynamic relationship between credit risk and liquidity is likely to undergo a change when the macro-economic regime shifts due to the policy intervention.

The SMP was initiated in May 2010 in the aftermath of the Greek debt crisis, which spilled over into the sovereign debt markets of several countries in the Euro-zone.[12] The distinctive feature of the program is the direct purchase of sovereign debt securities in the open market by the ECB with the intent of retaining them on its balance sheet until maturity ("hold-to-maturity strategy"). It should be noted that several features of the program were not made explicit at that time nor have they been since. In particular, neither the amounts proposed to be spent, the time frame over which the purchases would occur, nor the specific securities that would be purchased were announced. However, data on the outstanding aggregate value of the holding portfolio have since been published, albeit at a weekly frequency, without any reference to the specific date(s) during the week when the securities were bought. Furthermore, the ECB does not provide a breakdown describing the composition of these assets by national origin of issuance, maturity, coupon, or other characteristics.[13]

The SMP intervention could arguably have affected both the variables of interest in our study: It could have restored market liquidity, at least temporarily, in the Italian bond market and, through the

[10]We use the threshold test proposed by Hansen (2000) to investigate this structural break, as discussed in Appendix C.

[11]We exclude fiscal policy announcements, such as bail-outs, since they are likely to have had only an indirect effect on market liquidity.

[12]The ECB defines the SMP as follows: "Interventions by the Eurosystem in public and private debt securities markets in the euro area to ensure depth and liquidity in those market segments that are dysfunctional. The objective is to restore an appropriate monetary policy transmission mechanism, and thus the effective conduct of monetary policy oriented towards price stability in the medium term." See `http://www.ecb.europa.eu/home/glossary/html/act4s.en.html`.

[13]The ECB disclosed details of the securities holdings acquired under the program, revealing a country-by-country breakdown, on one date, February 21, 2013. As of that date, Italian debt accounted for roughly half the total (€103 billion out of a total of €218 billion). Spain ranked second (€44 billion), followed by Greece (€34 billion), Portugal (€23 billion) and Ireland (€14 billion). See Corradin and Rodriguez-Moreno (2014).

increase in the demand for these bonds, it could have reduced their yield, hence contemporaneously reducing the CDS spread. Consistent with Hypothesis 1, the SMP intervention could have affected the relationship between a change in credit risk and the resulting change in liquidity. The intervention could also have affected market sentiment, and hence the perception of investors regarding the risk of the Italian sovereign.

The second intervention measure, LTRO, provided three-year funding of €489 billion on December 21, 2011 and €523 billion on February 29, 2012. The long-term maturity of this massive funding action was unprecedented in ECB policy history, and even globally.[14] Not unlike the situation surrounding the SMP, information regarding the LTRO, and specifically the banks' usage of LTRO funds, is very sparse, and its event-like feature does not allow us to measure the gradual effect of this extraordinary ECB measure. However, the nature of its large funding liquidity shock qualifies it as a significant structural break impacting the market liquidity in the sovereign bond market through the availability of funding liquidity to market makers. We expect that the availability of massive amounts of medium-term funding from the ECB, at unusually low interest rates, should have shifted the incentives of banks to hold sovereign bonds, since they would have been able to pledge them as collateral for their funding. As the incentive to hold sovereign bonds improved, market makers should have been less concerned with illiquidity and credit risk.

The third instrument of monetary policy intervention is the policy guidance offered by the ECB through various policy pronouncements made by its board members, most prominently the comment in July 2012 by the President, Mario Draghi, that they would do "whatever it takes" to address the Euro-zone crisis.[15] This statement served to restore confidence in the markets and is also likely to have reduced both the CDS spread and market liquidity in the Italian sovereign bond market.

The last type of intervention employed by the ECB is the OMT program, under which it has the ability to make purchases ("outright transactions") in the secondary sovereign bond markets of the Euro-zone countries, subject to strict conditions.[16] However, although the operation was announced on August 2, 2012, and the technical framework of these operations was formulated on September 6, 2012, it has not been formally adopted thus far.

The argument for the supposition that the LTRO should have a larger impact on market liquidity than the other policy interventions relies largely on that action's positive effect on *both* credit risk and funding liquidity for the market maker banks. This is particularly due to the massive size and long maturity of the funding made available. In contrast, the SMP was too small and temporary, having no impact in terms of addressing the funding liquidity problem of the market makers by injecting liquidity into the system. It is, therefore, unlikely to have improved market liquidity significantly over

[14] LTRO is formally defined by the ECB as follows: "A regular open market operation executed by the Eurosystem in the form of a reverse transaction." Funding actions are usually carried out through monthly standard tenders and normally have a maturity of three months, but on December 8, 2011, the ECB announced an unprecedented three-year LTRO consisting of a three-year collateralized loan, under the rubric of a set of non-standard measures launched by the ECB. See `http://www.ecb.europa.eu/home/glossary/html/act4s.en.html`.

[15] In his speech on July 26, 2012, at the Global Investment Conference in London, Mario Draghi stated: "The ECB is ready to do whatever it takes to preserve the Euro. And believe me, it will be enough."

[16] According to the ECB, "A necessary condition for Outright Monetary Transactions is strict and effective conditionality attached to an appropriate European Financial Stability Facility/European Stability Mechanism programme. [...] The involvement of the IMF shall also be sought for the design of the country-specific conditionality and the monitoring of such a programme." See `http://www.ecb.europa.eu/press/pr/date/2012/html/pr120906_1.en.html`.

time. Finally, OMT has been announced, but not implemented so far.

In conclusion, our second hypothesis addresses the presence of a regime shift in the estimated relationship between credit risk and market liquidity around the dates of significant policy interventions by the ECB, allowing the data to inform us of the presence of any structural breaks over our sample period.[17]

H3 Global Risk Factors and Funding Liquidity: *After controlling for credit risk, both global systemic risk factors and the funding liquidity of the primary dealers have an effect on the market liquidity of the bonds.*

Global systemic factors may potentially affect market liquidity through the inventory channel, the increase in the risk aversion of market makers and traders in general, and through obligor-specific uncertainty and asymmetry of information. We test for the significance of widely known components of systemic risk: global uncertainty and appetite for risk, as measured by the US volatility index, USVIX; the increase in the cost of funding due to the banking crisis, measured by the Euribor-Eonia spread; the lack of funding liquidity, measured by the Eonia-German T-Bill spread.

The last two measures are the European counterparts of those employed in the context of the American fixed income market by Brunnermeier (2009) and others, who recommend splitting the Treasury-Eurodollar (TED) spread, the difference between the USD LIBOR and the risk free US Treasury bill rate, into two components.[18] As an alternative proxy for the (dollar) funding liquidity of Euro-zone banks, we also include the CCBSS. As explained by Baba, Packer and Nagano (2008) and Baba (2009), cross-currency basis swaps are used by banks to finance themselves in foreign currencies when the interbank market is illiquid, and the market for them is particularly active during periods of financial crisis.

Brunnermeier and Pedersen (2009) present a framework to distinguish between (asset) market liquidity (the ease and cost at which assets can be bought and sold) and funding liquidity (the ability of market makers to fund their positions). Their model identifies a channel whereby traders become reluctant to take positions when funding liquidity is tight, especially when their positions are capital intensive, calling for higher margins; in turn, such a constraint, when simultaneously binding for several market makers, lowers overall market liquidity. In their model, an adverse shock to primary dealer funding liquidity (the availability of funding) forces market makers to reduce their inventories and provide less liquidity to the markets, which consequently reduces market liquidity. When the impact of the funding liquidity shock on asset market liquidity is strong enough, the decrease in asset liquidity makes funding even tighter for market makers, causing a self-reinforcing liquidity spiral, in which both funding liquidity and asset liquidity continue to deteriorate.

[17] To investigate this issue, we perform Chow tests in Section VI.II, and a SupWald test, a modified Chow test with an unknown break point (see Chow (1960), Andrews (1993), and Hansen (1997)), in Section VII.III (see Appendix C for details of the procedure).

[18] Since an increase in the TED spread could originate from higher interest being charged on unsecured loans or a surge in demand for T-bills (or both), the first component captures an increase in the credit (or counterparty) risk perceived in the interbank market and is measured by the spread between the LIBOR and the Overnight Index Swap (OIS) rate, while the second component captures the need for liquidity of the banking sector which, looking for first-rate collateral, turns to treasuries, and is measured by the spread between the OIS rate and the treasury yield.

Following Brunnermeier and Pedersen's theoretical prediction, we employ a measure of the market makers' ability to raise funds in the market to finance their positions. We use the average difference between the individual funding rates of a subset of banks and the market-wide funding rate, the Euribor, as our metric of the funding liquidity of the market makers; we choose the subset of banks to correspond to the group of primary dealers in the Italian sovereign bond market.[19] The structure of the MTS market, where we can clearly identify the market makers, is ideal for investigating the relationship between funding liquidity and market liquidity, which, to our knowledge, has not yet been investigated in depth empirically, particularly in fixed income markets.

A direct measure of relative funding liquidity, i.e., the funding cost measure for primary dealers, can thus be obtained by considering the individual rate submissions of individual market makers, which are also members of the Euribor and Libor bank panels.[20] For each day t and rate r_τ, where r is either the Euribor or the Libor for Euros and τ is the term over which the rate is defined, we calculate the following daily funding liquidity measure:

$$Diffr_{t,\tau} = \frac{\sum_{i=1}^{M} r_{i,t,\tau}}{M} - \hat{r}_{t,\tau}$$

where $r_{i,t,\tau}$ is the submission rate for bank i and $\hat{r}_{t,\tau}$ is day-t "fixing" by the respective polling entity. We select only banks that are primary dealers on the MTS market and subtract the fixing of the rate, which measures the system-wise illiquidity, in order to capture only the funding illiquidity, which should be reflected in the market liquidity of the bonds.[21] We expect this variable to have a positive effect on the *Quoted Spread*: As the funding liquidity worsens and our measure grows, so should the market illiquidity, as predicted by Brunnermeier and Pedersen (2009).[22]

IV MTS Market Structure and Data Description

Our data consist of all real-time quotes, orders, and transactions that took place on the MTS European government bond market, and are provided by the MTS Group. These high-frequency data cover trades and quotes for the fixed income securities issued by twelve national treasuries and their local equivalents: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Portugal, Slovenia, and Spain. The MTS system is the largest interdealer market for Euro-denominated government bonds and is made up of many markets, including the EuroMTS (the "European market"),

[19] We also investigated an alternative variable, which may also affect funding liquidity, albeit indirectly: the credit quality of the market makers, proxied by *their* CDS spreads. However, the CDS spread measures the market makers' long-term credit risk and may be a noisy measure of short-term credit risk, which would presumably be more relevant for the ability of the market makers to fund themselves in the money market.

[20] We use data on rate submissions by individual panel banks from Eisl, Jankowitsch and Subrahmanyam (2013), who kindly agreed to share the data with us.

[21] We focus on a three-month term. The market makers submitting quotes for the Euribor are Barclays, Banca Intesa, Unicredit, JPM, Deutsche, BNPP, Citibank, Commerzbank, CA CIB, HSBC, ING, MPSI, RBS, Societe Generale, and UBS. The market makers submitting quotes for the Euro-Libor are Barclays, JP Morgan, Deutsche Bank, Citibank, HSBC, Royal Bank of Scotland, Societe Generale, and UBS.

[22] While we are aware of the debate regarding the manipulation of these rates, we expect that the effect of manipulation could, in part, be reduced because the measure we are using is in *relative* terms. Moreover, even if the bias does affect the relative funding costs, the variable should only be less informative. If this variable turns out to be statistically significant, it will mean that manipulation does not completely eliminate its informativeness.

EuroCredit MTS, and several domestic MTS markets. In this study, we will focus on the liquidity of Italian government bonds, regardless of whether the trading or quoting activity took place on the domestic or European market. This is also reflected in the definition and computation of the liquidity measures used later on in this paper.[23]

The MTS trading system is an automated quote-driven electronic limit order interdealer market, in which market makers' quotes can be "hit" or "lifted" by other market participants via market orders. EuroMTS is the reference electronic market for European benchmark bonds, which are bonds with an outstanding value higher than €5 billion.[24] Appendix A provides details of the market architecture, trading protocol, and data released for the MTS market.

The sample period of our study is from June 1, 2011 to December 31, 2012.[25] The time period we analyze provides a good window in which to study the behavior of European government bond markets during the most recent part of the Euro-zone sovereign debt crisis and the period leading up to it. Our dataset consists of 152 Italian government bonds. Table 1 presents the distribution of these bonds in terms of maturity and coupon rate, between maturity groups as well as bond types. The maturity groups were chosen based on the time distance between each bond maturity and the closest whole year. As Table 1 shows, the large majority (in numbers) of the bonds analyzed have short maturities (from 0 to 5 years). All bonds considered in this analysis belong to one of the following types: Buoni Ordinari del Tesoro (BOT) or Treasury bills, Certificato del Tesoro Zero-coupon (CTZ) or zero coupon bonds, Certificati di Credito del Tesoro (CCT) or floating notes, or Buoni del Tesoro Poliennali (BTP) or fixed-income Treasury bonds. The vast majority of the bonds in our sample belong to the BOT and BTP types. We exclude inflation and index-linked securities from our analysis.

INSERT TABLE 1 HERE

IV.I Credit and funding liquidity measures

In order to control for and characterize the effect of global credit and liquidity risk, we employ several macro-economic indicators, most of which are common in the academic literature. The Euribor-Eonia spread captures the (global) market credit risk, through an increase in the (spread) cost of funding, and is measured as the difference between the three-month Euro Area Inter-Bank Offered Rate (Euribor) for the Euro, covering dealings from 57 prime banks, and the three-month Euro OverNight Index Average (Eonia), or the effective swap rate against the overnight rate computed as a weighted average of all overnight interbank unsecured lending transactions reported by 44 banks in the Euro area. The Eonia-German T-Bill spread is a measure of funding liquidity (macro liquidity risk) and is the difference between the three-month Eonia and the yield of the three-month German Treasury bill.

[23]Three notable exceptions are the *Quoted Spread*, the *Quoted Quantity*, and the *Lambda*, as defined in Section IV.II. The domestic market is chosen as the reference for a liquidity measure, when the measure differs between the European and the Italian domestic market. However, in most cases, market makers post the same quotes for both the Italian domestic and European markets.

[24]See also Dufour and Skinner (2004).

[25]The start date of this sample is dictated by the availability of detailed tick-by-tick, second-by-second, data from MTS. Prior to June 1, 2011, the MTS data on quotes and quote revisions were not quite as detailed. The end date is dictated by a major change in the market structure that was implemented in December 2012, and that changed the role of market makers acting in the European section of the MTS market. Fortuitously, the period we consider covers a large part of the Euro-zone crisis.

The USVIX, measuring global systemic risk, is the implied volatility index of S&P 500 index options calculated by the Chicago Board Options Exchange (CBOE) and used widely as a market sentiment indicator. The Euro Stoxx 50 is a blue-chip index for the Euro-zone and covers 50 stocks from 12 Euro-zone countries. The CCBSS represents the additional premium paid per period for a cross-currency swap between Euribor and US Dollar Libor, and serves as a proxy for funding liquidity.[26]

Finally, the Italian Government-specific credit risk is measured by the spread of a senior five-year dollar-denominated CDS contract obtained from Bloomberg. The choice of this proxy for sovereign credit risk is debatable. An alternative potential proxy for Italian sovereign risk could be the BTP-Bund yield spread. We prefer to avoid using the BTP-Bund yield spread, or simply the BTP yield, as an explanatory variable because they are likely to be intimately connected to the bond quote and transaction prices that are also used to calculate our liquidity measures. CDS spreads are obviously related to the BTP yield and the BTP-Bund yield spread (as Figure 1 shows), through arbitrage in the basis between them, but at least are determined in a different market. Moreover, as the figure shows, the CDS spread typically leads the BTP-Bund spread during much of the sample period, especially during the crisis.[27]

INSERT FIGURE 1 HERE

IV.II Market liquidity measures

There is no consensus in the academic or policy-making literatures regarding the best metrics for assessing the liquidity of an asset. Thus, although we focus on the quoted bid-ask spread, *Quoted Spread,* for the main exposition, in Section VII.I we report the results for the other liquidity measures described here. The proxies we employ cover a wide range of metrics that have been used extensively in the literature.[28] The relationships we investigate allow us to compare the effectiveness of different proxies for estimating liquidity in the MTS market. The proxies we use can be divided into two main categories: quote-based and trade-based measures. Quote-based measures include the (absolute) bid-ask spread (*Quoted Spread*), total quoted quantity (*Quoted Quantity*), and the market depth measure, *Lambda*. Trade-based measures include the actual spread experienced by traders (*Effective Spread*) and the traded volume (*Volume*). In addition, we have two liquidity measures that are based on computed values using changes in traded prices, the *Amihud Measure* and the *Roll Measure*, comprehensive metrics that are widely used in the literature.

Quoted Spread is defined as the difference between the best ask and the best bid, per € 100 of face value, proxying for the cost of immediacy that a trader would face when dealing with a small trade. *Quoted Quantity*, on the other hand, measures the largest amount a trader could buy or sell at any point in time, if she were not concerned with execution costs. The depth measure *Lambda* attempts to combine the two previous proxies by measuring by how much a trader would move the best bid

[26] All global market data were obtained from Bloomberg.

[27] In Section VII, we investigate whether the intraday volatility of the bond yield, as measured from the MTS transaction data, affects the liquidity, while controlling for the credit risk. This modification does not significantly change the results, supporting our choice of the CDS spread as a measure of credit risk.

[28] In a companion paper, Pelizzon, Subrahmanyam, Tomio and Uno (2013), we study these liquidity proxies in a comprehensive manner in the context of the microstructure of the Italian sovereign bond market.

(ask) if she were to trade € 15 million of a given bond.[29] Mathematically, the *Lambda* on the ask side would be defined as $\lambda^a = E\left[(P_t^a - P_{t-1}^a)(Q_t)\,|Q_t = 15M\right] = E\left[\Delta P_t^a(Q_t)\,|Q_t = 15M\right]$, where P_t^a is the time t ask price following a buy trade of quantity $Q_t = 15M$, $and \lambda^b$ would be defined similarly. In order to represent both sides of the market, we consider the mean, $\lambda = \frac{\lambda^a + \lambda^b}{2}$, in our empirical estimations, as a market depth measure.

As for the trade-based measures, the effective bid-ask spread, *Effective Spread* is calculated as $Q \cdot (AP - M) \cdot 2$, where $Q = 1$ if it is a buy order, $Q = -1$ if it is a sell order, AP is the face value-weighted trade price, and M is the mid-quote in place at the time the order arrives. Since orders might "walk" the book, once the quantity offered at the best bid and ask price is depleted, effective and quoted spreads are bound to differ, given the endogenous relationship between the quoted spread and the trading decision regarding the quantities bid or offered. Moreover, we consider the traded volume, *Volume,* as a trade-based liquidity measure.

The *Amihud Measure* for bond i, on day t, is calculated in its daily formulation as $\frac{\|r_{it}\|}{V_{it}}$, where $\|r_{it}\|$ is the absolute mid-quote return between 9am and 5pm (the trading day, minus the first and last half-hours) for bond i on day t, and V_{it} is the bond i day t traded quantity, *Volume*, in millions of Euros. The *Roll Measure* for bond i on day t is calculated as $2\sqrt{-Cov(\Delta p_k, \Delta p_{k-1})}$, where Δp_k is the price change between transaction $k-1$ and transaction k. Following the literature, we calculate the covariances during a 21-day window; we require at least three entries to make this calculation, which means, for example, either three days with three trades each or one day with seven trades in the 21 days preceding the days for which the measure is calculated.[30]

All quote-based measures are calculated at a five-minute frequency for each bond, then averaged across bonds to calculate a daily market-wide measure.[31] The effective spread is calculated for our sample of the whole market, volume-weighting the trades of all bonds, while the volume is the sum of the face values of bonds traded on the MTS on a specific day.

V Descriptive Statistics

V.I Liquidity measures

Table 2, Panels A and B, presents the summary statistics for the activity and liquidity measures for Italian sovereign bonds traded on the MTS market, between June 2011 and December 2012, spanning the period of the Euro-zone sovereign crisis. The ten columns on the left report time-series averages of the daily statistics. These statistics have been calculated as the time-series averages of the cross-sectional averages of the corresponding measure, across all bonds that were quoted on the MTS, on a

[29] This amount was chosen since it is at the 90th percentile of the overall market in terms of trade size. As traders might split up large amounts over several subsequent trades, *Lambda* captures the price movement caused by a relatively large trade requiring immediacy. It is conceptually equivalent to the concept of market depth defined by Kyle (1985).

[30] This is standard practice in the prior literature, e.g., Dick-Nielsen (2009), and Friewald et al. (2012a).

[31] It is common in the sovereign bond literature to separate the bonds into on-the-run and off-the-run issues, or to only consider the former, reckoning that the former are more liquid and more sought after by investors. The Italian sovereign issuer, the *Tesoro*, often reissues existing bonds, thus enhancing their liquidity, and causing the on-the-run/off-the-run dichotomy to lose its relevance. In any event, we checked whether there were differences in the quoted or effective bid-ask spread for "new" issues compared to the prior issues and did not find any significant differences. For this reason, we average across all bonds without sorting them by remaining maturity or age since issue.

given day.[32] The three columns on the right show the cross-sectional averages, and the maximum and the minimum values, across 152 different bonds, of their respective time-series averages. While this study focuses on the analysis of the time-series data presented in the columns on the left, the columns on the right are referred to in this section in order to highlight the heterogeneity in the cross-section of bonds.

INSERT TABLE 2 HERE

The mean (median) number of bonds quoted each day on the MTS is 90 (90), and the daily volume of trading in the market is slightly above €2 billion (€1.9 billion), which translates into a daily traded volume of each quoted bond of about €30.5 million. Based on these numbers, the daily trading volume in the Italian sovereign bond market (as represented by the MTS) is much smaller than in the US Treasury market, by a couple of orders of magnitude, with the average traded quantity in the latter being around $500 billion per day.[33] The average daily trading volume in the MTS Italian bond market is even smaller than the US municipal market (around $15 billion), the US corporate bond market (around $15 billion), and the spot US securitized fixed income market (around $2.7 billion in asset-backed securities, around $9.1 billion in collateralized mortgage obligations, and around $13.4 billion in mortgage-backed securities).[34]

Our volume statistics are in line with the stylized facts documented in the previous literature, taken together with the consistent shrinkage of overall market volumes since the Euro-zone crisis began. Darbha and Dufour (2012) report that the volume of the Italian segment of the MTS market as a whole, over their 1,641-day sample, was €4,474 billion.[35] This translates into an average daily volume of about €3.8 billion.[36] Darbha and Dufour report that the daily volume per bond shrank from €12 million in 2004 to €7 million in 2007. Their sample includes only coupon-bearing bonds; thus, their figures for overall market volume are not directly comparable to ours.

The daily number of trades on the MTS Italian sovereign bond market is 265 in total (or about 3 per bond), which is similar to the 3.47 trades a day per corporate bond on TRACE, as reported in Friewald et al. (2012a). Dufour and Nguyen (2011) report an average of 10 trades per day per Italian bond in an earlier period, between 2003 and 2007. As with the trading volume, the number of trades declined during the crisis period compared to earlier years. Our sample period covers the most stressed months of the Euro-zone crisis, when the creditworthiness of several European countries was seriously questioned by market participants. As we will show later, the liquidity in the MTS market was intimately related to the evolution of spreads in the sovereign CDS market, and varied just as drastically, as the time series plots of the CDS spread and the *Quoted Spread* in Figure 2 show. Up to the end of 2011, at the peak of the crisis, the two series share a common trend, which is not repeated in the second half of our sample.

[32] The *Effective Spread* is calculated per transaction, then volume-weighted and averaged for the whole market. The *Quoted Spread*, the *Quoted Quantity*, and the *Lambda* are calculated at a five-minute frequency, then averaged per bond, and finally, across all bonds quoted on the MTS on a given day.

[33] See, for example, Bessembinder and Maxwell (2008).

[34] Details for the corporate bond, municipal bond, and securitized fixed income markets are provided in Friewald et al. (2012a), Vickery and Wright (2010), and Friewald, Jankowitsch and Subrahmanyam (2012b) respectively.

[35] Their sample spans the period from January 2004 through July 2010.

[36] This calculation assumes 250 business days per year. Cf. Table 1, page 34 of their paper.

INSERT FIGURE 2 HERE

Panel (a) of Figure 3 shows the evolution of the *Quoted Spread* and the *Effective Spread*, while Panel (b) presents the movements of *Quoted Quantity* and *Lambda*. The close correspondence between the liquidity variables can be seen, for example, by considering the highest spike for the *Quoted Spread* (448 bp), which happened on November 8, 2011. On that date, the Italian Prime Minister, Silvio Berlusconi, lost his majority in the parliament, which led to his resignation. The spike in the *Quoted Spread* corresponds to a similar spike in the *Effective Spread*, *Lambda*, and (the inverse of) the *Total Quoted Quantity*. The event clearly had medium-term effects, as the *Quoted Spread* persisted at around 100 bp for about two months, before returning to the time-series median value of 42 bp in January 2012, after the LTRO program had been launched in December 2011. Similar patterns can be observed for the other liquidity variables.

On average, the market-wide average *Quoted Spread* is €0.506 per €100 of face value: however, this arises with considerable heterogeneity across bonds, and ranges from one bond averaging €0.0009 to another averaging €1.405. The market-wide average *Quoted Spread* peaked on November 8, 2011 at an average of €4.477 per €100 of face value, while it was at its minimum of €0.131 at the beginning of the sample, and then again towards the second half of 2012. Similarly, the *Quoted Quantity* was at its highest around June 2011 (€182 million per bond) and then declined towards its time-series average of €123 million. The bonds are also heterogeneous in terms of their offered quantity, since they range from €70 million to €524 million offered on average per day.

Due to the endogeneity of the trading decisions of dealers, given the *Quoted Spread*, the *Effective Spread* in Figure 3 Panel (a) is typically much lower than the *Quoted Spread*, and varies from €0.03 to €0.71 per 100 of face value. This is in line with the figure of €0.70 for the 99th percentile of the quoted spread, at the time of trade execution, that appears in Darbha and Dufour (2012).[37] The *Lambda* measure is plotted in Panel (b) of Figure 3. This depth measure ranges from 0.0038 to 0.255, which means that, on the worst day, trading €15 million would move the price by €0.255 per bond, on average, toward the side of the market hit by the order. This measure is also heterogeneous across bonds, ranging from €0 to 0.05. It is relevant to note that the time-series development of this measure mirrors that of the *Quoted Spread*, even though it is a more comprehensive measure of liquidity. Incidentally, its behavior is also similar to that of the *Quoted Quantity*, which is derived from the same quote data.

INSERT FIGURE 3 HERE

Panel (a) of Figure 4 shows the total number of *Trades* and trading *Volume* (in billions of euros) exchanged on the MTS. The variables share a very strong commonality in movement and show a clear cyclical pattern. We reckon that the peaks coincide with auctions of new bonds, reopening of previous issues, and releases of relevant economic variables and events. The second panel of Figure 4 shows the dynamics of the two liquidity measures defined in the above section: the *Amihud Measure*,

[37] Although we do not focus on the cross-sectional differences between the bonds in this study, we report a multivariate analysis of the cross-sectional relationship between bond characteristics and liquidity measures in Appendix B, which summarizes the results from the companion paper Pelizzon et al. (2013).

which faithfully mirrors the behavior of the bid-ask spread, and the *Roll Measure*, which does not. The variation in the *Amihud Measure* over time, from a minimum of 0.25 bp/million to a maximum of 28.60 bp/million, is less dramatic than the changes in the *Quoted Spread*. This can be attributed to the fact that the *Amihud Measure* is derived from actual trading data, and thus corresponds more directly to the *Effective Spread*. The *Roll Measure*, on the other hand, should be closely related to the bid-ask spread, *assuming* a "bid-ask bounce"; however, since 78% of buy (sell) trades follow a buy (sell) trade in the Italian sovereign bond market, the *Roll Measure* performs poorly as its key assumption is infringed.[38]

INSERT FIGURE 4 HERE

The correlations between the liquidity variables are presented in Table 3. As expected, all the liquidity measures are very highly correlated with each other, which allows us to limit most of our analysis to the *Quoted Spread*, and repeat only the final specifications for the other variables, to confirm our findings. The *Trades* and *Volume* variables are not highly correlated with the standard liquidity variables and seem to be driven by other forces; hence, they should not be used as market liquidity proxies if better alternatives are available.

INSERT TABLE 3 HERE

V.II Credit and funding liquidity risk measures

Table 4 reports the summary statistics of the credit and funding liquidity risk variables. As shown in Figure 1, the Italian CDS spread for the period considered ranges from 145 bp to 592 bp, with a mean of 401 bp and a standard deviation of 108 bp, indicating the large changes in this variable during the period. The EuroStoxx50 market index also presents a significant level of volatility, with a daily standard deviation of 1.69%, while the American USVIX ranges from 13.45% to 48%. The short-term credit risk measure applicable to the Euro-zone, the Euribor-Eonia spread, shows somewhat smaller variation, ranging from 0.10% to 1.01%. The global funding liquidity measure Eonia-DeTBill spread indicates that the general level of funding costs is quite low, and ranges from 0.16% to 0.78%. The CCBSS variable, which captures the general level of funding liquidity in the system, and should be close to zero in the absence of funding constraints, ranges from 0.20% to 1.06%, indicating a large variability in the global liquidity conditions in the period considered. All the funding and credit variables suggest that the conditions in the Euro-zone financial system were at their worst around the third quarter of 2011, but improved during the first quarter of 2012, and then worsened, although to a lesser extent, around June 2012 and continued to decline towards the end of that year.

Finally, we consider two variables that aim to capture funding liquidity conditions specific to the market makers in the Italian bond market. As Table 4 shows, the funding conditions of these market makers, on average, are better than those of the other financial institutions in the Euribor and Euro

[38]Roll (1984) states: "Given no new information about the security, it is reasonable to assume further that successive transactions are *equally likely* to be a purchase or a sale by the market maker as traders arrive randomly on both sides of the market for exogenous reason of their own" (emphasis ours). In our sample, a buy (sell) is twice as likely to follow a buy (sell) than a sell (buy) transaction.

Libor rate-setting panels. However, the distribution of this variable indicates that this difference ranges from -2.4 bp to 0.7 bp for *diffEuribor* and from -3.3 bp to 2 bp for *diffEurLibor*, indicating that they do, at times, face worse funding constraints than the rest of the panel.

INSERT TABLE 4 AND FIGURE 5 HERE

The correlations between the credit and funding liquidity variables are shown in Table 5. As is to be expected, most variables are highly correlated with each other, with the expected signs.

INSERT TABLE 5 HERE

VI Results

In this section, we address the research questions highlighted in Section III, focusing on the dynamic relationships between credit risk and market liquidity and the effect of the ECB's *deus ex machina*. We conduct our analysis with a range of liquidity proxies, as defined and discussed in Section IV.I. However, to conserve space, especially in the context of the multiple specifications that we estimate, we only report detailed results in the text for the *Quoted Spread*, the bid-ask spread that is quoted on any given day. A similar analysis was performed for the other important liquidity proxies and the results are reported in Section VII.I.[39]

VI.I The dynamics of credit risk and liquidity

H1 The Dynamics of Credit Risk and Liquidity: *Credit risk is a significant factor in the determination of the market liquidity of Italian sovereign bonds. The dynamic relationship between credit risk and market liquidity is non-linear in the creditworthiness of the government.*

In order to test the above hypothesis and determine the nature of the relationship between the (changes in the) two variables of interest – namely the credit risk of Italian government bonds, as measured by the *CDS Spread*, ΔCDS_t, and the liquidity of the Italian government bonds, as measured by their bid-ask spread, ΔBA_t – we investigate first whether there exists a lead-lag relationship between them, using a Grange-causality test, a statistical notion of causality based on the relative forecasting power of two time-series for each other: Time-series j is said to "Granger-cause" time-series i if past values of j contain information that helps predict i, above and beyond the information contained in past values of i alone. The mathematical formulation of this test is based on linear regressions of ΔLM_t, a generally defined liquidity measure, and ΔCDS_t on their p lags.

Specifically, let ΔLM_t and ΔCDS_t be two stationary time-series. We can represent their linear

[39] We conduct our analysis using the MTS data after winsorizing them at the 0.5% level, to diminish the importance of outliers.

inter-relationships with the following vector autoregression (VAR) model:

$$\begin{aligned}
\begin{pmatrix} \Delta LM_t \\ \Delta CDS_t \end{pmatrix} &= \begin{pmatrix} K_{LM} \\ K_{CDS} \end{pmatrix} + \begin{pmatrix} a_{11_1} & a_{12_1} \\ a_{21_1} & a_{22_1} \end{pmatrix} \begin{pmatrix} \Delta LM_{t-1} \\ \Delta CDS_{t-1} \end{pmatrix} + \begin{pmatrix} a_{11_2} & a_{12_2} \\ a_{21_2} & a_{22_2} \end{pmatrix} \begin{pmatrix} \Delta LM_{t-2} \\ \Delta CDS_{t-2} \end{pmatrix} \\
&+ \begin{pmatrix} a_{11_3} & a_{12_3} \\ a_{21_3} & a_{22_3} \end{pmatrix} \begin{pmatrix} \Delta LM_{t-3} \\ \Delta CDS_{t-3} \end{pmatrix} + \cdots + \begin{pmatrix} a_{11_P} & a_{12_P} \\ a_{21_P} & a_{22_P} \end{pmatrix} \begin{pmatrix} \Delta LM_{t-P} \\ \Delta CDS_{t-P} \end{pmatrix} \\
&+ \begin{pmatrix} \epsilon_{LMt} \\ \epsilon_{CDSt} \end{pmatrix}
\end{aligned} \tag{1}$$

where $\epsilon_{\mathbf{t}} \sim N(\mathbf{0}, \mathbf{\Omega})$, and a_{ij_p}s are the p-lag coefficients of the model. We can conclude that ΔCDS Granger-causes ΔLM when the a_{12_p}s are contemporaneously different from zero. Similarly, we can surmise that ΔLM Granger-causes ΔCDS when the $a_{21}p$s are contemporaneously different from zero. When both of these statements are true, there is a feedback relationship between the two time-series.

The results of the Grange-causality test, with three lags, for the relationship between the changes in the *CDS Spread* and the *Quoted Spread*, are reported in Table 6, where we report Wald test statistics for the contemporaneous significance of the cross-variable terms for each equation.[40]

As the table shows, and as we argued in Section III, the *CDS Spread* Granger-causes liquidity in the bond market at a 1% level, while the opposite directionality is not significant at any of the usual confidence levels. As per Hypothesis 1, we find that a change in credit risk significantly affects market liquidity. The opposite relationship, however, posited in He and Milbradt (2014), is not statistically significant. One possible explanation for this result may be that the arguments used by them in the context of corporate bonds do not apply for sovereign bonds, since sovereign defaults are less common, due to the availability of monetary and fiscal devices to forestall such extreme events.

INSERT TABLE 6 HERE

In order to interpret the dynamics of the system, we calculate the impulse response functions (IRF) for the relationships between the variables. We do this for the rescaled variables, so that they have a mean of 0 and a standard deviation of 1, to ease interpretation.[41] Figure 6 shows the results, where the 5% confidence bands were bootstrapped based on 5,000 repetitions. As shown in Panel (b), a one-standard-deviation shock to the *CDS Spread* at time 0, corresponding to a 4.4% change, is followed by a change of 0.27 standard deviations in the *Quoted Spread*, corresponding to a 5.5% increase, and is absorbed by both variables in two days. The results are, hence, both statistically and economically significant and confirm the results of the Granger-causality. The IRF in Panel (a) shows that a shock at time 0 to market liquidity lasts until time 1, but only affects market liquidity itself, indicating that the reaction of the *CDS Spread* to a shock in market liquidity is never different from zero, in line with the findings of the Granger-causality tests.

INSERT FIGURE 6 HERE

[40] The (corrected) Akaike criterion suggests a lag-length of 3.

[41] We do not report the IRF with orthogonalized errors due to the low level of contemporaneous correlation (18.7%). However, the results after orthogonalizing are similar.

Since the data clearly indicate the direction of the Granger-causality, in order to determine the dynamics of the system (including the effect of ECB interventions and potential non-linearities), we focus in the rest of the paper only on the causal effects on the liquidity measure (ΔLM_t equation) This is sufficient to capture the dynamics of the credit-liquidity relationship, given the lack of statistical support for the causality going in the opposite direction. Therefore, we regress changes in the liquidity measure on the contemporaneous changes in the *CDS Spread*, and their respective lags. Equation 2 presents our baseline regression specification for the remainder of the paper:

$$\Delta LM_t = \alpha_0 + \sum_{i=1}^{M} \alpha_i \Delta LM_{t-i} + \sum_{j=0}^{N} \beta_j \Delta CDS_{t-j} + \epsilon_t \tag{2}$$

where ΔLM_t is the change in the liquidity measure from time $t-1$ to time t, and ΔCDS_t is the change in the CDS spread, as before. We estimate several variations of this baseline regression specification in Equation 2 for our main liquidity measure, the *Quoted Spread*, and the results are reported in Table 7, Panel A.[42]

In Specifications 1 to 6 of Table 7, Panel A, we consider several lags for both the autoregressive terms of the liquidity measure (*Quoted Spread*) and the change in the *CDS Spread*, and find that, for the CDS changes, the lags beyond the first (i.e., two or more days prior to the dependent variable observation) exhibit a low level of statistical significance. We estimate Equation 2 for different values of M and N (i.e., different lag lengths for the changes in the *Quoted Spread* and the *CDS Spread*, respectively). Various information criteria – Akaike, Modified Akaike, and Bayesian – are all minimized by a model with M=3 and N=1 (Specification 6), consistent with the VAR analysis, which we thus choose as our main specification. The Durbin-Watson test rejects the null hypothesis of autocorrelation of errors for all specifications containing at least one lag of the *Quoted Spread*, and the contemporaneous change in the *CDS Spread*, and so Specification 4 is sufficient to capture the dynamics of the system and still ensure well-behaved residuals. However, in an attempt to provide the model that best explains the data, we will focus on the more general Specification 6, which is indicated as the best fit by the aforementioned information criteria. Panel A shows that the regression model has significant explanatory power, with an adjusted R^2 for Specification 6 equal to 0.19.

INSERT TABLE 7 HERE

Turning to the dynamics of the system, the change in the *CDS Spread* has both a contemporaneous and a lagged effect on market liquidity, i.e., the reaction of market liquidity to changes in the *CDS Spread* occurs both the same day and the next. The *Quoted Spread* also shows evidence of an autoregressive component, being strongly related to the change in the *Quoted Spread* that took place the day before, with a negative sign: this suggests an overreaction adjustment dynamic in the *Quoted Spread*, as shown already in the IRF of Figure 6 Panel (a). This effect can be ascribed to the actions of the market makers, who adjust their quotes as a reaction, not only to the changes in the traded price, but also to the changes in the quotes of the other primary dealers. As for the significance of

[42]Throughout the paper, statistical significance is always determined on the basis of t-tests that are always calculated using heteroskedasticity-robust standard errors.

the lagged ΔCDS term, a partial explanation can be found in the timing of VaR-based models in practice. Since the calculation of the dealer's VaR generally takes place at the end of the day, the exposure to the credit risk is taken into account for the liquidity offered by the dealer only on the day following the credit shock, thus implying the significance of the lagged change in credit risk.[43]

Turning to the second half of Hypothesis 1, Equation 2 above implicitly assumes that the estimated relationship holds independent of the *level* of credit risk, in particular, when the *CDS Spread* is above a particular threshold level. For the reasons discussed in Section III, on account of changes in the macroeconomic environment, margin-setting, and downgrade concerns, it is possible that market makers are more sensitive to changes in credit risk when providing market liquidity when the *CDS Spread* breaches a particular threshold. We investigate this hypothesis by allowing the data to uncover the presence of a threshold in the level of the *CDS Spread*, above which a *different* relationship between changes in CDS and changes in market liquidity is observed. We use the test proposed by Hansen (2000), described in detail in Appendix C, to examine this hypothesis, estimating Equation 3 for different γ.

$$\begin{aligned}\Delta LM_t = {} & \alpha_0 + \alpha_1 \Delta LM_{t-1} + \alpha_2 \Delta LM_{t-2} + \alpha_3 \Delta LM_{t-3} + \beta_0 \Delta CDS_t + \beta_1 \Delta CDS_{t-1} \\ & + I\left[CDS \leq \gamma_0\right]\left(\tilde{\alpha}_0 + \tilde{\alpha}_1 \Delta LM_{t-1} + \tilde{\alpha_2} \Delta LM_{t-2} + \tilde{\alpha_3} \Delta LM_{t-3} + \tilde{\beta}_0 \Delta CDS_t + \tilde{\beta}_1 \Delta CDS_{t-1}\right) \\ & + \epsilon_t \end{aligned} \tag{3}$$

Figure 7 shows the test statistic for the estimated $\hat{\gamma_0} = 496.55$bp to be equal to γ_1 on the x-axis, and can be used to obtain a confidence interval. It is striking that this threshold has a point-estimate of 496.55, with a 5% confidence interval between 488 and 504, and is almost identical for various alternative specifications of the relationship (including whether or not lagged variables are included) and for the range of liquidity measures we employ, as indicated in the robustness checks of Section VII.I.[44]

INSERT FIGURE 7 HERE

The confirmation of the presence of a structural shift in the data when the CDS spread crosses a certain threshold is, therefore, quite robust and indicates how important the level of the *CDS Spread* is for market liquidity. As mentioned in the hypothesis section, Section III, this break point could be identified as the dividing line between the credit spreads for investment grade bonds and those for high-yield bonds. Once this line is crossed, it may change the clientele of investors that

[43] One variable that may also affect the inventory levels of market makers (e.g., through the risk management practices of dealer desks), and therefore market liquidity, is the volatility of the bond yield. In Section VII.II we repeat the analysis including this variable and our results are robust to this inclusion. Moreover, we also test whether the *CDS Spread* drives both changes in market liquidity and bond return volatility or whether the effects are the other way around, and show that it is the former relation that prevails, confirming that the analysis we have performed in this section is correct and robust to the insertion of volatility into the pool of endogenous variables.

[44] This threshold of 500 bp corresponds closely to the one indicated by many market participants, and corroborated in our conversations with market makers, as the critical threshold for the sustainability of Italian debt. It has also been identified by reports in the main Italian news agency as a psychologically important barrier, suggesting that Italian sovereign debt would spiral out of control if the spread persisted above this level. See ANSA-Agenzia Nazionale Stampa Associata, December 23, 2011. `http://www.ilsole24ore.com/art/notizie/2011-12-23/spread-torna-sfiorare-quota-063646.shtml?uuid=AaXuwtWE`

holds Italian sovereign bonds, and also involve different levels of margins, accounting treatment and regulatory capital requirements, fundamentally altering the relationship between changes in credit risk and market liquidity. For instance, on November 17, 2010, the clearing house LCH.Clearnet reported that the margins on Irish sovereign bond repo transactions would be raised from 16-18% to 31-33%, arguing that this decision had been taken "in response to the sustained period during which the yield differential of 10 year Irish government debt against a AAA benchmark has traded consistently over 500 bp".[45] Having identified the presence of a threshold, we need to determine how the relationship between changes in the *CDS Spread* and changes in market liquidity is modified when the threshold is breached. Panels B and C of Table 7 report the results of the threshold regressions for alternative specifications of Equation 2, estimated when the CDS spread has values below and above 500 bp.

As the panels show, the relationships below and above 500 bp are rather different from each other. When we investigate only the contemporaneous CDS variables, we find that changes in the *CDS Spread* have a significantly larger economic impact on market liquidity above the threshold of 500 bp than below: As the regression in Column 1 shows, the coefficient of the contemporaneous change below the threshold is 0.72, while that above it is 3.16, with the difference being statistically significant. This means that an increase in the *CDS Spread* by 10%, below the threshold of 500 bp, induces a contemporaneous increase in the bid-ask spread, the *Quoted Spread*, of 7%, while above the threshold it induces an increase of 32%. Adding the lagged variables we find, as reported in Column 6, that below 500 bp market liquidity reacts slowly to changes in the *CDS Spread*, with a significant impact of the autoregressive component and the lagged component of the change in the CDS, while the contemporaneous change in the *CDS Spread* on the same day is no longer significant. Above 500 bp, the relationship is rather different: market liquidity reacts immediately to changes in the *CDS Spread*, with the impact being largely contemporaneous, since the change in the CDS spread has no impact on the change in the market liquidity the following day. Our conclusion, therefore, is that, in a stressed environment, credit shocks have an immediate impact on market liquidity.[46]

Although the sample period we consider is relatively short (June 1, 2011 to December 31, 2012), we have clear evidence that the several various interventions that occurred during the period may have generated a structural break in the relationship between credit risk and market liquidity. Therefore, the second research question of this paper is to examine whether such a structural break can be detected statistically and related to policy changes. Again, we let the data alert us to the presence of a structural break over time.

VI.II Policy intervention and structural breaks

H2 Policy Intervention and Structural Breaks: *The monetary policy interventions of the central bank affect the dynamic relationship between credit risk and market liquidity.*

[45] Source: `http://www.lchclearnet.com/risk_management/ltd/margin_rate_circulars/repoclear/2010-11-17.asp` and `http://ftalphaville.ft.com//2010/11/17/407351/dear-repoclear-member/`

[46] As shown in Section VII.I, the results for the other liquidity measures we analyze are qualitatively similar, although the precise magnitudes vary. In all cases, the threshold of 500 bp is confirmed in a statistically significant manner. The magnified impact of changes in the CDS spread on market liquidity is also confirmed, although the quantitative impact varies across measures.

The period that we investigate has been characterized by many events: the deterioration of the sovereign crisis, several credit downgrades, a political crisis that induced changes in Euro-zone governments, and several interventions by European central banks, and in particular by the ECB. By virtue of its status as the central bank of the Euro-zone, the ECB has a major influence on its sovereign bond markets. As described in Section III, the ECB's monetary intervention takes many forms, ranging from formal guidance by its board members, in particular its President, to the injection of liquidity into the major banks in the Euro-zone, which themselves hold these bonds, and to direct purchases of sovereign bonds in the cash markets.

The purpose of this section is not to quantify the direct effect of these interventions on the Euro-zone credit risk (see Eser and Schwaab, 2014), or its bond market liquidity (see Ghysels et al., 2013), but to test whether the relationship between credit risk and liquidity was significantly affected by one or more of these interventions, by testing for the presence of a structural break. The scarce availability of public data concerning the quantity, nationality, and timing of purchases of bonds in the SMP framework prevents us from quantifying the specific effect of those purchases. Similarly, not knowing the extent of banks' access to LTRO funding and its usage, we are unable to investigate how the refinancing operation affected liquidity provision by the market makers. However, since the two interventions took place over finite and non-overlapping periods of time, we can investigate econometrically whether a structural break in the relationship between the two variables of interest occurred around the time of the announcement or implementation of the interventions. This analysis is relevant for our Hypothesis 2 for two main reasons: first, because if the data indeed exhibit structural breaks, our results will be biased if we ignore them, and second, because it will shed light on the relevant combination of conditions that affects the relationship between credit risk and liquidity.

We first investigate this hypothesis using the standard Chow (1960) test for "structural change breaks". As shown in Figure 8, we find that, from a statistical perspective, the test indicates a break at December 8, 2011 for the relationships between the *Quoted Spread*, and both the *CDS Spread* and its lag. Again, the result is robust to using each of the alternative liquidity measures. Although December 8 is identified purely based on the statistical evidence as the date where the significance of the Chow test ultimately crosses the 10% level for the relevant relationships between the quoted spread and the *CDS Spread*, it coincides *exactly* with the date of the announcement of the LTRO program by the ECB.[47] Our evidence suggests that this announcement had a clear impact on the restoration of market liquidity.

In order to account for this structural break in our estimations, we split the sample into two periods, and again perform the threshold test in both sub-samples. As shown in Figure 9, the threshold test confirms the presence of different relationships below and above the threshold level of 500 bp for the CDS spread in the first sub-sample (June 1, 2011 to December 8, 2011), but fails to identify a threshold for the second sub-sample. This result indicates that, thanks to the assurance of massive liquidity from the ECB, even if the Italian *CDS Spread* had breached the level of 500 bp, post-LTRO, the relationship between changes in the CDS spread and market liquidity would not have been altered, unlike in the period before the intervention. Panels A and B of Table 8 present the results of the

[47] The policy implementation announcement of December 8, 2011 can be found online at `http://www.ecb.europa.eu/press/pr/date/2011/html/pr111208_1.en.html`

estimation for the first sub-sample, split by the level of the *CDS Spread* (Panel A: $CDS \leq 500$ and $T = 2011$, Panel B: $CDS > 500$ and $T = 2011$), and confirms the results we presented above. The main difference is that, for the split sample, the relationship between the change in the *CDS Spread* and market liquidity, when the *CDS Spread* is above 500 bp, is even stronger in the pre-LTRO regime, with a 10% increase in the *CDS Spread* translating into a 53% contemporaneous increase in the quoted spread.

INSERT FIGURES 8 AND 9 AND TABLE 8 HERE

Table 8, Panel C, presents the results of the estimation for the second sub-sample (from January 2012 onwards) and shows that the presence of the autoregressive component in market liquidity is still apparent.[48] However, the contemporaneous relationship between changes in the CDS spread and changes in market liquidity is no longer significant in any specification, while there is a lagged adjustment of market liquidity related to changes in the *CDS Spread* on the previous day, with an economic intensity that is about half that in the full sample reported in Table 7, Panel A (0.600 vs. 1).

The results of the analysis of the structural break in the time series also allow us to argue that LTRO intervention was very effective in severing the strong connections between credit risk and market liquidity. It is interesting to observe that both SMP and LTRO interventions generated injections of liquidity into the system by the ECB. However, the magnitudes were completely different (€103 billion in August 2011 versus €489 billion in December 2011), and so were the mechanisms: in the first case the ECB bought the bonds directly, while in the second case it provided money to the banks to reduce their funding liquidity constraints.[49] In Section VII.IV we extend the subset and test for structural breaks preceding the LTRO announcement, hence explicitly allowing the data to indicate the beginning of the SMP as a break point. This test confirms the results in the sub-samples that we have found thus far. Section VII.III confirms the structural break analysis of this section using a different econometric approach.

VI.III Funding liquidity and other global risk factors

H3 Global Risk Factors and Funding Liquidity: *After controlling for credit risk, both global systemic risk factors and the funding liquidity of the primary dealers have an effect on the market liquidity of*

[48] We split the sample at the beginning of January 2012 in order to effectively separate the consequences of the announcement, which happened on December 8, 2011, and the subsequent adjustment period, which encompassed the introduction date, December 22, 2011, from the period following the implementation. The low frequency of our data (daily) does not allow us to clearly distinguish between the effects of the announcement and the implementation, since there are only nine observations in between the two dates.

[49] One issue that we cannot disentangle is whether this effect is related to the ECB intervention or to the short-selling ban on the CDS market under the European Market Infrastructure Regulation (EMIR) imposed by the European Securities Market Authority (ESMA), which may have reduced the relevance of this market, or at least its informativeness. However, data from the DTCC indicate that the net notional amount for Italian CDS declined by just 16% in the period of our study, while the gross notional amount increased by 44%. Hence, the ban seems not to have had a major effect on the traders' behavior with regard to the Italian sovereign CDS market. Moreover, when testing for a structural break, we allow the data to indicate the most likely point in the period of our sample. The date we identify statistically is not close to either the announcement or the implementation of the naked CDS ban.

the bonds.

In the analysis reported above, we focused exclusively on the contemporaneous and lagged effects in the relationship between market liquidity and the Italian *CDS Spread*. We now consider several other mechanisms that are not related to Italian sovereign risk alone, but may affect market liquidity indirectly. In particular, we analyze the possibility that global risk factors and funding liquidity could contemporaneously affect both the Italian *CDS Spread* and bond market liquidity, as well as specific market maker funding liquidity. We test whether global risk factors affect bond market liquidity directly *in addition to* their indirect effect through the Italian *CDS Spread*.[50]

More specifically, we analyze the effects of stock market risk factors, measured by the returns on the EuroStoxx50 index, global uncertainty, and the global appetite for risk bearing, measured by the volatility index, USVIX. We also investigate the general increase in the cost of funding by banks in the Euro-zone, because of bank credit risk and the banking crisis, measured by the Euribor-Eonia spread, global banks' funding liquidity risk, measured by the Eonia-German T-Bill spread, and the macro-funding constraints in the Euro versus the US Dollar markets, measured by the CCBSS. To measure the funding liquidity of the Italian sovereign bond market makers, we use the average of the difference between the Euribor submissions of individual market makers and the Euribor "fixing" (diffEuribor) as our measure of the market liquidity constraint the market makers face on a given day, as described in Section IV.I.[51] In the following analysis, we aim to investigate how changes in funding costs from one day to the next affect market liquidity.

Clearly, all these measures are largely correlated (especially during turbulent periods, as in our sample period), and therefore they could all be individually significant. However, one has to be cautious about including all of them in the same specification since they capture similar sources of risk, especially in the sub-sample with the most limited number of observations of the three we are investigating (the sub-sample from 2011 with *CDS Spread* above 500). For this reason, we first estimate the models including all the variables and then proceed to a more parsimonious model via a stepwise procedure. We do this separately for each of the three samples we consider. We report the resulting specifications in Table 9.

INSERT TABLE 9 HERE

Column 1 of Table 9 shows that, during the second half of 2011, when the *CDS Spread* is below 500 bp, the most relevant variables that have a direct impact on the *Quoted Spread* are the changes in the Italian *CDS Spread*, the global funding liquidity variable as measured by the CCBSS, and the specific funding liquidity risk of the market makers captured by the changes in diffEuribor. They are

[50] Previous work on the topic by Longstaff, Pan, Pedersen, and Singleton.suggests that a large proportion of sovereign credit risk can be explained by global factors.

[51] An alternative candidate for quantifying the market makers' funding constraints would be their *CDS Spread*. However, this variable is largely correlated with the Italian *CDS Spread* itself. In addition, the *CDS Spread* primarily captures credit risk, and therefore might be more apt to capture the long-term funding liquidity of banks (with the most common CDS contracts being of five-year maturity.) rather than that at the short end.

all significant at the 5% level in explaining changes in liquidity. It is important to note, however, that the most significant variable from both the statistical and the economic point of view is still the change in *CDS Spread*.

Column 2 of Table 9 shows that, for 2011, when the *CDS Spread* is above 500 bp, the most parsimonious model for explaining the change in the *CDS Spread* on top of the CDS contains the Euribor-Eonia spread. This, together with the strong significance of the changes in the *CDS Spread*, indicates that, under conditions of extreme market stress, the primary dealers adjust their quotes rapidly to changing credit risk perceptions, and prudential risk management together with internal capital constraints induce them to reduce market liquidity as soon as the quoted asset and the overall market increase in credit risk.[52] Note that, in this case, the funding costs of the market makers seem to be overlooked in favor of the banking sector credit risk. Column 3 of Table 9 shows that, for 2012, the only variable that is individually significant is the contemporaneous change in the CCBSS, a macro-liquidity variable that is likely to influence liquidity in all Euro-zone markets.

From the analysis of several macro-variables, we can conclude that, on the one hand, credit risk variables have a lower impact on market liquidity, once the massive operations of the ECB through the LTRO take effect; on the other hand, the Eurozone-wide macro-liquidity factor, the CCBSS, continues to play a role on top of the asset-specific *CDS Spread*. These results do not mean that the other variables do not have an impact on the *Quoted Spread*, but rather that their effect is only indirect, through the changes in the Italian *CDS Spread*.

To our knowledge, ours is the first analysis that shows the relevance of the specific funding costs of the market makers measured by the differential funding rate, and the effect of the LTRO intervention of the ECB, in significantly improving the funding liquidity of banks. This improvement in funding liquidity, in turn, had a positive influence on the market liquidity in the Italian sovereign bond market.[53]

VII Robustness checks

VII.I Results for other liquidity measures

To check the robustness of the results in the previous sections, we repeated the analysis estimating Equation 2 using the other liquidity variables described in Section IV.II, namely the *Quoted Quantity*, the *Effective Spread*, and *Lambda*. The number of lags for each variable and the *CDS Spread* are determined using the same methodology as for the *Quoted Spread*. The results are reported in Table 10, while Figure 10 shows the plots of the identification of the threshold in the relationship between changes in liquidity and changes in the Italian *CDS Spread* level for the 2011 sub-sample, and the significance of the Chow test for the presence of a structural break, as performed in Section VI.II for the *Quoted Spread*.

INSERT TABLE 10 AND FIGURE 10 HERE

[52] This is not dissimilar to the observations in Friewald et al. (2012a), where similar reactions of market liquidity in the US corporate bond market in times of crisis are documented.

[53] A related analysis of this linkage between bank balance sheets and sovereign risk is provided by Acharya, Drechsler and Schnabl (2012).

Figure 10 show that the structural break around the LTRO announcement is also a feature of the alternative liquidity measures (Panels b, d, and f), and so is the 500 bp threshold in the regression of the changes in the liquidity measure on its lags and the changes in Italian CDS and its lag, for the 2011 sub-sample (Panels a, c, and e). A 10% change in the Italian *CDS Spread* is contemporaneously associated with a 25% decrease in *Quoted Quantity*, a 34% increase in the *Effective Spread*, and a 89% increase in *Lambda* when the CDS spread for Italian bonds is above 500 bp, compared to a 7% decrease, a 12% increase, and a 25% increase when the Italian *CDS Spread* is below the same threshold. After the ECB intervention, a change in the Italian CDS spread has no effect on either *Quoted Quantity* or *Lambda*, and only a marginal effect on *Effective Spread*. The sensitivity of the *Effective Spread* is lower than that of the *Quoted Spread* because of the endogeneity of the trading decision: Traders will choose to trade when the *Quoted Spread* is comparatively low, thus dampening the sensitivity of the effective spread to changes in market conditions. The dynamics of the relationship between credit risk and liquidity are confirmed by the analysis of the alternative liquidity measures, so that the lagged change in credit risk is significant when the market is quiet, while, in a stressed market, when the Italian CDS is above 500 bp, the liquidity changes contemporaneously with the credit risk.[54]

VII.II Controlling for Price Volatility

A variable we have not included in the analysis so far is the intraday price volatility of the bonds. Microstructure models (e.g., Glosten and Milgrom (1985) among others) suggest that an increase in price volatility should decrease the amount of liquidity offered to the market by market makers because of concerns about the risk of the inventory they carry. Moreover, the effect of heightened credit risk could affect liquidity through price volatility only and not necessarily directly. For example, a worsened public finance situation could accentuate the uncertainty regarding the true value of the sovereign bond and the informativeness of its price, and hence affect the market liquidity. As a matter of fact, the price volatility σ_t^2 (measured as the intraday variance of the five-minute mid-quote changes for each bond, averaged into a market-wide daily measure) and the *Quoted Spread* are correlated (57%) in our sample.

We thus need to test the effect of a change in credit risk, *after* controlling for the effect of volatility on the liquidity measure. We therefore estimate a VAR, as in Equation 1, with the changes in the *CDS Spread*, *Quoted Spread*, and bond price volatility, σ_t^2. The lag structure selected by the modified Akaike criterion is 4, due to the stickiness of the volatility measure. Table 11 reports the estimations.

INSERT TABLE 11 HERE

The Grange-causality test shows that the changes in the *CDS Spread* Granger-cause both the *Quoted Spread* and the bond price volatility, but the bond price volatility does not Granger-cause the changes in the CDS and the *Quoted Spread*. This means that our analysis on the relation between credit risk and market liquidity risk performed above is robust to the inclusion of bond price volatility as an additional variable in the VAR system. We also replicated Specification 6 from Table 8 for the

[54]This is in line with the discussion in Section III, where the frequency of intervention by risk managers on an intraday basis during crisis periods was highlighted.

three sub-samples, while including the contemporaneous price volatility. The results are reported in Table 12.

INSERT TABLE 12 HERE

Table 12 shows that the contemporaneous bond price volatility is indeed significant at the 1% level: it increases the adjusted R^2 by about 20% and is always significant in the three sub-samples considered, with a significant reduction of the coefficient from 0.115 to 0.062 from 2011 to 2012. However, the economic impact of a change of the same size is lower for the price volatility than for a change in *CDS Spread*.

VII.III Structural break tests with unknown break date

Andrews (1993) and Andrews and Ploberger (1994) develop a test to identify the presence of structural breaks when the break date is unknown. The null hypothesis of the Chow test is that a given date is not a break date and the alternative is that the date is indeed a break date (for a difference in the parameters vector between the two sub-samples before and after the date). The Andrews and Andrews and Ploberger tests, on the contrary, have as their null hypothesis that no date is a structural break, and the alternative hypothesis is that there is (at least) one break point in the dataset.

Given our goal of identifying a single date within a period of turmoil, the Andrews and Andrews and Ploberger tests provide the correct approach, although they are less widely used than the standard Chow test. The two test statistics we consider are $aveF$, the average of the Chow tests after testing whether each day in the sample is a structural break, and $supF$, the largest value of the same Chow tests – as suggested by Andrews and Ploberger (1994) and Andrews (1993), respectively – and are described in detail in Appendix C. Figure 11 Panels (a) and (b) show the results of the $aveF$ and $supF$ tests, respectively.

INSERT FIGURE 11 HERE

Testing for a structural break in our preferred specification (Column 6 in Table 7), we find that the tests do indicate the presence of a structural break: the $aveF$ ($supF$)-statistic is equal to 17.05 (23.39), rejecting the hypothesis of no structural breaks with a p-value of about zero (1%). Figure 11 Panel (a) shows the largest spike in the F-statistic, which corresponds to December 8, 2011. We thus reach the same conclusion as in Section VI.II.

We further investigate whether we are able to find other structural breaks in the two sub-samples before and after December 8, 2011. At a 5% level, both tests fail to reject the null hypothesis of no structural breaks for the sub-sample after December 8, 2011. However, for the sub-sample before December 8, both tests fail to reject the alternative hypothesis of a structural break, at a 5% level. Figure 12 Panel (b) shows that the largest spike in the F-statistic corresponds to October 27, 2011, which marks the beginning of the November and December period, when the *CDS Spread* exceeded the 500 bp threshold, hence corroborating our findings on the level of the *CDS Spread*. We verify that there is no other structural break for the sample before October 27, 2011 by testing and rejecting the null hypothesis of structural breaks. Unfortunately, we could not perform a structural break test for the period from October 27, 2011 until December 8, 2011 because the sample period is too limited. Table 13 shows the results of estimating Specification 6 in the three sub-samples found with this procedure. The results are strikingly similar to those in Table 8.

INSERT FIGURE 12 AND TABLE 13 HERE

VII.IV Extending the dataset

The intraday MTS dataset that we use in this analysis extends back to June 2011. Before that, MTS provided data on the three best bid and ask quotes on each date only, a much more limited quote sample. While, as we argued, the financial crisis is the most relevant period in which to investigate the issue of credit risk and liquidity, we want to investigate whether our findings on the relationship between the *CDS Spread* and the *Quoted Spread* are robust to the use of a longer sample period. Moreover, the SMP intervention took place in August 2011, at the very beginning of our sample, and it is important to verify whether our structural break results carry through or identify a different break, possibly around the SMP intervention.

To investigate this issue, we extended the database back to July 1, 2010, calculating the *Quoted Spread* from the three best bid and ask quotes each day. The Granger-causality tests based on the VAR estimation confirm our previous results: the *CDS Spread* Granger-causes the *Quoted Spread* and not vice versa. The results are reported in Table 14.

INSERT TABLE 14 HERE

Furthermore, we performed the structural break test for the extended sample, using the methodology presented in Section VII.III, and the results confirm that a break took place on December 8, 2011. The test fails to find other breaks at a 5% level. Moreover, the results regarding the 500 bp CDS level break also carry through in the extended dataset (available upon request). Finally, this analysis confirms that the results presented above are robust and other ECB interventions such as the SMP do not constitute a structural break in the relationship between CDS and *Quoted Spread*, and that the analysis we have performed with the dataset starting from June 2011 does not strictly depend on the chosen time frame.

VIII Conclusion

The sovereign debt crisis in the Euro-zone has been the most important development in the global economy of the past three years. This crisis stemmed from both liquidity and credit risk concerns in the market and led to a sharp spike in CDS and sovereign bond yield spreads in late 2011, particularly in the Euro-zone periphery. It was only after the launch of the LTRO program – and to a greater extent after Mario Draghi's "whatever it takes" comment in July 2012 and the OMT program that was subsequently launched – that the market's alarm diminished. Consequently, CDS spreads as well as sovereign bond yields had dropped to sustainable levels in most Euro-zone countries by late 2012. Hence, there is no doubt, *prima facie*, that the ECB programs were a crucial factor in, at least partially, abating the crisis, although it is still an open issue whether the fundamental problems of the Euro-zone have been addressed.

These events provide us with an unusual laboratory in which to study how the interaction between credit risk and illiquidity played out, in a more comprehensive framework than has been used in previous studies of corporate or other sovereign bond markets, for the reasons we highlighted in the introduction. We employ a wide range of liquidity measures and investigate several hypotheses about the main drivers of the dynamic relationship between credit risk, global systemic factors, global funding liquidity, the market makers' funding liquidity and market liquidity. Our main findings are that, prior to ECB intervention, the relationship between credit risk and market liquidity was strong, and depended not simply on the dynamics of credit risk but also on the *level* of credit risk.

Using a new econometric methodology that allows us to identify the threshold above which the dynamic relationship is altered, we estimate that this level corresponds to a CDS spread of 500 bp. This break point of 500 bp is often identified as the dividing line between the credit spread for investment grade bonds and that for speculative grade bonds. Once this threshold is crossed by the Italian sovereign, the clientele of investors that holds its bonds may be fundamentally altered. Furthermore, the margin requirements, the accounting treatment, and regulatory capital regulations will be quite different, thus fundamentally altering the relationship between changes in credit risk and market liquidity. On top of the specific Italian sovereign risk, other global factors such as the Euribor-Eonia spread and CCBSS are relevant to the relationship between credit risk and market liquidity, together with the market makers' specific funding liquidity measure.

We also examine the improvement in market liquidity following the intervention by the ECB. Our analysis of the data indicates that there is a clear structural break in it following the announcement of the implementation of the LTRO on December 8, 2012. Remarkably, the data show that, following the ECB intervention, the improvement in liquidity (or the reduction in illiquidity) in the government bond market strongly attenuated the dynamic relationship between credit risk and market liquidity, to such an extent that, although the CDS spread breached the 500 bp mark once again, market liquidity and the relationship between credit risk and market liquidity did not change significantly between the regimes below and above this level. Actually, the only variable that still has an impact on market liquidity after the ECB intervention is the global funding liquidity variable, CCBSS. Thus, the ECB intervention not only vastly improved the liquidity of the market, but also substantially loosened the link between credit risk and market liquidity. This conclusion is confirmed by the Granger-causality analysis, aimed at investigating whether liquidity risk drives credit risk or vice versa. Our analysis shows that credit risk drives the illiquidity of the Italian sovereign bond market. We verify the robustness of our results through a cohort of tests, where we control for bond return volatility, employ a longer time-series of data, and investigate alternative methods of assessing the structural break.

Our results will be of interest to the Euro-zone national treasuries, helping them to understand the dynamic nature of the relationship between credit risk, global risk factors, and market liquidity, which has strong consequences for the pricing of their issues in the auctions as well as in secondary markets. The ECB may also derive some insights from our analysis that could help them to better understand the impact of the unconventional instruments of new monetary policy. Apart from targeting both funding and market liquidity, the central bank ought also to focus on the market's perceptions of sovereign credit risk. The introduction of the LTRO program, having the objective of providing short-term liquidity to banks, shows that the channel from bank bailout to sovereign risk (described by Acharya, Drechsler and Schnabl (2012) could also be reversed: offering liquidity to banks may improve the market liquidity of sovereign bonds and also indirectly reduce sovereign risk! Our analysis could be similarly employed by market regulators (the national central banks or European market regulators such as ESMA), since it identifies the main factors that affect sovereign bonds' market liquidity in the Euro area.

Given the strong linkage between bank and sovereign risk, our findings will be of interest to bank regulators, helping them to improve their tools for monitoring both bank capital adequacy and liquidity risk. In particular, our analysis highlights an important aspect of the sterilization of the effect of credit risk on market liquidity through ECB intervention: Market liquidity is largely affected by investor behavior, their risk attitudes and perceptions, and regulatory restrictions. This indicates that changes in bank regulation (with regard to sovereign credit risk, market risk or liquidity risk) have a strong impact on market liquidity. Therefore, close coordination between different regulators (market regulators and bank regulators) is fundamental to the avoidance of strong negative externalities, for example that the liquidity of a market freezes because bank capital requirements for holding sovereign bonds increase or the liquidity coverage ratio changes adversely, with even more perverse effects on the probability of default of the country and the consequent costs to tax payers.

The relevance of our findings to other countries bears mention. The results of our paper will also be of interest to economists, central bankers, and finance ministry officials: we demonstrate the structural linkages between monetary policy, credit risk, and market liquidity in the sovereign bond market, and a rationale for including this issue in monetary policy making. The insights we provide have implications for monitoring the capital adequacy of banks, margining, and collateral management by clearing corporations and traders, and the functioning of the repo market.

Appendix A: The MTS Datasets and Market Structure

There are four types of databases currently offered by MTS. At the highest level, "daily summaries" including aggregate price and volume information regarding the trading of European bonds are published. At the second level, the "trade-by-trade" data including all transactions, stamped at the millisecond level, are available. However, neither of the two aggregate databases has any information on the price quotations of the instruments at the dealer or even the market-wide level. The publicly available dataset at the third level includes the best three bid and ask prices and the aggregate quantities offered at those levels. Prior studies that use this dataset are unable to describe the market in its entirety, as the two dimensions indicating willingness to trade, quotes, and orders, for primary dealers and dealers respectively, were not available previously. Only *actual trading* events are observable, and *trading intent* as a pre-trade measure cannot be measured. Thus, it is not possible to study liquidity provision, as measured by the dealers' willingness to trade, as evidenced by their bid and offer quotations, based on this dataset. In contrast, the dataset we analyze in the present study is at the fourth level, is by far the most complete representation of the market available, and has been released only recently. It covers *all* trades, quotes, and orders that took place on the MTS market between June 1, 2011 and December 31, 2012. Every event is stamped at the millisecond level, and the order IDs permit us to link each order to the trade that was eventually consummated from it. Every quote in this market, henceforth called "proposals, can be followed in the database in terms of their "revisions" over time, thanks to a "single proposal" identifier.

Market participants can decide whether they want to trade a government bond on the European market or on that country's domestic market. While every Euro-zone bond is quoted on the domestic markets, only bonds that are issued for an amount higher than a certain threshold can be traded on the EuroMTS Even though the two markets are not formally linked, most dealers participate in both venues. The previous literature (Cheung, de Jong and Rindi (2005), Caporale and Girardi (2011)) has shown that the two markets essentially constitute a single venue.[55] Thus, in our analysis, we consider trading in both markets. The liquidity measures used in this paper do not depend on where the order placement and trading activity take place.

There are two kinds of traders in the sovereign bond markets, primary dealers and other dealers. Primary dealers are authorized market-making members of the market. That is, they issue standing quotes, which can either be single-sided or double-sided, on the bonds they have been assigned. They indicate the quantity they are willing to trade and the non-negative fraction of that quantity they are willing to "show" to the market. Primary dealers can be on the passive side, when their proposals are "hit" or "lifted," and/or on the active side of the market, when they submit orders aimed at "hitting" or "lifting" another primary dealer's standing quote. Primary dealers have market-making obligations that, in spite of some relaxations that were made after 2007, still require each primary dealer not to diverge from the average quoted times and spreads calculated among all market makers. In this market, the event of crossed quotes is guaranteed not to occur, except by chance, since, when the opposite

[55]By this we mean that a sell or buy order could "trade-through" a better price if the trader sent the order to the market with the worse of the bid or ask price, respectively. However, MTS assures market participants that their trading platforms always show quotations from both the domestic and the European market, when available.

sides of two proposals cross, a trade takes place for the smaller of the two quoted quantities.[56] Other dealers with no market-making responsibilities can originate a trade only by "hitting" or "lifting" the primary dealers' standing quotes with market orders. However, it should be noted that primary dealers are also on the active side of 96% of the trades present in our database.

[56]While this is one way for the primary dealers to trade, it seldom happens. Hence, we do not include trades originating in this manner in our sample.

Appendix B: The Bond Characteristics

To confirm that the findings of previous literature regarding the relationship between liquidity measures and bond characteristics apply to this market as well, we estimate cross-sectional regressions to study the drivers of liquidity in the Italian sovereign bond market. Specifically, we explore whether each of our defined liquidity measures can be explained by product characteristics and trading activity variables.

We estimate cross-sectional regressions where we use time-series averages of all variables. We analyze coupon-bearing bonds and non-coupon-bearing bonds separately, according to the following regressions:

$$\begin{aligned}
\text{Coupon: } LM_i =& \beta_1 + \beta_2 AmountIssued_i + \beta_3 Daily\ Trades_i + \\
&+\beta_4 CouponRate_i + \beta_{5-8} MaturityDummies_i \\
&+\beta_9 \frac{Time\ to\ Maturity}{Maturity}_i + \beta_{10} \left(\frac{Time\ to\ Maturity}{Maturity}_i\right)^2 + \epsilon_i
\end{aligned} \tag{4}$$

$$\begin{aligned}
\text{Non-Coupon: } LM_i =& \beta_1 + \beta_2 AmountIssued_i + \beta_3 Daily\ Trades_i \\
&+\beta_{4-7} MaturityDummies_i + \\
&+(\beta_8 AmountIssued_i + \beta_9 NTrades_i) \cdot FDummy_i \\
&+\beta_{10} \frac{Time\ to\ Maturity}{Maturity}_i + \beta_{11} \left(\frac{Time\ to\ Maturity}{Maturity}_i\right)^2 + \epsilon_i
\end{aligned} \tag{5}$$

where *Amount Issued*$_i$ is the bond i amount issued, taking into consideration eventual re-issuance, *Daily Trades*$_i$ is the bond i average number of daily trades, *Coupon Rate*$_i$ is the coupon rate in percentage points, Maturities Dummies$_i$ are dummies which equal 1 if bond i belongs to a maturity group and 0 otherwise, *Time to Maturity* and *Maturity* are calculated considering the issuance date and the maturity date, and $FDummy_i$ equals one when bond i is a floating rate bond and zero otherwise. LM_i is the ith liquidity measure. Our proxies for liquidity are as follows: *Quoted Spread*, *Effective Spread*, *Quoted Quantity*, *Roll Measure*, and *Amihud Measure*. The results for the coupon-bearing bonds from Equation 4 are presented in Table 15, Panel A, while the results for non-coupon-bearing bonds, as per Equation 5, are presented in Table 15, Panel B.

INSERT TABLE 15 HERE

As far as coupon bonds are concerned, the two spread measures (*Quoted Spread* and *Effective Spread*) show similar results. The relationships between them and the *Time-to-maturity* (or, conversely, *Age*) of the bond are highly non-linear. As shown in Figure 13, which plots the averages, for the sample of 60 coupon-bearing bonds, of the bid-ask spread and the time-to-maturity, it is clear that, within the same maturity group, bonds that are on-the-run and bonds that are close to maturity have the lowest bid-ask spreads, while those in their "mid-life" have higher spreads, reflecting an inverted U-shaped pattern.

INSERT FIGURE 13 HERE

In our estimations, we include the ratio of *Time-to-maturity* to *Maturity* and its square as independent variables. The coefficients are both significant, and the signs clearly confirm the initial conjecture from the graphs. The parameters imply that the spread increases from the issue date and reaches its maximum at around one-fourth of the total maturity, and then declines as the maturity date approaches. Since the base case is the 3-year maturity group, the maturity dummies (Maturity5 to Maturity30) show the positive relationship between spread and maturity. The number of trades has a negative sign, meaning that the larger the trading activity, the smaller is the spread. Darbha and Dufour (2012) find, for the period from January 2004 to July 2010, that the more recently issued bonds with larger issue sizes have smaller values of *Quoted Spread*, which we also confirm for our sample period, June 2011 to December 2012. On the other hand, bonds of a longer maturity (as measured by the dummies) have larger spreads. This is consistent with what Dufour and Nguyen (2011), and Darbha and Dufour (2012) find for the MTS market, and with what Goyenko et al. (2011) report for US Treasury bonds. Darbha and Dufour (2012) suggest that, during the period from August 2007 to July 2010, prior to the Euro-zone crisis, investors shifted funds into short-term bonds. This explains why the *Amihud Measure* (market impact) is higher for longer-maturity bonds. The cross-sectional regressions for floating rate and zero coupon bonds yield similar results to those for coupon bonds. Although the *Roll Measure* should produce similar results to those for the effective spread, *Daily Trades* is the only variable that is consistent with this conjecture. These results for the *Roll Measure* are somewhat puzzling; however, it should be noted that the pattern of trades in our sample violates the crucial assumption needed for the Roll measure to act as a good proxy for the bid-ask spread. The *Amihud Measure* has a negative relation with age and the number of trades, and a positive relation with maturity. These results are consistent with those for the *Quoted Spread* and *Effective Spread*.

Appendix C: Methodological Appendix

Threshold Analysis

In empirical settings, a regression such as the ordinary least squares (OLS) specification $y_i = \beta' x_i + e_i$, where y_i is the dependent variable that is regressed on the independent variable x_i, is often repeated for sub-samples, either as a robustness check or to verify whether the same relationship applies to appropriately grouped observations. The sample split is often conducted in an exogenous fashion, thus dividing the data according to the distribution of a key variable (such as size and book-to-market quantile portfolios in a Fama-French (1993) setting). Hansen (1996, 2000) develops the asymptotic approximation of the distribution of the estimated threshold value $\hat{\gamma}$, when the sample split, based on the values of an independent variable q_i, can be rewritten as

$$Y = X\theta + X_\gamma \delta + e \qquad \text{where } X_\gamma = XI(q \leq \gamma)$$

or $y_i = \theta' x_i + \delta I(q_i \leq \gamma) x_i + e_i$, where $I(q_i \leq \gamma)$ equals 1 if $q_i \leq \gamma$, and 0 otherwise. He shows that, under a set of regularity conditions, which exclude time-trending and integrated variables, the model can be estimated by least squares, minimizing $SSR_n(\theta, \delta, \gamma) = (Y - X\theta - X_\gamma \delta)'(Y - X\theta - X_\gamma \delta)$.[57] Concentrating out all parameters but γ yields $S_n(\gamma) = SSR_n(\hat{\theta}(\gamma), \hat{\delta}(\gamma), \gamma) = Y'Y - Y'X_\gamma^*('X_\gamma^*{}'X_\gamma^*)^{-1} X_\gamma^*{}'Y$ with $X_\gamma^* = [X\ X_\gamma]$. The parameters θ and δ are formulated as functions of γ, and the sum of squared residuals depends exclusively on the observed variables and on γ. Thus, the value of γ that minimizes $S_n(\gamma)$ is its least squares estimator $\hat{\gamma}$, and the estimators of the remaining parameters $\hat{\theta}(\hat{\gamma})$ and $\hat{\delta}(\hat{\gamma})$ can be calculated.

When there are N observations, there are at most N values of the threshold variable q_i, or, equivalently, N values that the $SSR(\gamma)$ (step-)function can take. After re-ordering the values q_i in $(q_{(1)}, q_{(2)}, ... q_{(N)})$, such that $q_{(j)} \leq q_{(j+1)}$, the method is implemented by

1. estimating by OLS $y_i = \theta_2' x_i + \delta I(q \leq q_{(j)}) x_i + e_i$ (or equivalently, when all parameters are allowed to depend on the threshold, estimating separately $y_i = \theta_1' x_i + e_{1i}$ where $q_i \leq q_{(j)}$ and $y_i = \theta_2' x_i + e_{2i}$ where $q_i > q_{(j)}$),
2. calculating the sum of squared residuals, $SSR(q_{(j)}) = \sum e_i$ (or $= \sum e_{1i} + \sum e_{2i}$),
3. repeating 1 and 2 with $q_{(j+1)}$,
4. finding the least squares estimate of γ as $\hat{\gamma} = \arg\min_{q_{(j)}} S(q_{(j)})$, and
5. repeating the estimation of the equations on the sub-samples defined by the $\hat{\gamma}$ threshold, calculating heteroskedasticity-consistent standard errors for the parameters.

As suggested by Hansen (1999), we allow each equation to contain at least 20% of the observations, and, to minimize computing time, we search only through 0.5%-quantiles. Although Hansen (1999) presents an extension of the procedure to several thresholds, we focus in this paper on a single sample split.

[57] A theory for the latter case was developed in Caner and Hansen (2001).

To test the presence of the threshold, thus testing whether $\theta_1 = \theta_2$, the usual tests cannot be used, since γ is not identified under the null hypothesis (the "Davies' Problem", as analyzed by Davies (1977, 1987)). Hansen (1996) provides a test whose asymptotic properties can be approximated by boostrap techniques.

To provide confidence intervals for the threshold estimate $\hat{\gamma}$, Hansen (2000) argues that no-rejection regions should be used. To test $\gamma = \gamma_0$, the likelihood ratio test can be used such that $LR(\gamma) = (SSR(\gamma) - SSR(\hat{\gamma}))/\hat{\sigma}^2$, where $\hat{\sigma}^2 = SSR(\hat{\gamma})/N$ is the estimated error variance, will be rejected if $\hat{\gamma}$ is sufficiently far from γ, i.e. the test statistic is large enough. In its homoskedastic version, the test has a non-standard pivotal distribution, such that the test is rejected at an α-confidence level if $LR(\gamma) > -2\ln(1-\sqrt{\alpha})$. In this paper, we choose $\alpha = 0.95$, consistent with Hansen (2000); thus, the null hypothesis is considered rejected if $LR(\gamma) >= -2\ln(1-\sqrt{0.95}) = 7.35$. This level is plotted as a horizontal line in the plots of the test. The confidence interval for the threshold will be $[\gamma_L, \gamma_U]$, such that $LR(\gamma\,|\gamma < \gamma_U\,) > 7.35$, and $LR(\gamma\,|\gamma > \gamma_U\,) > 7.35$, or, graphically, the portion of the x-axis where the plot of the test is below the 7.35 horizontal line.

In Section VI we claim that we can clearly identify a threshold for the CDS spread at around 500 bp for the regression of the change in the quoted spread on the changes in the CDS spread and their lags, but only for the period up to December 31, 2011 and not for the sub-sample after this date. The plots of the test are presented in Figure 9. The conservative no-rejection regions imply that the threshold in our case is above a CDS spread of 350 bp; thus, the point-estimate provides little information in 2012.

The Chow Test

The Chow test is a standard break point analysis used widely in the economics literature. Based on two nested regressions, it follows an $f_{k,T-2k}$-distribution and its statistic is

$$F = \frac{(SSR_0 - SSR_1)/k}{SSR_1/(T-2k)}$$

where SSR_0 and SSR_1 are the SSR of the restricted regression, $y_t = x_t'\beta + \epsilon_t$ (with $t = 1, ..., T$), and the unrestricted regression, $y_t = x_t'\beta + g_t x_t'\gamma + \epsilon_t$, respectively.

In the unrestricted regressions, the observations following the break point t^*, selected by the dummy variable g_t (such that $g_t = 1$ if $t < t^* \leq T$ and 0 otherwise), are allowed to depend on x_t through the composite parameters $\beta + \gamma$, while the previous observations depend on x_t through β only. The restriction $\gamma = 0$ thus imposes the condition that all y_t depend on x_t in a homogeneous fashion. In our study, we calculate the Chow test statistics using each day as a potential break point, and allow all the regression parameters to change from one sub-sample to another.[58]

Structural Break Tests

The Chow test has a null hypothesis, which is that the parameters after a specific date are equal to those that generated the data before the break date. The alternative hypothesis is that the two

[58]We exclude the first and last 10% of the observations, in order to estimate meaningful regressions.

sets of parameters are indeed different. A test statistic can be calculated from the statistics resulting from the Chow test, the Fs, to test whether a structural break took place at an *unknown* date. After computing the F statistics for a subset of dates, e.g. all the dates in the sample except for the first and last i%, several test statistics can be calculated from them.

Andrews (1993) and Andrews and Ploberger (1994) show that the supremum and the average, respectively, of the F statistics converge to a pivotal non-standard distribution, depending on the number of parameters tested and the relative number of dates tested. While some p-values are tabulated by those authors, a generalized approach for quantifying the p-values of any test statistics is provided in Hansen (1997).

The test statistics that we calculate to test for a structural break at an unknown date are therefore:

$$supF = \sup_t F_t$$
$$aveF = \frac{\sum_t F_t}{T}$$

Tables

Table 1: ***Maturity* and *Coupon Rate* by Maturity Group and Bond Type.** This table presents the distribution of the bonds in terms of *Maturity* and *Coupon Rate*, by maturity group (Panel A) and bond type (Panel B). Maturity groups were determined by the time distance between bond maturities and the closest whole year. Our dataset, obtained from the Mercato dei Titoli di Stato (MTS), consists of transactions, quotes, and orders for all 152 fixed-rate and floating Italian government bonds (Buoni Ordinari del Tesoro (BOT) or Treasury bills, Certificato del Tesoro Zero-coupon (CTZ) or zero coupon bonds, Certificati di Credito del Tesoro (CCT) or floating notes, and Buoni del Tesoro Poliennali (BTP) or fixed-income Treasury bonds) from June 1, 2011 to December 31, 2012.

Panel A

Maturity Group	# Bonds	Coupon Rate	Maturity	MinMaturity	MaxMaturity
0.25	8	[a]	0.26	0.21	0.27
0.50	27	[a]	0.51	0.36	0.53
1.00	33	[a]	1.01	0.83	1.03
2.00	11	[b]	2.02	2.01	2.09
3.00	11	3.16	2.98	2.93	3.02
5.00	13	3.87	5.03	4.92	5.25
6.00	13	[c]	6.67	5.29	7.09
10.00	19	4.45	10.41	10.10	10.52
15.00	7	4.57	15.71	15.44	16.00
30.00	10	5.88	30.88	29.30	31.79

Panel B

Bond Type	N	Coupon Rate	Maturity	MinMaturity	MaxMaturity
BOT	68	ZCB	0.72	0.21	1.03
BTP	60	4.34	11.91	2.93	31.79
CCT	13	Floating	6.70	5.29	7.09
CTZ	11	ZCB	2.02	2.01	2.09

[a] All bonds in this group are BOT, Buoni Ordinari del Tesoro (Treasury bills)
[b] All bonds in this group are CTZ, Certificati del Tesozo Zero-coupon (zero coupon bonds, ZCB)
[c] All bonds in this group are CCT, Certificati di Credito del Tesoro (floating bonds)

Table 2: **Time-series Descriptive Statistics of Trade- and Quote-based Liquidity Measures.** This table shows the time-series distribution of various liquidity measures defined in Section IV.II. The sample consists of the quotes and trades from 406 days in our sample. Each day's data are summarized by the cross-sectional (across bonds) average. However, *Quoted Bonds* is the number of bonds actually traded on each day, *Trades* is the total number of trades on the day, and *Fill Ratio* is the fraction of ordered quantity that is in fact filled. *Quoted Spread* is the difference between the best bid and the best ask, *Effective Spread* is the effective bid-ask spread paid by the traders, *Quoted Quantity* is the face-value quantity offered on average per bond on the bid and ask side in millions of euros, *Lambda* is a measure of depth, and the *Amihud* and *Roll Measures* are illiquidity measures. Our dataset, obtained from the Mercato dei Titoli di Stato (MTS), consists of transactions, quotes, and orders for all 152 fixed-rate and floating Italian government bonds (Buoni Ordinari del Tesoro (BOT) or Treasury bills, Certificato del Tesoro Zero-coupon (CTZ) or zero coupon bonds, Certificati di Credito del Tesoro (CCT) or floating notes, and Buoni del Tesoro Poliennali (BTP) or fixed-income Treasury bonds) from June 1, 2011 to December 31, 2012.

	Time Series										Cross-Section			
Panel A: Activity Measures														
Variable	N	Mean	STD	Min	5th Pct	25th Pct	Median	75th Pct	95th Pct	Max	N	Mean	Min	Max
Quoted Bonds	406	89.781	2.108	86.000	87.000	88.000	90.000	92.000	93.000	94.000				
Trades	406	265.256	108.064	43.0000	116.000	194.000	249.000	321.000	449.000	837.000	152	3.520	0.2512	19.000
Fill Ratio	406	0.685	0.091	0.0777	0.556	0.654	0.698	0.740	0.789	0.872	152	0.689	0.1154	0.901
Panel B: Liquidity Measures														
Volume	406	2.027	0.953	0.3235	0.772	1.442	1.888	2.431	3.781	7.188	152	30.482	1.4606	190.000
Quoted Spread	406	0.506	0.376	0.1314	0.176	0.299	0.419	0.551	1.236	4.477	152	0.346	0.0009	1.405
Effective Spread	406	0.148	0.094	0.0314	0.057	0.088	0.120	0.177	0.327	0.706	152	0.125	0.0010	0.619
Quoted Quantity	406	122.519	17.787	42.9455	96.238	112.485	122.537	132.299	153.195	181.985	152	128.472	70.2121	524.494
Lambda	406	0.019	0.020	0.0038	0.006	0.009	0.014	0.023	0.052	0.255	152	0.013	0.0000	0.045
Amihud	406	3.394	3.649	0.2510	0.566	1.288	2.188	4.343	9.596	29.243	152	2.515	0.0010	18.406
Roll	406	0.038	0.014	0.0115	0.019	0.028	0.036	0.045	0.066	0.085	152	0.031	0.0000	0.168

Table 3: **Time-series Correlations of Trade- and Quote-based Liquidity Measures.** This table shows the time-series correlations between various liquidity measures defined in Section IV.II. The sample consists of the quotes and trades from 406 days in our sample. Each day's data are summarized by the cross-sectional (across bonds) average. However, *Quoted Bonds* is the number of bonds actually traded on each day, *Trades* is the total number of trades on the day, and *Fill Ratio* is the fraction of ordered quantity that is in fact filled. *Quoted Spread* is the difference between the best bid and the best ask, *Effective Spread* is the effective bid-ask spread paid by the traders, *Quoted Quantity* is the face-value quantity offered on average per bond on the bid and ask side in millions of euros, *Lambda* is a measure of depth, and the *Amihud* and *Roll Measures* are illiquidity measures. Our dataset, obtained from the Mercato dei Titoli di Stato (MTS), consists of transactions, quotes, and orders for all 152 fixed-rate and floating Italian government bonds (Buoni Ordinari del Tesoro (BOT) or Treasury bills, Certificato del Tesoro Zero-coupon (CTZ) or zero coupon bonds, Certificati di Credito del Tesoro (CCT) or floating notes, and Buoni del Tesoro Poliennali (BTP) or fixed-income Treasury bonds) from June 1, 2011 to December 31, 2012.

	Quoted Spread	Effective Spread	Quoted Quantity	Lambda	Roll	Amihud	Volumes	Trades
Quoted Spread	1	0.890	-0.591	0.904	0.474	0.695	-0.326	-0.211
Effective Spread		1	-0.557	0.789	0.543	0.705	-0.304	-0.204
Quoted Quantity				-0.496	-0.229	-0.539	0.399	0.230
Lambda				1	0.41	0.636	-0.238	-0.148
Roll					1	0.299	-0.162	-0.064
Amihud						1	-0.185	-0.09
Volumes							1	0.929
Trades								1

Table 4: **Time-series Descriptive Statistics of Global Credit and Liquidity Risk Measures.** The global systemic variables are the return of the Euro 50 Index Euro50, the spread between three-month Euribor and three-month Eonia Euribor-Eonia, the spread between three-month Eonia and the yield of a three-month German T-Bill Eonia-DeTBill, the USVIX, and the Cross-Currency Basis Swap Spread CCBSS, and the measures of local funding liquidity constraints, diffEURIBOR and diffEURLIBOR. Global variables are described in detail in Section IV.I. All data were obtained from Bloomberg.

Variable	N	Mean	STD	Min	5th Pct	25th Pct	Median	75th Pct	95th Pct	Max
Italian CDS	406	401.523	108.244	145.098	194.015	318.554	421.296	491.711	552.843	591.536
Euro 50	406	−0.0002	0.0169	−0.0632	−0.0287	−0.0086	−0.0000	0.0095	0.0266	0.059
Euribor-Eonia	406	0.4761	0.2820	0.1040	0.1175	0.2200	0.3990	0.7495	0.9510	1.006
Eonia-DeTBill	404	0.3418	0.1630	0.0660	0.1210	0.2030	0.3078	0.4735	0.6220	0.788
USVIX	394	21.8880	7.3773	13.4500	14.8000	16.6400	18.8600	24.7900	37.3200	48.000
CCBSS	406	50.2142	20.2852	20.8000	24.5000	29.5000	50.9375	64.6500	87.8600	106.500
diffEURIBOR	392	−0.006	0.006	−0.024	−0.016	−0.010	−0.006	−0.002	0.002	0.007
diffEURLIBOR	403	−0.007	0.011	−0.033	−0.026	−0.015	−0.005	0.001	0.012	0.020

Table 5: **Correlations between Time-series Global Credit and Liquidity Risk Measures.** The global systemic variables are the return of the Euro 50 Index Euro50, the spread between three-month Euribor and three-month Eonia Euribor-Eonia, the spread between three-month Eonia and the yield of a three-month German T-Bill Eonia-DeTBill, the USVIX, and the Cross-Currency Basis Swap Spread CCBSS. Global variables are described in detail in Section IV.I. All data were obtained from Bloomberg.

	CDS	Eur50	USVIX	CCBSS	Euribor-Eonia	Eonia-DeTBill	diffEURIBOR	diffEURLIBOR
CDS	1	-0.86	0.354	0.803	0.620	0.375	-0.202	-0.094
Eur50		1	-0.572	-0.694	-0.538	-0.295	0.098	0.170
USVIX			1	0.523	0.655	0.658	0.212	-0.662
CCBSS				1	0.903	0.632	-0.145	-0.483
Euribor-Eonia					1	0.759	-0.120	-0.684
Eonia-DeTBill						1	0.065	-0.652
diffEURIBOR							1	-0.216
diffEURLIBOR								1

Table 6: **Results for the Granger Causality Analysis of Italian CDS Spread and Quoted Spread.** This table presents the results for the regressions of the day-t changes in *Quoted Spread*, ΔBA_t, and Italian CDS spread ΔCDS_t, on the lagged terms of both variables, in a VAR(3) setting as shown in Equation 1. The data have a daily frequency. The significance refers to heteroskedasticity-robust t-tests. Heteroskedasticity-robust F-test statistics and their significance are reported for the null of $\Delta BA_t = \Delta BA_{t-1} ... = 0$ ($BA \xrightarrow{GC} CDS$), and $\Delta CDS_t = \Delta CDS_{t-1} ... = 0$ ($CDS \xrightarrow{GC} BA$) respectively. We also report the contemporaneous correlation in the model residuals. Our dataset consists of 406 days of trading in Italian government bonds, from June 1, 2011 to December 31, 2012, and is obtained from the MTS (Mercato dei Titoli di Stato) Global Market bond trading system. The CDS spread refers to a USD-denominated, five-year CDS spread. The CDS spread is obtained from Bloomberg.

Variable	ΔBA_t	ΔCDS_t
Intercept	-0.002	0.001
ΔBA_{t-1}	-0.369***	-0.008
ΔCDS_{t-1}	1.264***	0.266***
ΔBA_{t-2}	-0.131*	0.013
ΔCDS_{t-2}	-0.296	-0.113*
ΔBA_{t-3}	-0.166***	-0.006
ΔCDS_{t-3}	0.056	0.003
Granger Causality Tests		
$BA \xrightarrow{GC} CDS$	.	1.012
$CDS \xrightarrow{GC} BA$	5.189***	.
Residuals Correlation		
ΔBA_t	1.000	0.187
ΔCDS_t	0.187	1.000

* Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

Table 7: **Results for the Regression of the Quoted Spread for the Whole Sample and Sub-Samples.** This table presents the results for the regression of the change in the *Quoted Spread* (the change in the quoted bid-ask spread) on day t, ΔBA_t, in Equation 2, on its lagged terms, and the change in the CDS spread on day t, ΔCDS_t, and its lagged terms, using daily data for the *Quoted Spread* and the CDS spread. The statistical significance refers to heteroskedasticity-robust t-tests. Our dataset consists of 406 days of trading in Italian government bonds, from June 1, 2011 to December 31, 2012, and is obtained from the Mercato dei Titoli di Stato (MTS) Global Market bond trading system. The CDS spread refers to a USD-denominated, five-year CDS spread obtained from Bloomberg. Sub-samples are taken with regards to the CDS level.

Variable	1	2	3	4	5	6
Panel A: Whole Sample N=402						
Intercept	-0.002	-0.002	-0.002	-0.003	-0.002	-0.003
ΔBA_{t-1}	.	-0.279 ***	-0.337 ***	-0.324 ***	-0.316 ***	-0.371 ***
ΔCDS_t	1.092 ***	1.072 ***	.	0.859 ***	0.825 **	0.851 **
ΔCDS_{t-1}	.	.	1.132 ***	0.922 ***	1.000***	1.000 ***
ΔCDS_{t-2}	.	.	.	.	-0.353	.
ΔBA_{t-2}	.	.	.	.	.	-0.152 **
ΔBA_{t-3}	.	.	.	.	.	-0.161 ***
Adj R^2	0.051	0.127	0.13	0.159	0.163	0.188
Panel B: Below 500 N=309						
Intercept	0.000	0.000	0.001	0.001	0.001	0.002
ΔBA_{t-1}	.	-0.252 ***	-0.307 ***	-0.300 ***	-0.289 ***	-0.339 ***
ΔCDS_t	0.721 **	0.677 **	.	0.447	0.431	0.453
ΔCDS_{t-1}	.	.	1.254 ***	1.161 ***	1.205 ***	1.226 ***
ΔCDS_{t-2}	.	.	.	.	-0.214	.
ΔBA_{t-2}	.	.	.	.	.	-0.130 *
ΔBA_{t-3}	.	.	.	.	.	-0.152 **
Adj R^2	0.026	0.088	0.147	0.155	0.154	0.178
Panel C: Above 500 N=93						
Intercept	-0.027	-0.026	-0.003	-0.019	-0.01	-0.02
ΔBA_{t-1}	.	-0.376 ***	-0.383 **	-0.318 **	-0.359 ***	-0.365 ***
ΔCDS_t	3.156 ***	3.327 ***	.	3.606 ***	3.357 ***	3.499 ***
ΔCDS_{t-1}	.	.	0.602	-0.851	-0.48	-0.701
ΔCDS_{t-2}	.	.	.	.	-1.047	.
ΔBA_{t-2}	.	.	.	.	.	-0.139
ΔBA_{t-3}	.	.	.	.	.	-0.176 **
Adj R^2	0.209	0.332	0.093	0.336	0.349	0.354

* Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

Table 8: **Results for the Sub-Samples Based on Time and CDS Level.** This table presents the results for the regression of the change in the *Quoted Spread*, or the change in the bid-ask spread on day t, $\Delta \mathrm{BA}_t$, in Equation 2, on its lagged terms, and the change in the CDS spread on day t, $\Delta \mathrm{CDS}_t$, and its lagged terms, using daily data for the *Quoted Spread* and CDS spread. The significance refers to heteroskedasticity-robust t-tests. The sub-samples are based on our dataset, which consists of 406 days of trading in Italian government bonds, from June 1, 2011 to December 31, 2012, and is obtained from the MTS (Mercato dei Titoli di Stato) Global Market bond trading system. The CDS spread refers to a USD-denominated, five-year CDS spread obtained from Bloomberg. Sub-samples are taken with regards to the time frame and the CDS level.

Whole Sample						
Variable	1	2	3	4	5	6
Panel A: $\mathrm{CDS}_t \leq 500$, T= 2011 N=112						
Intercept	0.007	0.009	0.01	0.006	0.007	0.009
$\Delta \mathrm{BA}_{t-1}$	.	-0.201	-0.312 ***	-0.296 ***	-0.28 ***	-0.311 ***
$\Delta \mathrm{CDS}_t$	1.084 **	1.042 **	.	0.731	0.7	0.725
$\Delta \mathrm{CDS}_{t-1}$	.	.	1.739 ***	1.585 ***	1.636 ***	1.643 ***
$\Delta \mathrm{CDS}_{t-2}$	.	.	.	.	-0.246	.
$\Delta \mathrm{BA}_{t-2}$	.	.	.	.	.	-0.06
$\Delta \mathrm{BA}_{t-3}$	.	.	.	.	.	-0.119
Adj R^2	0.051	0.084	0.173	0.192	0.187	0.193
Panel B: $\mathrm{CDS}_t > 500$, T= 2011 N=36						
Intercept	-0.05	-0.049	-0.012	-0.009	-0.002	-0.019
$\Delta \mathrm{BA}_{t-1}$	.	-0.255	-0.315	0.018	-0.076	0.003
$\Delta \mathrm{CDS}_t$	3.981 ***	4.022 ***	.	5.269 ***	4.835 ***	5.219 ***
$\Delta \mathrm{CDS}_{t-1}$	.	.	0.803	-2.919 ***	-2.225 *	-2.662 **
$\Delta \mathrm{CDS}_{t-2}$	.	.	.	.	-1.12	.
$\Delta \mathrm{BA}_{t-2}$	.	.	.	.	.	-0.103
$\Delta \mathrm{BA}_{t-3}$	.	.	.	.	.	-0.329 ***
Adj R^2	0.382	0.43	0.008	0.511	0.519	0.588
Panel C: T= 2012 N=254						
Intercept	-0.005	-0.007	-0.007	-0.006	-0.007	-0.01
$\Delta \mathrm{BA}_{t-1}$	.	-0.366 ***	-0.38 ***	-0.378 ***	-0.375 ***	-0.491 ***
$\Delta \mathrm{CDS}_t$	0.431	0.420	.	0.313	0.305	0.272
$\Delta \mathrm{CDS}_{t-1}$	.	.	0.614 **	0.553 **	0.587 **	0.600 ***
$\Delta \mathrm{CDS}_{t-2}$	.	.	.	.	-0.176	.
$\Delta \mathrm{BA}_{t-2}$	.	.	.	.	.	-0.284 ***
$\Delta \mathrm{BA}_{t-3}$	.	.	.	.	.	-0.187 ***
Adj R^2	0.005	0.136	0.146	0.147	0.145	0.205

* Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

Table 9: **Results for the Specification Including Macro Variables.** This table presents the results for the regression of the change in the *Quoted Spread*, or the change in the bid-ask spread on day t, ΔBA_t, on its lagged terms, and the change in the CDS spread on day t, ΔCDS_t, and its lagged terms, and a cohort of macro credit and liquidity variables, as resulting from a general-to-specific stepwise approach. The significance refers to heteroskedasticity-robust t-tests. The sub-samples are based on our dataset, which consists of 406 days of trading in Italian government bonds, from June 1, 2011 to December 31, 2012, and is obtained from the MTS (Mercato dei Titoli di Stato) Global Market bond trading system. The CDS spread refers to a USD-denominated, five-year CDS spread obtained from Bloomberg. Sub-samples are taken with regards to the time frame and the CDS level.

Variable	Below 500, 2011	Above 500, 2011	2012
Intercept	0.004	-0.030	-0.007
ΔBA_{t-1}	-0.306 ***	0.061	-0.496 ***
ΔBA_{t-2}	-0.070	-0.095	-0.307 ***
ΔBA_{t-3}	-0.122	-0.345 ***	-0.188 ***
ΔCDS_t	0.058	5.047 ***	-0.050
ΔCDS_{t-1}	1.702 ***	-2.533 **	0.566 **
ΔEuribor-Eonia$_t$	.	1.924 **	.
$\Delta CCBSS_t$	0.695 **	.	0.836 ***
ΔdiffEURIBOR$_t$	0.043 **	.	.
Adj R^2	0.258	0.62	0.233

* Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

Table 10: **Other Liquidity Variables: Results for Sub-samples Based on Time and CDS Level.** This table presents the results for the regression of the change in several liquidity measures shown in Equation 2, on their lagged terms, and the change in the CDS spread on day t, ΔCDS_t, and its lagged terms, using daily data for the liquidity measures and CDS spread. The results for changes in the liquidity measures *Quoted Quantity* ΔQQ_t, *Effective Spread* ΔES_t, and *Lambda* $\Delta\lambda_t$ are presented in Panels A, B, and C, respectively. The liquidity measures are described in Section IV.II. The significance refers to heteroskedasticity-robust t-tests. The sub-samples are based on our dataset, which consists of 406 days of trading in Italian government bonds, from June 1, 2011 to December 31, 2012, and is obtained from the MTS (Mercato dei Titoli di Stato) Global Market bond trading system. "Below 500" and "Above 500" indicate a sample split based on the level of the CDS spread for Italian bonds; "2011" and "2012" refer to a sample split based on the timing of the observation. The CDS spread refers to a USD-denominated, five-year CDS spread obtained from Bloomberg. Sub-samples are taken with regards to the time frame and the CDS level.

Variable	Whole Sample	Below 500	Above 500	Below 500 2011	Above 500 2011	2012
			Dependent Variable: Quoted Quantity, ΔQQ_t			
Intercept	-0.001	-0.002	-0.004	-0.003	-0.002	0.002
ΔQQ_{t-1}	-0.395***	-0.380***	-0.349***	-0.381**	-0.341**	-0.372***
ΔQQ_{t-2}	-0.325***	-0.335***	-0.234*	-0.207	-0.249	-0.415***
ΔQQ_{t-3}	-0.232***	-0.235**	-0.226**	-0.150	-0.253	-0.307***
ΔCDS_t	-0.310*	-0.103	-1.731***	-0.036	-2.486**	-0.197
ΔCDS_{t-1}	-0.355	-0.446*	-0.455	-0.742*	0.845	-0.046
R^2	0.195	0.189	0.275	0.173	0.290	0.232
			Dependent Variable: Effective Spread, ΔES_t			
Intercept	-0.002	-0.001	-0.029	-0.000	-0.039	-0.008
ΔES_{t-1}	-0.423***	-0.372***	-0.602***	-0.239***	-0.403**	-0.573***
ΔES_{t-2}	-0.315***	-0.300***	-0.384***	-0.237***	-0.199	-0.438***
ΔES_{t-3}	-0.227***	-0.209***	-0.279**	-0.218**	-0.205	-0.291***
ΔCDS_t	1.278***	0.956**	3.128***	1.153**	3.386***	0.905*
ΔCDS_{t-1}	0.538	0.414	1.073	1.142**	0.803	-0.315
R^2	0.212	0.181	0.313	0.153	0.229	0.288
			Dependent Variable: Lambda, $\Delta\lambda_t$			
Intercept	0.000	0.000	-0.027	0.007	0.022	-0.020
$\Delta\lambda_{t-1}$	-0.561***	-0.555***	-0.576***	-0.523***	-0.332**	-0.625***
$\Delta\lambda_{t-2}$	-0.315***	-0.334***	-0.233**	-0.176	-0.157	-0.427***
$\Delta\lambda_{t-3}$	-0.302***	-0.256***	-0.382***	-0.146	-0.378***	-0.416***
$\Delta\lambda_{t-4}$	-0.110**	-0.050	-0.266***	0.006	-0.430***	-0.195***
ΔCDS_t	0.559	-0.157	5.157***	0.067	8.863***	-0.318
ΔCDS_{t-1}	1.419**	1.542**	-0.067	2.522**	-3.291*	0.324
R^2	0.263	0.247	0.427	0.245	0.541	0.293

[*] Significant at a 10% level. [**] Significant at a 5% level. [***] Significant at a 1% level.

Table 11: **Results for the Granger Causality with the Variance of the Returns.** We regress changes in the liquidity measure, changes in credit risk, and changes in the volatility of the returns, on their own lags and the lags of the other two variables, in a VAR(4) setting as shown in Equation 1. The significance refers to heteroskedasticity-robust t-tests. Our dataset consists of 406 days of trading in the government bonds, from June 1, 2011 to December 31, 2012, and is obtained from the MTS (Mercato dei Titoli di Stato) Global Market bond trading system. The CDS spread refers to a USD-denominated, five-year CDS spread. The CDS spread is obtained from Bloomberg.

Variable	ΔBA_t	ΔCDS_t	$\Delta\sigma^2_t$
Intercept	-0.002	0.001	0.005
ΔBA_{t-1}	-0.354 ***	-0.009	0.838 **
ΔCDS_{t-1}	1.272 ***	0.267 ***	0.966
$\Delta\sigma^2_{t-1}$	-0.005	0.000	-0.736 ***
ΔBA_{t-2}	-0.075	0.014	0.868 **
ΔCDS_{t-2}	-0.304	-0.122 *	0.089
$\Delta\sigma^2_{t-2}$	-0.015	-0.001	-0.590 ***
ΔBA_{t-3}	-0.146 *	0.000	0.348
ΔCDS_{t-3}	-0.075	0.012	-0.391
$\Delta\sigma^2_{t-3}$	-0.013	-0.001	-0.398 ***
ΔBA_{t-4}	-0.049	0.000	0.317
ΔCDS_{t-4}	0.449 *	-0.056	1.068
$\Delta\sigma^2_{t-4}$	0.003	0.001 -	0.183 ***
Granger Causality Tests			
$BA \xrightarrow{GC} CDS + \sigma^2$		1.60	
$CDS \xrightarrow{GC} BA + \sigma^2$		3.81***	
$\sigma^2 \xrightarrow{GC} CDS + BA$		0.34	
Residuals Correlation			
ΔBA	1.000	0.191	0.613
ΔCDS	0.191	1.0000	0.066
$\Delta\sigma^2$	0.613	0.066	1.000

* Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

Table 12: **Results for the Regressions in Table 8, Controlling for the Variance of the Returns.** We regress changes in the liquidity measure on its own lagged changes, changes in credit risk, and the volatility of the returns. The significance refers to heteroskedasticity-robust t-tests. Our dataset consists of 406 days of trading in the government bonds, from June 1, 2011 to December 31, 2012, and is obtained from the MTS (Mercato dei Titoli di Stato) Global Market bond trading system. The CDS spread refers to a USD-denominated, five-year CDS spread. The CDS spread is obtained from Bloomberg.

Variable	Below 500, 2011	Above 500, 2011	2012
Intercept	0.004	-0.015	-0.009
ΔCDS_t	0.852 **	2.82 ***	0.246
ΔCDS_{t-1}	1.166 ***	-1.417 **	0.589 ***
ΔBA_{t-1}	-0.161	-0.006	-0.374 ***
ΔBA_{t-2}	0.017	-0.12	-0.209 ***
ΔBA_{t-3}	-0.075	-0.269 ***	-0.142 **
$\Delta\sigma^2_t$	0.115 ***	0.126 ***	0.062 ***
Adj R-Sq	0.441	0.785	0.38

* Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

Table 13: **Results for the Regressions in Table 8, Using an Alternative Sub-sampling Procedure.** We regress changes in the liquidity measure on its own lagged changes, and changes in credit risk and its lag. The significance refers to heteroskedasticity-robust t-tests. Our dataset consists of 406 days of trading in the government bonds, from June 1, 2011 to December 31, 2012, and is obtained from the MTS (Mercato dei Titoli di Stato) Global Market bond trading system. The CDS spread refers to a USD-denominated, five-year CDS spread. The CDS spread is obtained from Bloomberg. The sub-sampling procedure is detailed in Section VII.III.

From to	06/01/2011 10/26/2011	10/26/2011 12/07/2011	12/07/2011 12/31/2012
Intercept	-0.006	-0.008	-0.012
ΔBA_{t-1}	-0.261*	-0.199	-0.504***
ΔBA_{t-2}	-0.076	0.012	-0.281***
ΔBA_{t-3}	-0.152	-0.210	-0.211***
ΔCDS_t	0.570	4.172***	0.296
ΔCDS_{t-1}	1.898***	-0.904	0.488**
Adj R-Sq	0.193	0.527	0.224

* Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

Table 14: **Results for the Granger Causality Analysis of Italian CDS Spread and Quoted Spread: From 2010 to 2012.** This table presents the results for the regressions of the day-t changes in *Quoted Spread* ΔBA_t, and the Italian CDS spread ΔCDS_t, on the lagged terms of both variables, in a VAR(3) setting as shown in Equation 1. The data have a daily frequency. The significance refers to heteroskedasticity-robust t-tests. Heteroskedasticity-robust F-test statistics and their significance are reported for the null of $\Delta BA_t = \Delta BA_{t-1} ... = 0$ ($BA \xrightarrow{GC} CDS$), and $\Delta CDS_t = \Delta CDS_{t-1} ... = 0$ ($CDS \xrightarrow{GC} BA$) respectively. We also report the contemporaneous correlation in the model residuals. Our dataset consists of 635 days of trading in Italian government bonds, from July 1, 2010 to December 31, 2012, and is obtained from the MTS (Mercato dei Titoli di Stato) Global Market bond trading system. The CDS spread refers to a USD-denominated, five-year CDS spread. The CDS spread is obtained from Bloomberg.

Variable	ΔBA_t	ΔCDS_t
Intercept	-0.002	0.001
ΔBA_{t-1}	-0.360***	-0.010
ΔCDS_{t-1}	1.122***	0.263***
ΔBA_{t-2}	-0.193***	0.005
ΔCDS_{t-2}	-0.102	-0.101**
ΔBA_{t-3}	-0.178***	-0.004
ΔCDS_{t-3}	0.117	0.0177
Granger Causality Tests		
$CDS \xrightarrow{GC} BA$	6.632***	.
$BA \xrightarrow{GC} CDS$	.	0.844
Residuals Correlation		
ΔBA_t	1.000	0.192
ΔCDS_t	0.192	1.000

* Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

Table 15: **Results for the Cross-sectional Regressions of Liquidity Measures on Bond Characteristics.** This panel presents the results from the cross-sectional regression (Equation 4) of time-averaged liquidity measures on bond characteristics and number of trades defined in Section IV.II. The sub-sample consists of 60 Italian coupon-bearing bonds. Heteroskedasticity-robust t-statistics are reported in parentheses. R^2 values are reported below the parameter estimates. Our dataset consists of transactions, quotes, and orders for all 152 fixed-rate and floating Italian government bonds (Buoni Ordinari del Tesoro (BOT) or Treasury bills, Certificato del Tesoro Zero-coupon (CTZ) or zero coupon bonds, Certificati di Credito del Tesoro (CCT) or floating notes, and Buoni del Tesoro Poliennali (BTP) or fixed-income Treasury bonds) from June 1, 2011 to December 31, 2012.

Panel A Sub-sample: Coupon-Bearing Bonds					
Variable	Quoted Spread	Effective Spread	Total Quantity	Amihud	Roll
Amount Issued	−0.009 ***	−0.004 **	1.219	0.072	−0.002
Daily Trades	−0.028 ***	−0.008 ***	−1.306 **	−0.311 ***	−0.003 ***
Coupon Rate	0.006	0.008	2.216	−0.267	−0.001
Maturity 3	0.357 ***	0.103 **	152.389 ***	−0.402	0.041
Maturity 5	0.41 ***	0.131 **	150.261 ***	0.193	0.048
Maturity 10	0.541 ***	0.182 ***	139.074 ***	1.238	0.074 **
Maturity 15	0.737 ***	0.239 ***	125.012 ***	4.15 ***	0.096 ***
Maturity 30	1.145 ***	0.432 ***	99.698 ***	10.396 ***	0.111 **
TTM/Maturity	0.841 ***	0.309 ***	−172.211 **	7.588 ***	0.12 **
$(\text{TTM/Maturity})^2$	−0.595 ***	−0.236 ***	135.715 **	−2.814	−0.094 *
R^2	0.985	0.985	0.986	0.978	0.887
N	60	60	60	60	60

* Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

Table 15: (continued) Panel B presents the results from the cross-sectional regression (Equation 5) of time-averaged liquidity measures on bond characteristics and number of trades defined in Section IV.II. The sub-sample consists of 92 Italian zero-coupon and floating rate bonds. Heteroskedasticity-robust t-statistics are reported in parentheses. R^2 values are reported below the parameter estimates.

Panel B Sub-sample: Non-Coupon-Bearing Bonds					
Variable	Quoted Spread	Effective Spread	Total Quantity	Amihud	Roll
Amount Issued	−0.015 **	−0.009 **	5.048 *	−0.056	−0.002 ***
Daily Trades	0.	0.	−7.846 ***	−0.036	0.
Maturity 0.25	−0.242 ***	−0.076 ***	238.539 ***	−1.596 **	−0.019 ***
Maturity 0.5	−0.146 **	−0.025	234.896 ***	−1.27	−0.009
Maturity 1	−0.064	0.002	222.01 ***	−0.962	−0.004
Maturity 2	0.155 *	0.085	223.089 ***	0.01	0.019 *
Maturity 6	0.585 ***	0.246 ***	179.395 ***	3.547 ***	0.05 ***
TTM/Maturity	1.241 ***	0.459 ***	−428.022 ***	6.726 ***	0.114 ***
$(\text{TTM/Maturity})^2$	−0.987 ***	−0.367 ***	341.19 ***	−4.675 ***	−0.104 ***
R^2	0.904	0.865	0.926	0.782	0.772
N	92	92	92	92	92

[a] Floating coupon bonds have a maturity of six years
* Significant at a 10% level. ** Significant at a 5% level. *** Significant at a 1% level.

Figures

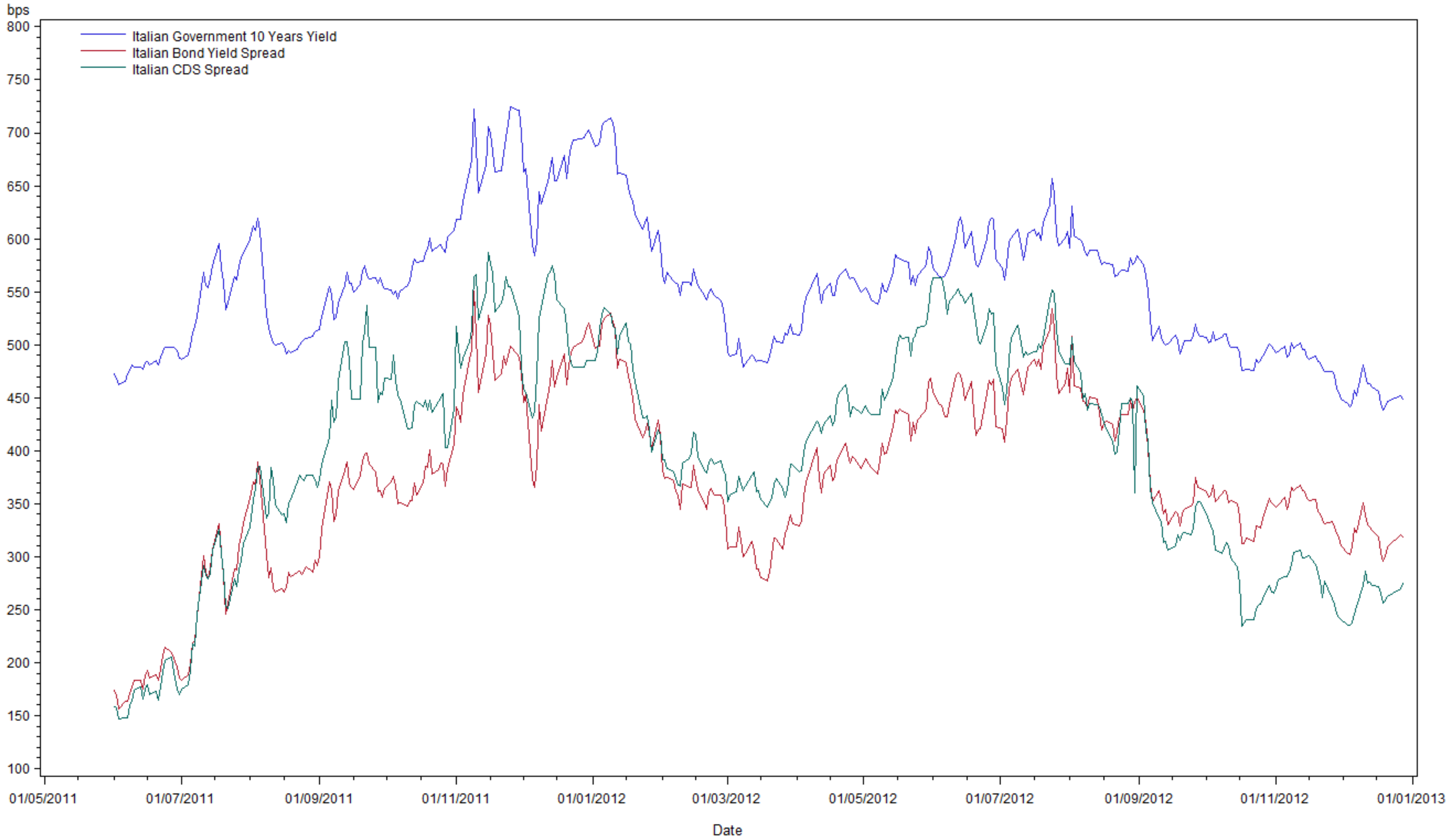


Figure 1: **Time Series of Bond Yield, Bond Yield Spread and CDS Spread.** The bond yield spread is calculated between the Italian and German bonds with ten years to maturity. The CDS Spread is the spread for a five-year US-denominated CDS contract. All data were obtained from Bloomberg and span our data sample, June 1, 2011 to December 31, 2012.

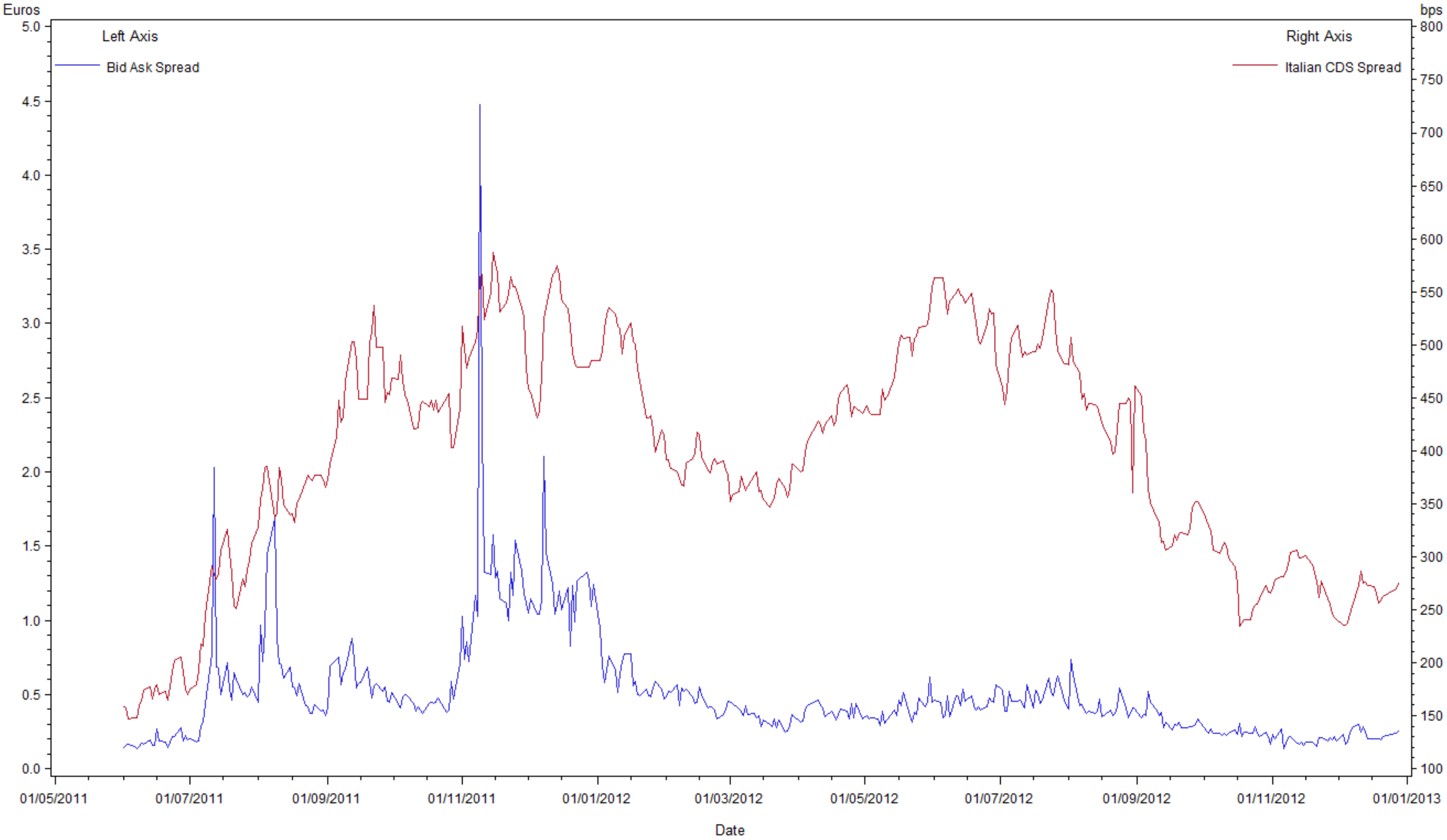
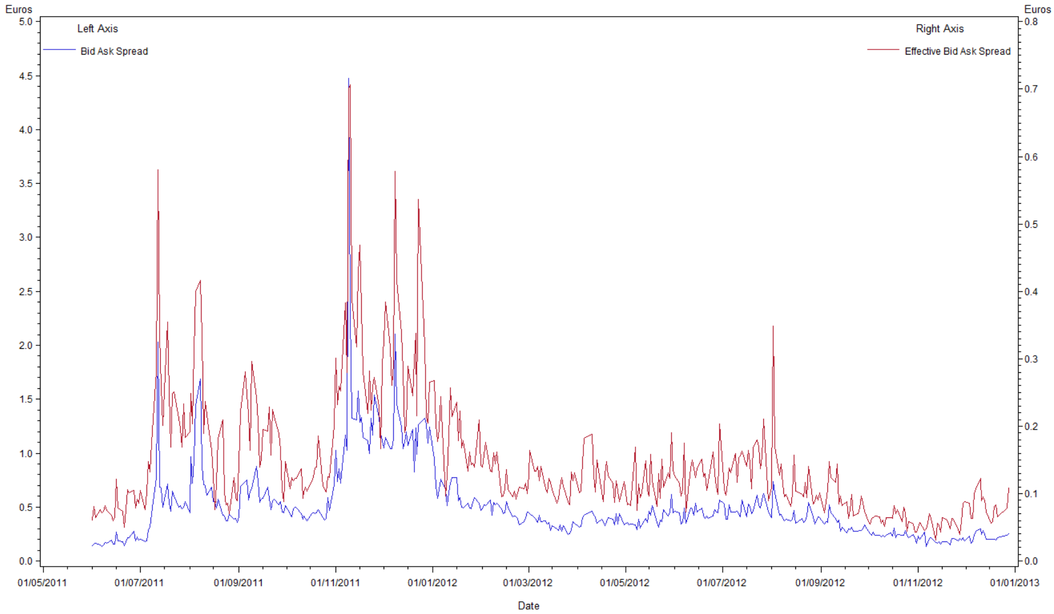
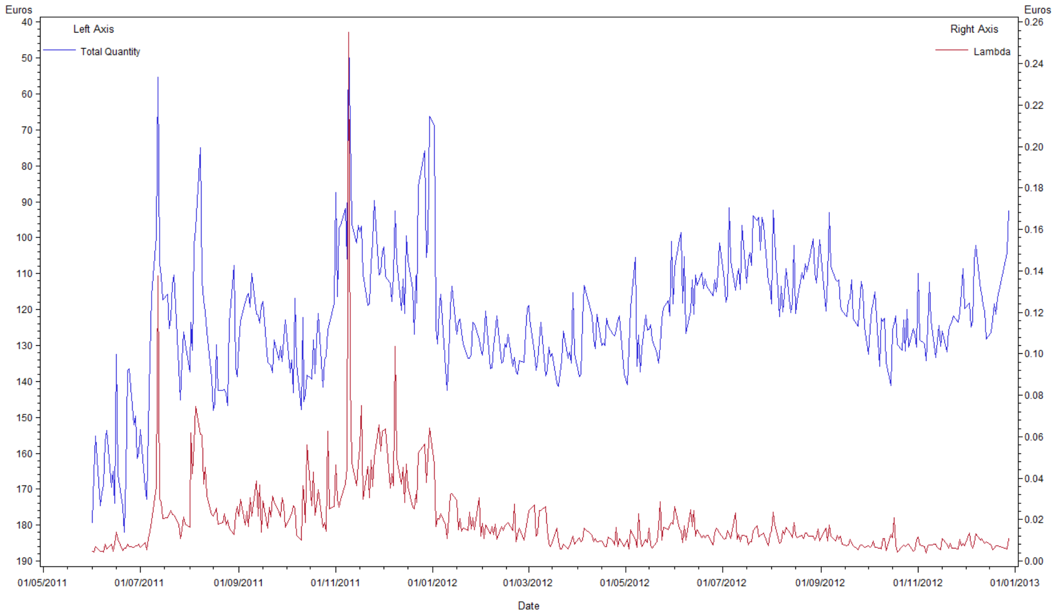


Figure 2: **Time Series of Bid-Ask Spread and CDS Spread.** The figure shows the evolution of the MTS market-quoted spread, left-hand axis, in euro, and the Italian CDS spread, right-hand axis, in bps. Our dataset consists of transactions, quotes, and orders for all 152 fixed-rate and floating Italian government bonds (Buoni Ordinari del Tesoro (BOT) or Treasury bills, Certificato del Tesoro Zero-coupon (CTZ) or zero coupon bonds, Certificati di Credito del Tesoro (CCT) or floating notes, and Buoni del Tesoro Poliennali (BTP) or fixed-income Treasury bonds) from June 1, 2011 to December 31, 2012. Data for the CDS spread were obtained from Bloomberg for a five-year US-denominated CDS contract.

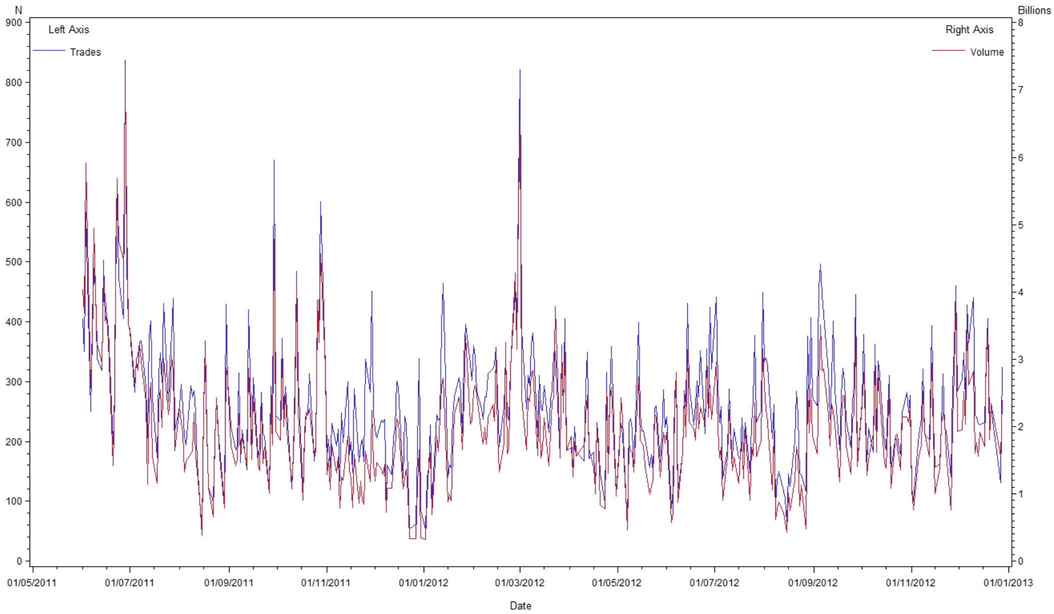


(a) Quoted and Effected Bid-Ask Spread

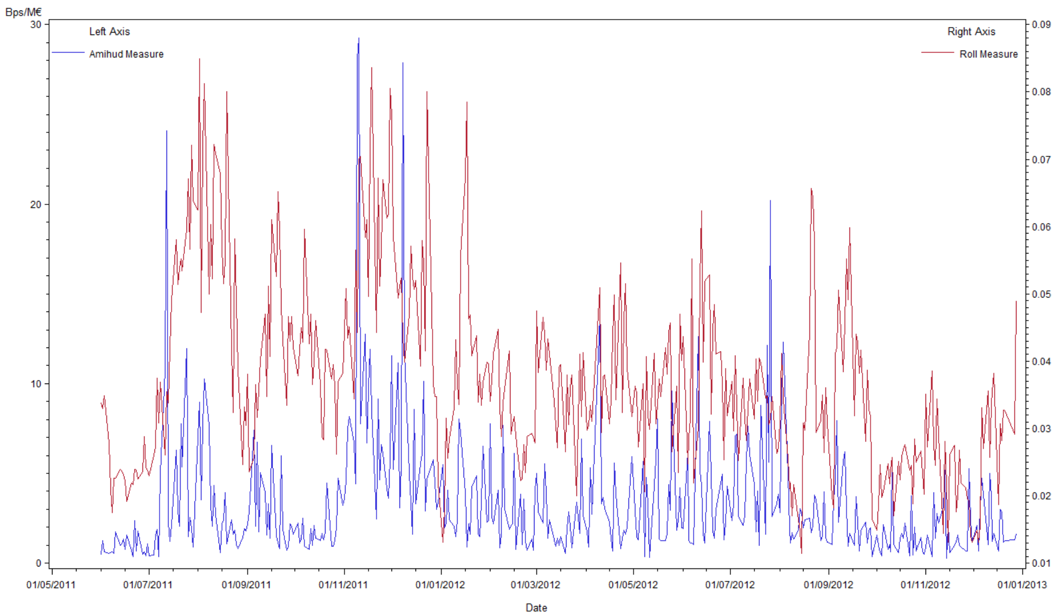


(b) Quoted Quantity and Lambda

Figure 3: **Time Series of Liquidity Measures.** Panel (a) shows the time-series evolution of the Quoted and Effective Spread, while Panel (b) shows the depth measure Lambda and Quoted Quantity. Our liquidity measures are described in detail in Section IV.II. Our data set consists of transactions, quotes, and orders for all 152 fixed-rate and floating Italian government bonds (Buoni Ordinari del Tesoro (BOT) or Treasury bills, Certificato del Tesoro Zero-coupon (CTZ) or zero coupon bonds, Certificati di Credito del Tesoro (CCT) or floating notes, and Buoni del Tesoro Poliennali (BTP) or fixed-income Treasury bonds) from June 1, 2011 to December 31, 2012.

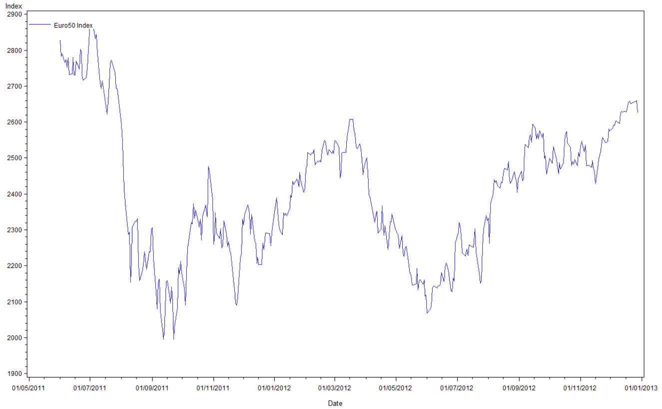


(a) Trades and Volume

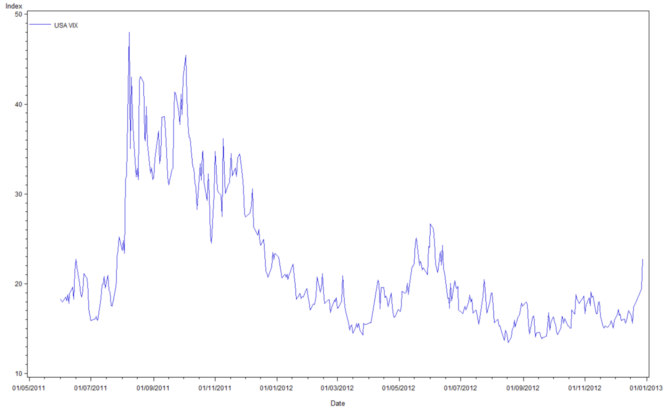


(b) Amihud and Roll Measures

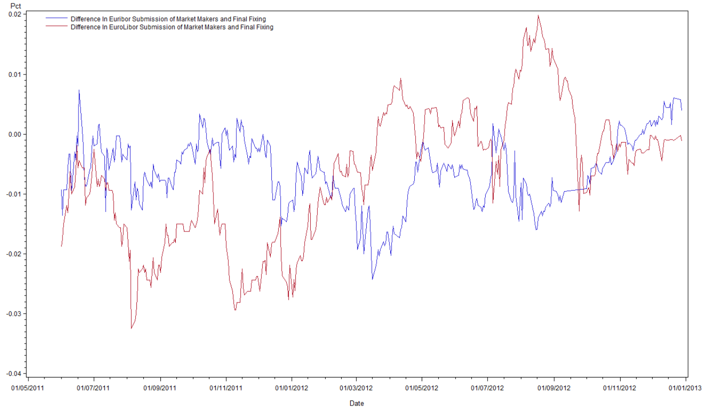
Figure 4: **Time Series of Liquidity Measures and Volume.** Panel (a) shows the time-series evolution of the overall market volume, right-hand axis, in billions of euro, and the overall number of trades, left-hand axis. Panel (b) shows the time-series evolution of the classical liquidity measures of Roll and Amihud. Our liquidity measures are described in detail in Section IV.II. Our dataset consists of transactions, quotes, and orders for all 152 fixed-rate and floating Italian government bonds (Buoni Ordinari del Tesoro (BOT) or Treasury bills, Certificato del Tesoro Zero-coupon (CTZ) or zero coupon bonds, Certificati di Credito del Tesoro (CCT) or floating notes, and Buoni del Tesoro Poliennali (BTP) or fixed-income Treasury bonds) from June 1, 2011 to December 31, 2012.



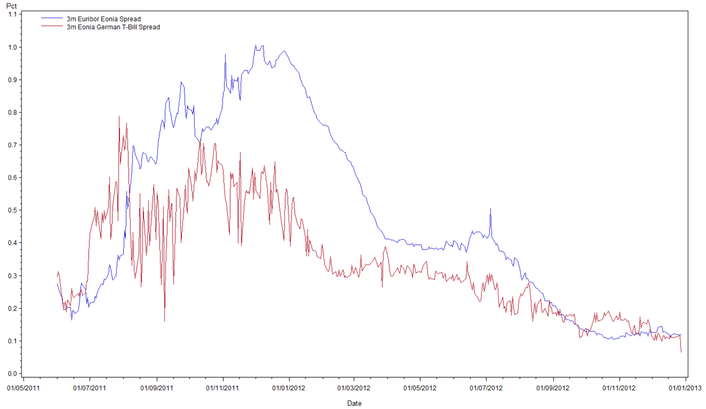
(a) Euro Stocks Index



(b) USVIX Index

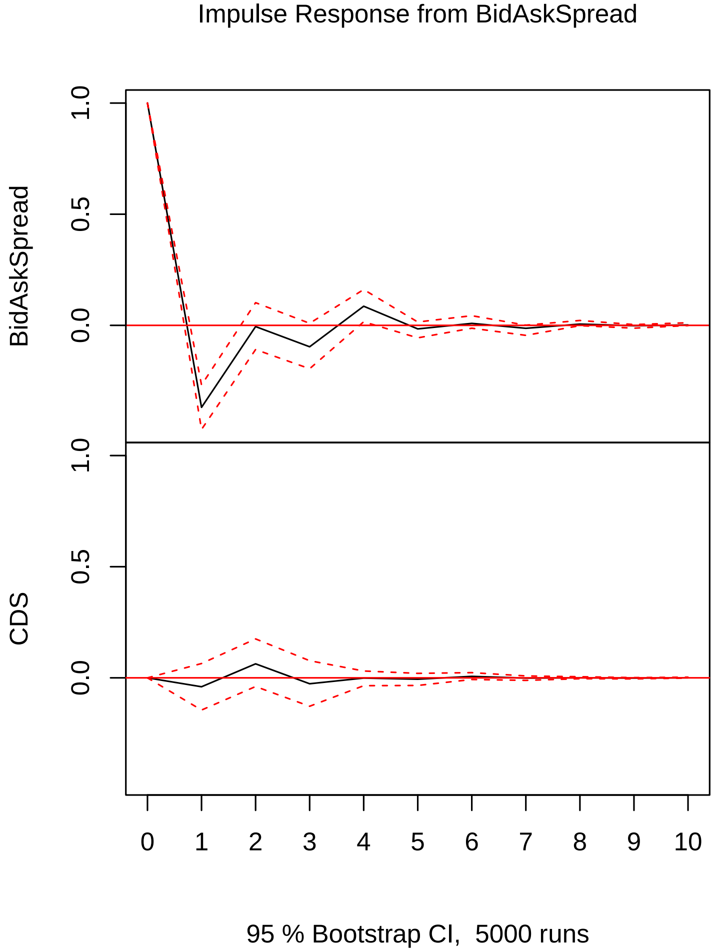


(c) Cross Currency Basis Swap Spread

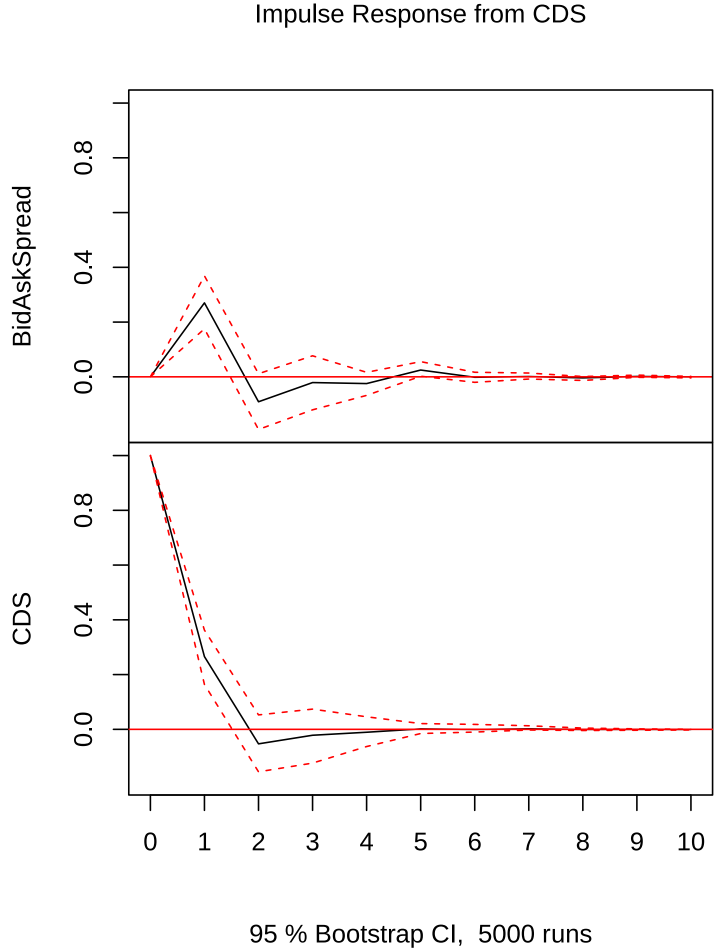


(d) 3-Month Euribor-Eonia and Eonia-German T-Bill Spreads

Figure 5: **Time Series of Macro, Liquidity, and Credit Risk Variables.** The time-series evolution of the global variables Euro 50 Index, the USVIX, the Cross-Currency Basis Swap Spread, and the spreads between three-month Euribor and three-month Eonia and between three-month Eonia and the yield of a three-month German T-Bill are shown in Panels (a), (b), (c), and (d), respectively. Global variables are described in detail in Section IV.I. Our dataset is obtained from Bloomberg and covers the period from June 1, 2011 to December 31, 2012.



(a) Shock to the bond market liquidity



(b) Shock to CDS spread

Figure 6: **Impulse Response Functions for the VAR(3) System in Equation 1**. This graph shows the evolution of the impulse response functions to a shock in the bond market liquidity, as measured by the Quoted Spread and the CDS spread, in Panels (a) and (b) respectively. The VAR(3) system that produces these IRFs is presented in Equation 1 and discussed in Section VI.I. Our dataset consists of transactions, quotes, and orders for all 152 fixed-rate and floating Italian government bonds from June 1, 2011 to December 31, 2012.

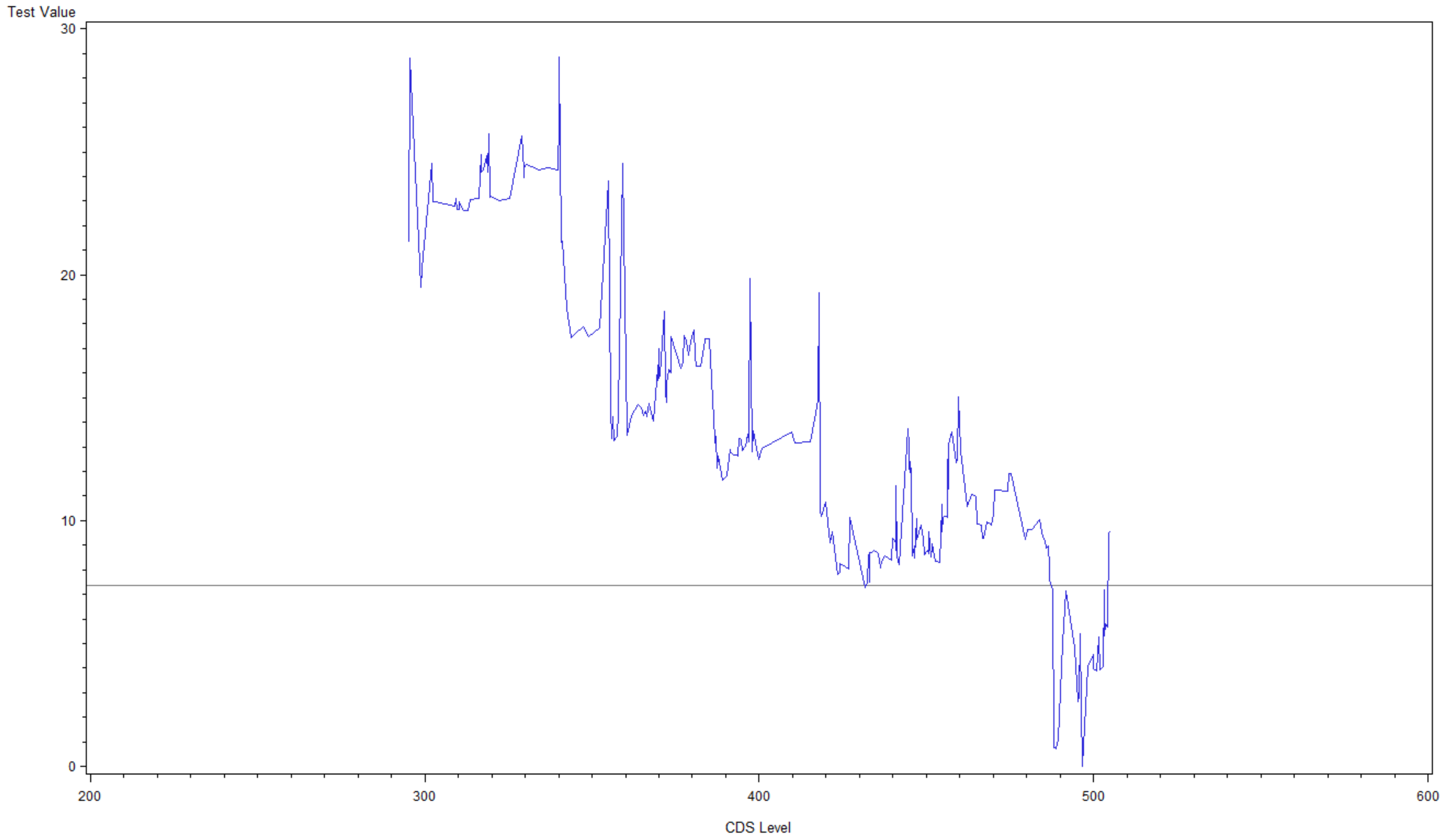
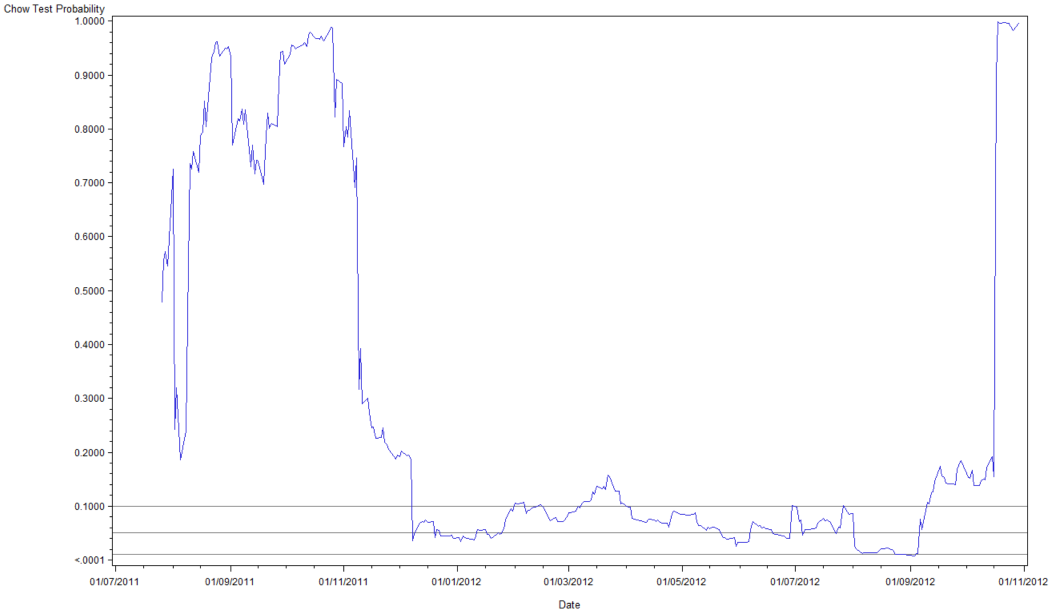
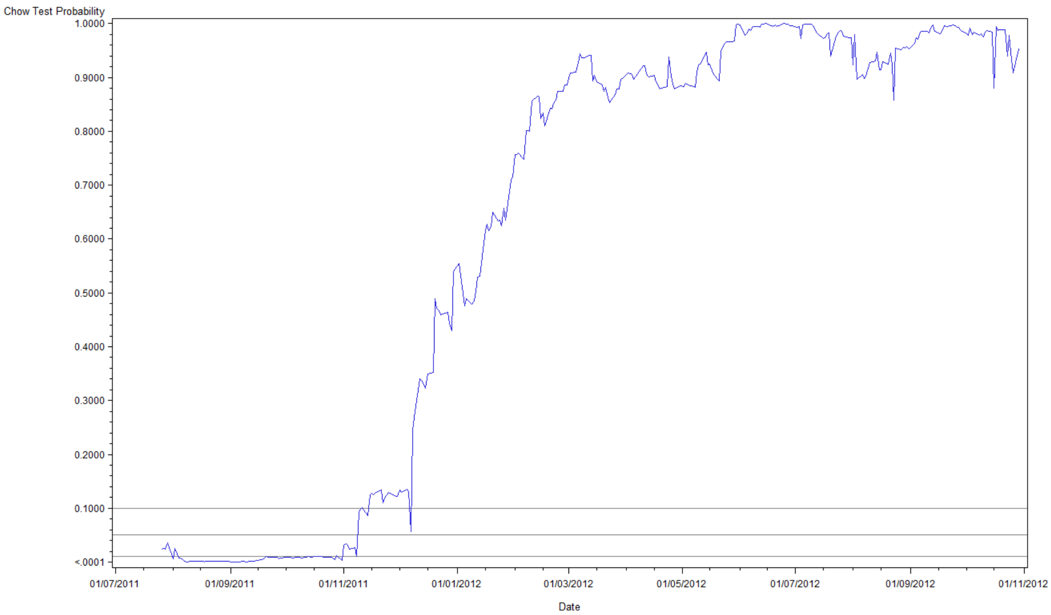


Figure 7: **Test Statistic for CDS Threshold for Specification 6.** The test statistic described in Appendix C is plotted here for the regression $\Delta LM_t = \alpha_0 + \alpha_1 \Delta LM_{t-1} + \alpha_2 \Delta LM_{t-2} + \alpha_3 \Delta LM_{t-3} + \beta_0 \Delta CDS_t + \beta_1 \Delta CDS_{t-1}$, estimated on the whole sample and using Quoted Spread as the liquidity measure. The test statistic is normalized at 0 at the threshold that minimizes the sum of squared residuals. The horizontal line at 7.35 marks the 5% confidence values for the threshold. Our dataset consists of transactions, quotes, and orders for all 152 fixed-rate and floating Italian government bonds, from June 1, 2011 to December 31, 2012.

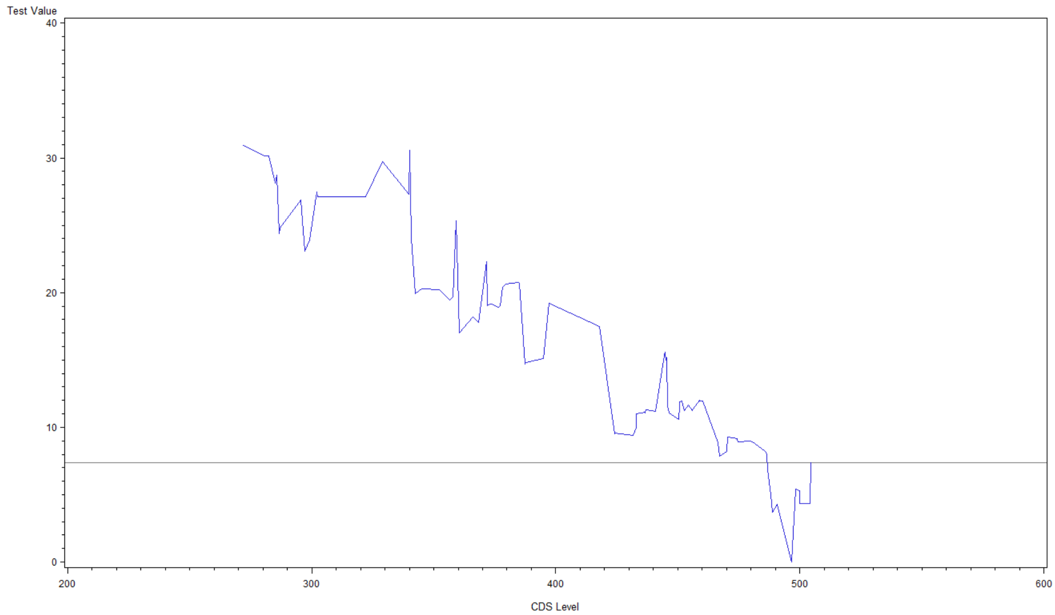


(a) Chow Test $\Delta BA_t = \alpha + \Delta CDS_t$

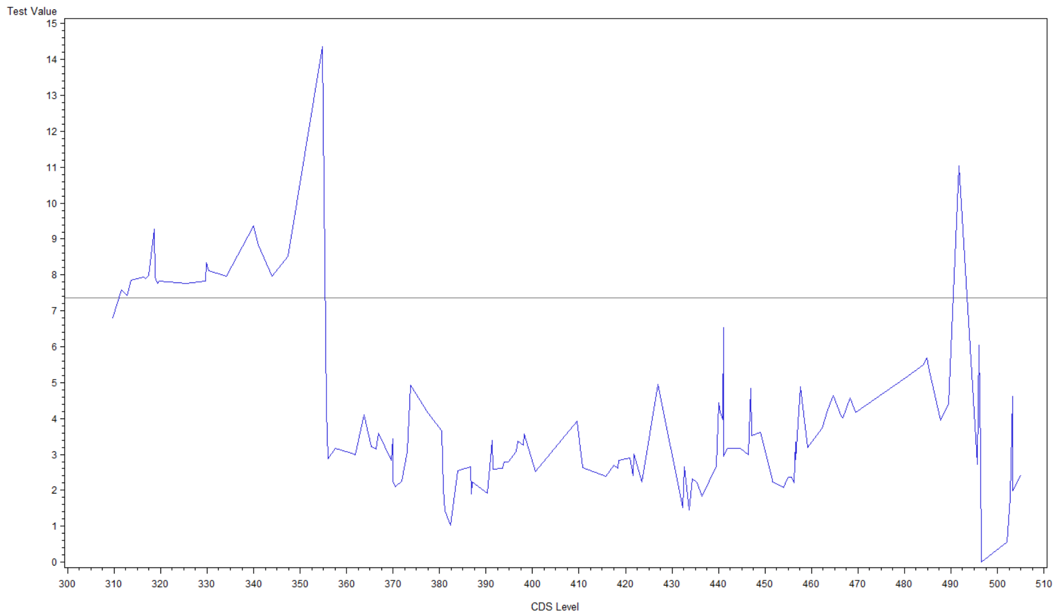


(b) Chow Test $\Delta BA_t = \alpha + \Delta CDS_{t-1}$

Figure 8: **Chow Test Significance for Different Specifications.** Panels (a) and (b) show the significance of the Chow test calculated by testing each day in our sample as a structural break point for the specifications $\Delta BA_t = \alpha + \Delta CDS_t$ and $\Delta BA_t = \alpha + \Delta CDS_{t-1}$, respectively, where ΔBA_t is the change in quoted spread on the MTS market and ΔCDS_t is the change in Italian CDS from day t-1 to day t. The CDS data were obtained from Bloomberg and cover the period from June 1, 2011 to December 31, 2012.

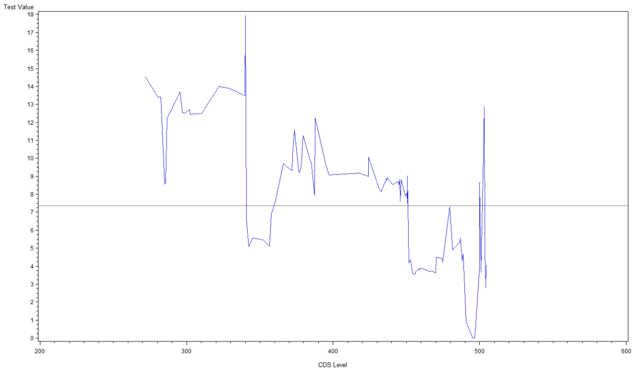


(a) Threshold Localization: 2011 Sample

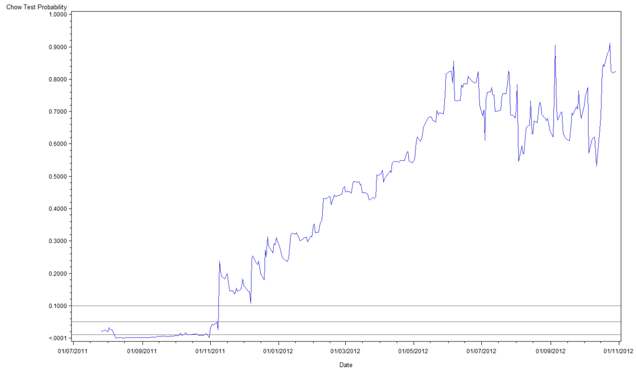


(b) Threshold Localization: 2012 Sample

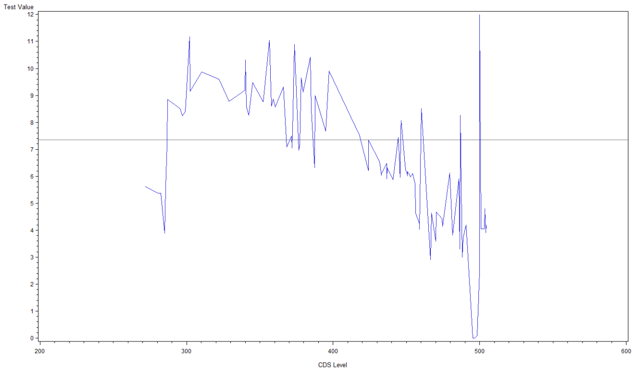
Figure 9: **Test Statistic for CDS Threshold for Specification 4 in Different Sub-samples.** The test statistic described in Appendix C is plotted here for the regression $\Delta LM_t = \alpha_0 + \alpha_1 \Delta LM_{t-1} + \alpha_2 \Delta LM_{t-2} + \alpha_3 \Delta LM_{t-3} + \beta_0 \Delta CDS_t + \beta_1 \Delta CDS_{t-1}$, estimated on the different sub-samples. The test statistic is normalized at 0 at the threshold that minimizes the sum of squared residuals for each sub-sample. The horizontal line at 7.35 marks the 5% confidence values for the threshold.



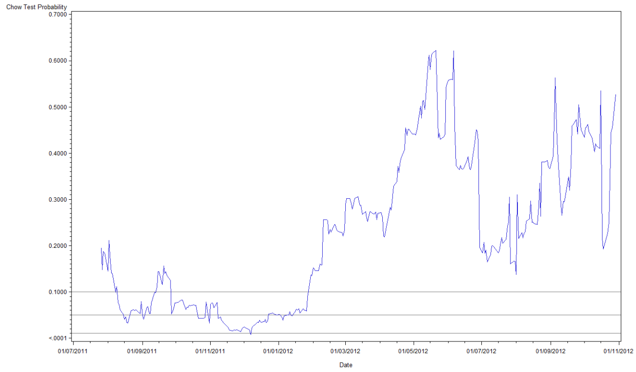
(a) Quoted Quantity: Threshold Localization



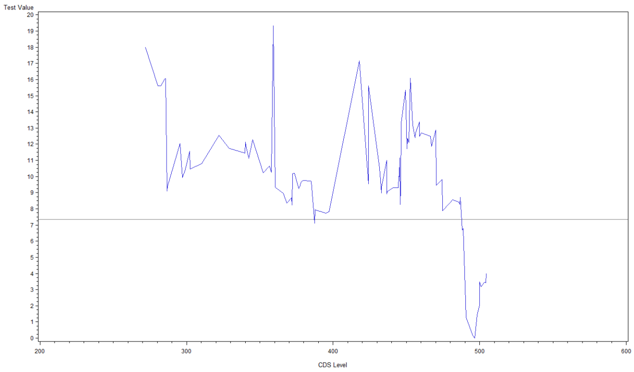
(b) Quoted Quantity: Structural Break



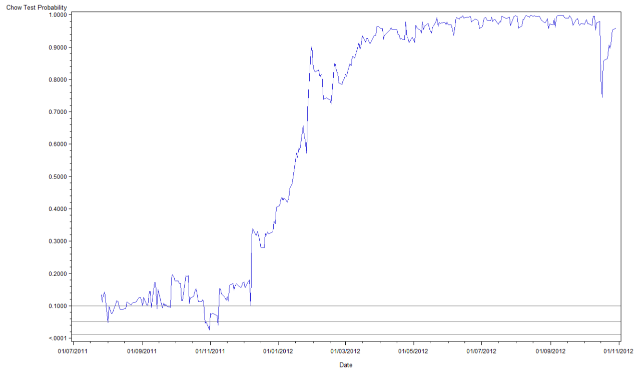
(c) Effective Spread: Threshold Localization



(d) Effective Spread: Structural Break

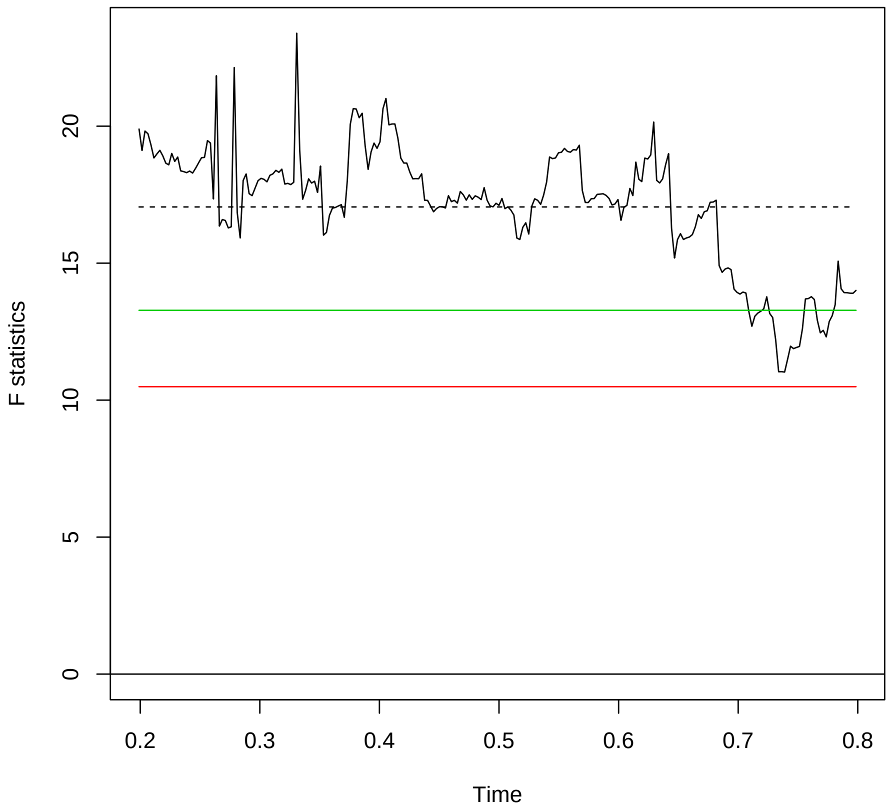


(e) Lambda: Threshold Localization

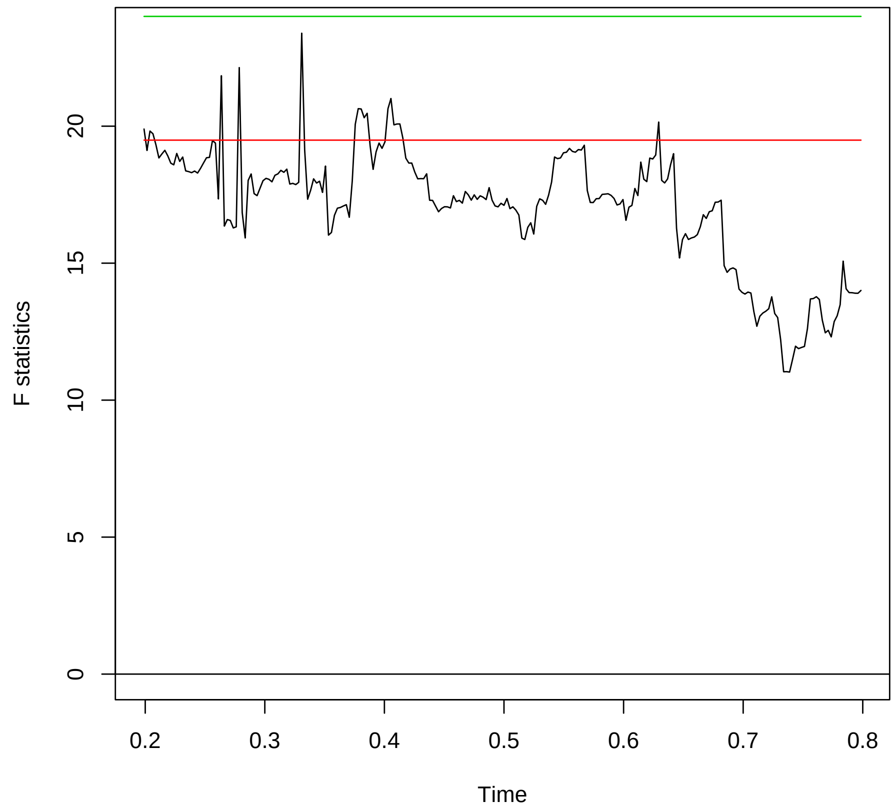


(f) Lambda: Structural Break

Figure 10: **Test Statistic for CDS Threshold and Significance of the Chow Test for Structural Break for Different Liquidity Measures.** Panels (a), (c), and (e) plot the test statistic for the regression $\Delta LM_t = \alpha_0 + \alpha_1 \Delta LM_{t-1} + \alpha_2 \Delta LM_{t-2} + \alpha_3 \Delta LM_{t-3} + \beta_0 \Delta CDS_t + \beta_1 \Delta CDS_{t-1}$, estimated on the 2011 sub-samples for the liquidity measure *Quoted Quantity*, *Effective Spread*, and *Lambda*, respectively. The test statistic is normalized at 0 at the threshold that minimizes the sum of squared residuals for the 2011 sub-sample for each liquidity measure. The horizontal line at 7.35 marks the 5% confidence values for the threshold. Panels (b), (d), and (f) plot the significance of the Chow test calculated by testing each day in our sample as a structural break point for the specification $\Delta LM_t = \alpha + \Delta CDS_{t-1}$ in the overall sample, for the liquidity measure *Quoted Quantity*, *Effective Spread*, and *Lambda*, respectively. The horizontal lines mark the 10%, 5%, and 1% significance levels.

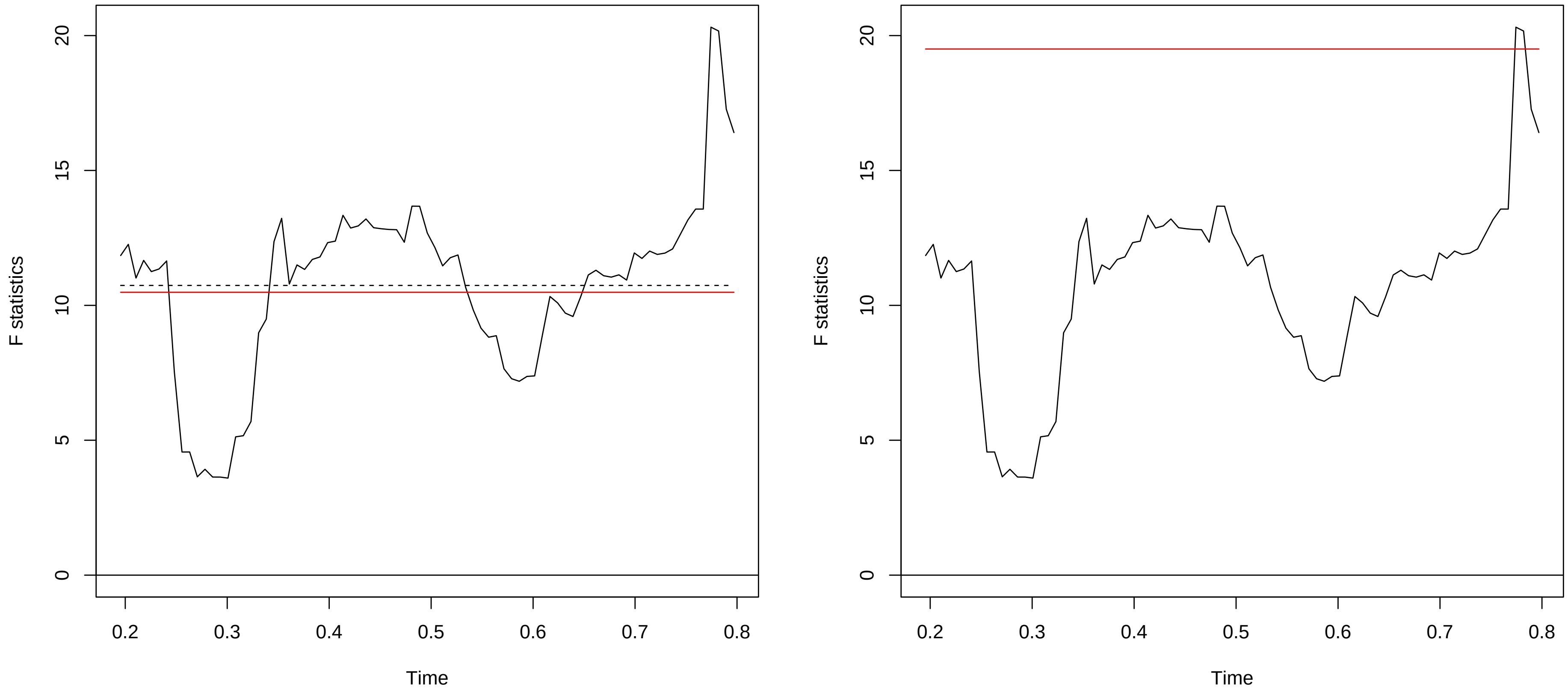


(a) AveF= 17.05*** P=0.000



(b) SupF = 23.39** P=0.013

Figure 11: **Structural Break Tests.** Panels (a) and (b) show the value of the Chow test calculated by testing each day in our sample as a structural break point for the specifications $\Delta BA_t = \alpha + \Delta CDS_t + \Delta CDS_{t-1} + \Delta BA_{t-1} + \Delta BA_{t-2} + \Delta BA_{t-3}$, where ΔBA_t is the change in quoted spread on the MTS market and ΔCDS_t is the change in Italian CDS from day t-1 to day t. Panel (a) shows the average of the F values (dotted) and the 5% and 1% confidence levels for the AveF test in red and green, respectively, while Panel (b) shows the 5% confidence level for the SupF test. The CDS data were obtained from Bloomberg and cover the period from June 1, 2011 to December 31, 2012.



(a) AveF = 10.74, P = 0.044**

(b) SupF = 20.31, P = 0.038**

Figure 12: **Structural Break Tests.** Panels (a) and (b) show the value of the Chow test calculated by testing each day in our sample as a structural break point for the specifications $\Delta BA_t = \alpha + \Delta CDS_t + \Delta CDS_{t-1} + \Delta BA_{t-1} + \Delta BA_{t-2} + \Delta BA_{t-3}$, where ΔBA_t is the change in quoted spread on the MTS market and ΔCDS_t is the change in Italian CDS from day t-1 to day t. Panel (a) shows the average of the F values (dotted) and the 5% confidence level for the AveF test in red, while Panel (b) shows the 5% confidence level for the SupF test. The CDS data were obtained from Bloomberg and cover the period from June 1, 2011 to December 31, 2012.

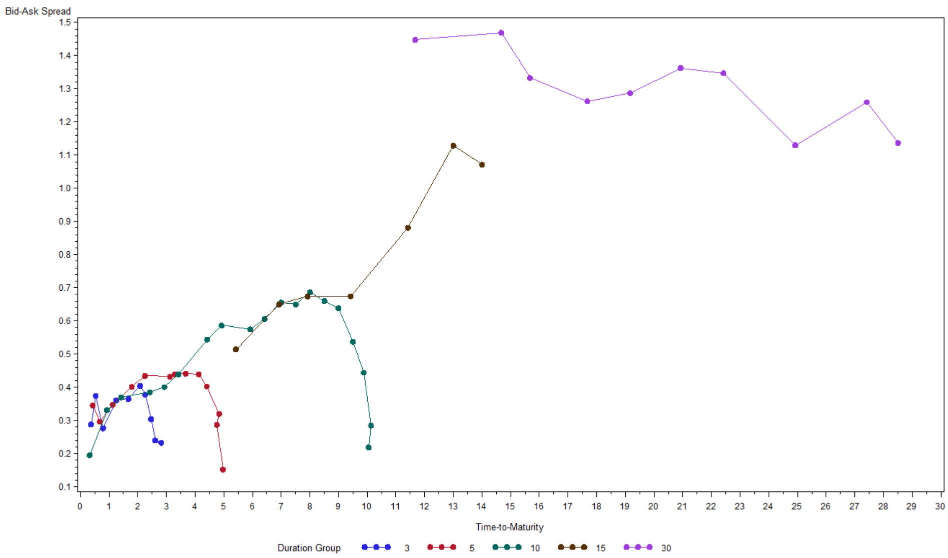


Figure 13: **Cross-sectional Relationship between *Bid-ask Spread* and *Time-to-Maturity*.** This figure shows the non-linear relationships between *Age* or *Time-to-Maturity* and *Maturity* in the cross-section. Every dot is one of the 58 coupon-bearing bonds in the sample. The y-axis is the *Quoted Bid-Ask Spread*, while the x-axis is the *Time-to-Maturity* (i.e. the origin is the maturity date). Different colors correspond to different maturity groups. Our dataset consists of transactions, quotes, and orders for all 152 fixed-rate and floating Italian government bonds (Buoni Ordinari del Tesoro (BOT) or Treasury bills, Certificato del Tesoro Zero-coupon (CTZ) or zero coupon bonds, Certificati di Credito del Tesoro (CCT) or floating notes, and Buoni del Tesoro Poliennali (BTP) or fixed-income Treasury bonds) from June 1, 2011 to December 31, 2012.

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