Liquidity and tail-risk interdependencies in the euro area sovereign bond market

This paper shows that liquidity linkages in European sovereign bond markets can amplify fundamental economic shocks.

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European Stability Mechanism

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Abstract

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Keywords: Liquidity; Tail risks; Feedback loops; Spillovers

JEL codes: G01, G15, F36

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The likelihood of severe contractions in an asset's liquidity can feed back to the ex-ante risks faced by the individual providers of such liquidity. These self-reinforcing effects can spread to other assets through informational externalities and hedging relations. We explore whether such interdependencies play a role in amplifying tensions in European sovereign bond markets and are a source of cross-market spillovers. Using high-frequency data from the inter-dealer market, we find significant own- and cross-market effects that amplify liquidity contractions in the Italian and Spanish bond markets during times of heightened risk. The German Bund's safe-haven status exacerbates these amplification effects. We provide evidence of a post-crisis dampening of cross-market effects following crisis-era changes to euro area policies and institutional architecture. We identify a structural break in Italy's cross-market conditional correlation during rising political tensions in 2018, which significantly reduced liquidity. Overall, our findings demonstrate potential for the provision of liquidity across sovereign markets to be vulnerable to sudden fractures, with possible implications for euro area economic and financial stability.

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1 Introduction

The designers of the Maastricht Treaty envisaged that a combination of fiscal rules and market discipline would ensure the safety of euro area national government bonds. The European sovereign debt crisis revealed serious flaws in this approach. The abrupt repricing of sovereign bonds forced some countries to seek financial assistance from the official sector and raised fears over the survival of the euro.

A prominent literature (De Grauwe and Ji, 2012, 2013; Aizenman et al., 2013; Dewachter et al., 2015; Bocola and Dovis, 2019) questions whether the repricing of some euro area national sovereign bonds that occurred during the crisis was larger than implied by developments in economic fundamentals. This raises the possibility that non-fundamental amplifiers become more important when commitment to the euro wanes. Bolton and Jeanne (2011); De Grauwe (2012) and Corsetti and Dedola (2016) regard this as linked to the fact that euro area countries issue debt in a currency that is outside of their direct control. Reducing the impact of *non-fundamental* factors, which represent sources of endogenous risk, is crucial for the stability of the Economic and Monetary Union.[1] Despite the widely recognised importance of this vulnerability, there is little *direct* empirical evidence of the transmission channels through which non-fundamental factors can affect euro area sovereign bond markets.

We fill this gap in the literature by documenting the role that the interdependencies between liquidity and tail risk play in amplifying sovereign bond market tensions. Our use of *high-frequency* (intra-day) data mitigates some of the endogeneity concerns that arise using lower frequency data (Ghysels et al., 2017) and allows us to provide a causal interpretation of the feedback loops between liquidity and tail risks. Our focus on *tail risks* more accurately represent periods of market stress, when the pricing of risk can deviate from economic fundamentals and the role of non-fundamental factors are more

[1] Market-based exposures and interdependencies are labelled as endogenous risk by Danielsson and Shin (2003) and have been further explored in the wake of the Great Financial Crisis by Danielsson et al. (2012) and Ang and Longstaff (2013). The latter find that both U.S. and European systemic sovereign risk appears to be beyond what economic fundamentals can explain.

likely at play. We utilise financial *market microstructure* variables to estimate the effects of changes in a sovereign's liquidity on the perception of its credit risk. We also assess liquidity and tail risk changes in one sovereign bond market on the liquidity conditions and tail risks of another. This allows us to test whether there are *spillovers* from non-fundamental factors. Our empirical methodology and sample of countries also allows us to assess the effect of *safe havens* as a mechanism through which the liquidity-tail risk interdependencies in euro area sovereign bond markets are amplified. Finally, our sample allows us to examine differences in our results from the crisis and post-crisis periods. This facilitates an assessment of whether crisis-induced changes to the euro area *institutional architecture* and policies have boosted the resilience of national sovereign bond markets to non-fundamental factors. We believe these contributions represent a substantial extension of the existing literature.

Our results demonstrate substantial own- and cross-market linkages between liquidity provision and tail risks in the German, Italian and Spanish sovereign bond markets. We represent variation in tail risks through the movements in conditional quantiles, derived using the VAR-for-VaR approach (White et al., 2015). It is well known that liquidity is more fragile in market declines (Karolyi et al., 2012) and therefore analysis of negative tail quantiles can exploit this characteristic. Conditional value-at-risk (VaR) models allow for non-linear movements in expected extreme quantiles. We demonstrate that contractions in measures of Italian and Spanish liquidity are associated with subsequent falls in their own market's 1% VaR. These results are consistent with theoretical models that explain the depth of the limit order book in relation to adverse selection risk and inventory holding costs. In terms of cross-market effects, we find that reductions in the Italian and Spanish VaR (i.e. greater potential losses) are related to contemporaneous *increases* in the German 99% VaR (i.e. lower potential losses) and a positive conditional expected German return. This shows the role that the German Bund, as the benchmark asset for the euro area, can have in amplifying the interdependency between tail risks and liquidity in national sovereign bond markets.

The hedging behaviours of dealers (Dunne, 2019) and information linkages identified by

Cespa and Foucault (2014) can affect the size of own- and cross-market effects from liquidity contractions and their feedback on VaR in European sovereign debt markets. The greater the correlation across markets, the larger the spillovers. Hence, sudden liquidity contractions in one part of the market, with connections to other parts through the participation of the same liquidity providers, produces an amplification of the initial responses to developments in economic fundamentals due to reduced information or to the breakdown of hedging relationships. Liquidity contractions can exacerbate the size of a reaction to fundamentals because the desire for liquidity itself, and the premium required as compensation for a lack of liquidity, increases during episodes of increased uncertainty. Liquidity possesses self-reinforcing tendencies (liquidity begets liquidity) and there are cross-market interactions that also generate spillovers and network externalities in the provision of liquidity. Crucial to the secondary effects of liquidity contractions is the effect that changes in fundamentals have on *future* conditional correlation between bond markets connected by the behaviour of a common set of liquidity providers. These liquidity effects feed back to expectations of the risks associated with providing liquidity (i.e. to the VaR). The change in VaR itself then feeds back to the risk premium required for holding a given sovereign bond, amplifying the initial sovereign bond market tensions.

The transmission mechanisms at play have immediate effects on liquidity supplied and can result in significant cross-market spillovers. This ultimately stems from the fact that dealers are highly sensitive to the expected size of losses that are likely to occur with some given probability (i.e., the value at risk) in the next trading period. This sensitivity gives rise to extremely fast reactions to events that adversely affect the VaR. O'Hara (2015) highlights how high-frequency trading algorithms can dramatically magnify the speed of response to such events, with much of this activity involving the strategic cancellation and re-setting of limit orders. In this setting, liquidity dries-up so fast that it largely prevents flights (in terms of trades out of the market) from actually occurring. Typically, slow dealers, or inappropriately designed algorithms, will be hit by the market orders of faster and better dealers/algorithms within a short time and before investors get a chance to react. Dealer-to-customer trading will also simply decline towards zero until there is a sizeable price change in the inter-dealer market and until liquidity returns around a new consensus value. Therefore, sovereign bond market "flights" are primarily an inter-dealer market phenomenon rather than a true flight by end-investors.

We focus on the German, Italian and Spanish sovereign bond markets.[2] The German Bund effectively serves as the euro area benchmark bond, while Italy's large sovereign debt stock means that it is amongst the most liquid but also perceived to be amongst the most risky assets in the European sovereign bond market (Beber et al., 2009).[3] Spain required official-sector financial assistance in 2012 to help recapitalise its banking sector, before experiencing a strong post-crisis economic recovery. We use data at 15-minute intervals from the MTS (Mercato dei Titoli di Stato), Europe's premier sovereign bond trading platform. Our examination of two sample periods with very different drivers of investor concerns provide us with some further insights of the interdependencies of liquidity and tail risks in euro area sovereign bond markets. The June 2011 to December 2012 sample represents a period of *aggregate* or *systemic* risk, while the market tensions that arose around the changes in government in Italy and Spain in 2018 were examples of *idiosyncratic* risk.

Overall, our results indicate that the interdependencies between liquidity and tail risk can be sensitive to perceptions of the integrity of the euro. This is consistent with models (such as that of Cespa and Foucault (2014)) that assume each asset's return has a common and idiosyncratic component in which externalities are associated with the common component. A more significant sharing of commonalities drives correlation between assets.[4]

Interpreted in this way, the European sovereign debt crisis was a period during which

[2]These are amongst the largest and most liquid sovereign bond markets in the euro area. It is possible, if not likely, that smaller (i.e. less liquid) markets would experience even greater interdependencies between liquidity and tail risk. Future work could try to extend this work to include some smaller euro area sovereign bond markets to see if our results hold.

[3]See also O'Sullivan and Papavassiliou (2019) and references therein.

[4]See Gavilan2019 for a recent examination of commonality in liquidity in the euro area sovereign bond market.

the integrity of the euro was undermined through concerns over convertibility.[5] These concerns were successfully addressed by Draghi's commitment in July 2012 to do 'whatever it takes to preserve the euro'. This period is characterised by low correlations of returns across sovereign markets, which introduced difficulties for the pricing of one asset against another and for hedging. We find a significant reduction in the negative feedback between risk and liquidity following Draghi's speech. The post-crisis period that we examine provided conditions that are more benign for liquidity suppliers due to low interest rates and the ECBs asset purchase programme. Nevertheless, the rise in Italian political tensions in May 2018 represented a re-emergence of idiosyncratic risks that produced strong interactions between liquidity contractions and tail risks. In the absence of low rates and quantitative easing, these political tensions could have had much more severe effects. This implies further changes to the euro area institutional architecture are required to improve the resilience of euro area sovereign bond markets.

Our paper is structured as follows. In the next section, we describe the interdependencies between liquidity and tail risk that we wish to explore. The third section describes the dataset and is followed by a section that outlines the empirical strategy that we follow. We then discuss the results of our analysis before concluding.

2 Liquidity and tail risk feedback loops

The transmission mechanism we examine draws a connection between the *microstructure* determinants of liquidity in electronic limit order books and *liquidity linkages* across asset markets. The MTS is a limit order book (LOB) market that facilitates trading between dealers. Dealers usually also participate in request-for-quote electronic trading platforms to provide liquidity to their customers. This two-tiered structure can be used to explain sudden contractions of liquidity provision in the interdealer context, as described in Dunne et al. (2015). However, even without this degree of complexity, the potential

[5] See, for example, Speech by Mario Draghi, Global Investment Conference, London 26 July 2012 and Draghi (2013), "The policy and the role of the European Central Bank during the crisis in the euro area."

for a contraction of liquidity in response to an increase in the ex-ante VaR of the returns distribution (or of the order arrivals distribution) is quite straightforward.

The LOB consists of the list of prices and amounts of bonds that dealers are prepared to buy and sell at a given moment. Dealers post limit-orders to earn a proportion of the spread between the sell or buy price and the fundamental value of the bond. In simple models of this type of market, there is a fixed cost faced by dealers when placing a limit order that is equated with expected profits.[6] These depend on the likelihood of the trade (market order) that arrives being of sufficient size to fill the marginal limit order at each limit order price. Unfilled limit orders involve only a cost. Even in this simple setting, the limit order book has a finite equilibrium amount of liquidity provided at each of the limit prices that represent progressively higher costs to the liquidity demander.

If the fixed costs of liquidity provision are high and if transactions inherently occur infrequently and are typically small, then it will be optimal for dealers to set limit order prices that start far from the fundamental value with small amounts of liquidity provided at each limit order price. The depth of the LOB will also be low, and eventually zero, as the gap between limit order prices and the fundamental value widens. Such thinness in the order book is typical of liquidity provision in small-country bond markets and for off-the-run bonds in all countries. Episodes of variability in the order arrival intensity make such markets more prone to liquidity dry-ups. The mere possibility of this occurring could drive up the liquidity premium of certain bonds and lead to self-propagating increases in tail risk.

More realistic models allow for adverse selection, where market orders / fills may be informed about the direction of movement in a bonds underlying value.[7] This behaviour can further suppress the appetite for liquidity provision, either in terms of the pricing (distance of limit orders from the expected fundamental value) or the amount supplied at any given offer or bid price. In this case, an increase in the expected size of price movements for a given likelihood (i.e., the VaR) should decrease the provision of liquidity.

[6] See the baseline model of Seppi (1997) and those outlined in Chapter 6 of Foucault et al. (2013).
[7] See Glosten (1994) and the extended model of Seppi (1997).

This endogenously decreases the arrival rate of orders and begets more decreases in the provision of liquidity.

The risks faced by dealers when providing liquidity in sovereign bond markets can be reduced by *hedging*. This requires markets to be highly correlated and for correlation to be structurally stable. This hedging behaviour provides a relevant explanation for the extension of liquidity across European sovereign debt markets that was prevalent following the introduction of the euro and during the pre-crisis period. In the stable environment of the Great Moderation and the recently established European Monetary Union, it was possible for dealers to extend liquidity provision across related markets because they could confidently hedge a position in one market against that in another (Dunne, 2019; Bessler et al., 2016). This behaviour also tends to improve liquidity where it is already of high quality because of the additional trades that arise when the liquid benchmark bond is used to hedge positions acquired in smaller (i.e. less liquid) markets. This liquidity channel proved fragile once cross-country correlations became unstable during the European Sovereign Debt Crisis. There are a number of important channels identified in extant literature assessing cross-asset liquidity linkages. Bernardo and Welch (2004) provide a model of liquidity contraction in which each risk-neutral investor fears having to liquidate holdings after a run, but before prices can recover back to fundamental values. In this model, liquidity runs and crises are not caused by liquidity shocks per se, but by the fear of *future* liquidity shocks. He and Milbradt (2014) study the interaction between default and liquidity for corporate bonds via a rollover channel. A default-liquidity loop arises due to an assumption that the secondary bond market will be illiquid in default. Earlier endogenous default worsens a bond's secondary market liquidity, which in turn amplifies equity holders' rollover losses and leads to earlier endogenous default.

Cespa and Foucault (2014) instead examine the role of information externalities in liquidity linkages and contagion. The authors show that cross-asset learning makes the liquidity of asset pairs interconnected: if the liquidity of one asset drops, its price becomes less informative for liquidity providers in another asset, and therefore the liquidity of the second asset drops as well. While Cespa and Foucault (2014) propose liquidity shocks as the source of the disturbance to these linkages, it is also valid to assume that a breakdown in cross-asset liquidity could be due to changes in the correlation of the assets' returns.

Their model assumes that each assets' return has a common and idiosyncratic component. The information linkages arise due to the shared common component. In the context of euro area sovereign bond markets, it makes sense to interpret the common component in relation to the integrity of the euro. Any hint of break-up or undermining of the euro would be associated with a smaller common component and each sovereign having a more significant idiosyncratic component. Events like the European Sovereign Debt Crisis may have undermined the integrity of the euro, leading to a lower correlation across sovereign markets as more fragile sovereign markets experiencing re-denomination risk becomes dominated by its idiosyncratic, country-specific, credit risk. This introduces difficulties for the pricing of one asset against another. Dealers operating in markets dominated by idiosyncratic movements have much larger risk exposures due to difficulties hedging.

Of course, a range of other mechanisms that affect liquidity and the risk of default may further amplify the feedback effects we uncover. These include the real effects of higher funding costs on growth, as well as the feedback from higher default probability such as those due to fear of flights (as in Bernardo and Welch (2004)) and fear of post-default illiquidity (as in He and Milbradt (2014)). Although our use of high-frequency data means we cannot capture these longer-term aspects empirically, we gain insights about these background influences through our sub-sample analysis. Indeed, our analysis provides evidence of a transmission channel between expected tail risk and liquidity that serves as an amplification mechanism for the solvency issues explored in other studies.

A substantial literature on spillovers across asset markets (and in particular, bond markets) identifies several fundamental explanations for such linkages but there remains significant unexplained connectedness. For example, De Santis (2014) finds that spillovers from Greece affected spreads in countries with weaker fiscal fundamentals, lower competitiveness and a greater need for foreign financing during the European sovereign debt crisis. However, he also notes that a large fraction of cross-country spillovers remains unexplained. Our examination of the effects of the policy reaction on linkages (i.e., Draghi's speech and Outright Monetary Transactions) has similarities with the recent contribution of Gilbert (2019) in which a local projections method is used to identify the significance of spillovers of shocks to euro area sovereign bond market yield spreads. Our analysis provides evidence of the microstructural linkages that can help explain such yield spread spillovers.

3 Data description

We examine the feedback loops between liquidity and tail risks in euro area sovereign bond markets using data from the MTS trading platform. This is the most comprehensive interdealer electronic fixed-income market for euro-denominated government bonds. Caporale and Girardi (2011) provide empirical evidence that trades on the MTS platform have a sizable informational content and the MTS has been utilised for numerous studies (Caporale and Girardi, 2013; Paiardini, 2014; Pelizzona et al., 2016; Schneider et al., 2018). Gavilan et al. (2019) find a very high co-movement between quoted prices in Bloomberg and MTS, suggesting prices in the MTS are representative of market activities. The MTS market supports pre- and post-trade capabilities as well as trade execution across cash and repo markets, which takes place based on the principle of price-time priority (O'Sullivan and Papavassiliou, 2019).

A major advantage of our dataset is that is available at an intra-day frequency. Ghysels et al. (2017) note that very high frequency data can help resolve important endogeneity issues. They match the timing and amounts purchased with the prevailing intraday quotes to isolate the immediate effect of ECB sovereign bond purchases from the impact of the other shocks that hit the market during the rest of the day. They demonstrate that using daily averages can produce misleading results. In Appendix B we show that using daily (moving) averages under-represents the degree of volatility in our time series. This is in line with Engle et al. (2019), who show that intraday market liquidity causes volatility dynamics in the US treasury market. Since our analysis is focused on the propagation effects of large shocks that affect the tails of the distribution of sovereign bond returns, we conduct our empirical analysis using intra-day data.[8]

We examine two very different samples (and within these we consider variation across smaller sub-samples). The first period studied runs from 1 June 2011 to 31 December 2012 and includes the height of the European sovereign debt crisis. This period also includes Draghi's promise to do 'whatever it takes' to save the euro (26th July 2012), a move that is widely credited with helping to restore calm in euro area sovereign bond markets. The second period runs from 1 January 2018 to 31 December 2018, and includes a sharp rise in sovereign bond market tensions due to national political uncertainty. In this sample period, tensions arose after a period of stability during which correlations had almost returned to pre-crisis levels and stabilised. There was also a very low interest rate and the presence of quantitative easing in the form of the Extended Asset Purchase Programme by the Eurosystem. In this later period, the source of the tension was more idiosyncratic and unexpected than during the sovereign debt crisis. Therefore, a comparison across these two periods allows us to compare the connection between liquidity and tail risk around periods of aggregate (or systemic) risk and idiosyncratic (or country-specific) risk.[9]

For each sample, we retrieve data for the German, Italian and Spanish benchmark sovereign bonds with 10-year maturity. We define benchmark bonds as the most liquid (i.e. those with the highest number of transactions) amongst all on-the-run (i.e. the most recently auctioned) bonds of a given maturity.[10] This is standard practice in the literature using MTS data. For each trading day, we compute 15-minute intervals between 9.00am - 5.30pm. We use the *median* value from each interval in order to avoid outliers affecting the reliability of our estimated time-varying quantiles. This approach

[8] See Appendix B for a replication of our analysis using daily data.

[9] The cross-market correlations between Italian returns and euro area core sovereign bond market returns declined dramatically in May 2018 as analysed in Cronin and Dunne (2019).

[10] We noticed that for each ISIN there are often small gaps between the issue date reported by Bloomberg and the beginning of data observed on the MTS platform. We manually corrected for these discrepancies. We provide the full list of our benchmark ISINs is provided in Table 1.

leads to a substantially smoother time series.[11] We remove days during which a change in the benchmark of one of the sovereign bonds has taken place, as well as dates in which some observations are missing. After these adjustments, we retain 14220 observations for the 2011-12 sample and 7158 observations in the 2018 sample. Table 1 lists the ISINs identified as benchmarks in our 2011-12 and 2018 samples.

Figure 1 displays the mid prices of our benchmark bonds in both samples. Vertical lines represent changes in the benchmark bond. In the 2018 sample, the Italian benchmark bond does not change, while the German benchmark bond changes only once and the Spanish twice. This is a by-product of our approach to identifying benchmark bonds. Indeed, Germany and Italy issued several 10-year sovereign bonds during 2018. However, these (newly-issued) bonds were less liquid (i.e. had smaller transaction volumes in each month) than previously-issued bonds. Liquidity is a defining characteristic of a benchmark bond and therefore we retain the most liquid at all times. Spanish and Italian mid prices both fell considerably at the end of May 2018, amid market tensions stemming from political events. In contrast, the German Bund returns go up around that period. We compute the following two liquidity measures for the benchmark bonds:

- **Relative bid-ask spread**: defined as the bid-ask spread divided by the mid price: $100((A_t - B_t)/M_t)$, where the mid price is computed as: $(A_t + B_t)/2$, where A_t and B_t are, respectively, ask and bid prices.
- **Quoted depth**: best bid quantity plus best ask quantity.

These are commonly-used measures of liquidity in the sovereign bond market literature (Beber et al., 2009). The spread and depth measures can be combined to obtain a *liquidity index*, similar to that constructed by Beber et al. (2009), as follows:

$$Liquidity = \left(\frac{Quoted\ Depth}{100 * Relative\ BidAskSpread} \right),$$

implying that an increase in liquidity can be due to an increase in quoted depth, a

[11]Unlike Dufour and Nguyen (2012) and Paiardini (2014), we do not rule out observations with quoted spreads higher than 50 basis points, as we are interested in the *tails* of the returns distribution.

reduction of the relative bid-ask spread, or both. This measure is more amenable to analysis using VAR-for-VaR since it does not have as much clustering of quantiles at the lower end of the distribution, as occurs in the case of the spread or depth.[12] Our intention is to examine the extreme liquidity risks (e.g., the lowest quantile). Since spreads are clustered around a small number of values, it is not possible to identify a precise tail-quantile (there would, for example, be no difference between the values of the empirical quantiles between 1% and 25% and therefore the conditional 1% VaR would be static). The depth at best is also affected by this problem, because there tends to be many cases of minimum amounts at the best limit orders (e.g., 10 million). The depth/spread ratio is better behaved than its components in terms of its lower percentiles (i.e., we get significant variability in the conditional 1%VaR for this liquidity measure). This measure is also favoured by (Beber et al., 2009).

We provide some simple summary statistics for our benchmark bonds in Table 2. A common feature is that all countries' sovereign bonds are more liquid (i.e. higher quoted depth, lower relative spread) in 2018 than during the sovereign debt crisis. During the crisis, the Spanish relative spread is considerably larger than the Italian, which is unsurprising given that Spain eventually had to seek financial assistance from the European Stability Mechanism. Overall, the Italian BTP is the most liquid, possibly because the MTS platform was originally an Italian-only platform.

4 Empirical strategy

We employ a variety of techniques for our examination of the feedback loops between liquidity provision and tail risks. First, we assess cross-market interlinkages of tail risks using the VAR-for-VaR approach (White et al., 2015). We use this model to estimate the (time-varying) relationships between the Value-at-Risk (VaR) of different sovereign bond

[12]Figure 2 plots the computed liquidity indices for Germany, Italy and Spain. The reduced liquidity during the European sovereign debt crisis and the sudden contraction during May 2018 in the Italian and Spanish bonds are readily apparent. Interestingly, the spike in German liquidity appears to coincide with the contraction in the other markets.

returns. The VaR is a standard metric used to measure investor's ex-ante exposure to time-varying extreme tail-risks. This facilitates an examination of the extent to which tail risks in German, Italian and Spanish sovereign bond markets are interconnected.

Second, as in DeSola-Perea et al. (2019), we use the Marginal (equivalently, Conditional) Expected Shortfall as a complement to the VAR-for-VaR analysis. This approach complements the conditional VaR analysis by identifying assets in which the return on the sovereign bond of interest, conditional on a tail event in the market asset, is not a tail event. This can help identify safe-haven assets, where the marginal expected shortfall would be *positive* despite the general tendency for all other assets to be experiencing negative returns, and is indicative of a hedge against tail events elsewhere.

Finally, to derive a deeper understanding of the feedback loop between tail risks and liquidity in the German, Italian and Spanish sovereign bond markets, we investigate the relationship between our liquidity index and the VaR of the sovereign bond returns using a VAR-X model and VAR-for-VaR modelling of the liquidity-risk relation.

VAR-for-VaR

The VAR-for-VaR methodology of White et al. (2015) is essentially a vector autoregression applied to quantile relations, which permits the estimation of autoregressive cross-effects. This extends the Conditional Autoregressive Value at Risk (CAViaR) model of Engle and Manganelli (2004) to a multivariate context. The most obvious benefit from estimating a CAViaR or VAR-for-VaR model is that it often produces more credible time-varying VaR estimates relative to those derived from GARCH variances that assume normally-distributed returns. The CAViaR and VAR-for-VaR approaches use probability-based weighted deviations of observations around the proposed VaR values using the method of Koenker and Bassett (1978). A big advantage of the VAR-for-VaR is that it allows the direct modelling of the distribution of return quantiles, and therefore is not constrained by distributional assumptions.

White et al. (2015) suggest a framework for assessing the response of conditional VaR to shocks in the underlying absolute returns. Two structural shocks to the absolute returns outcomes (assumed to be uncorrelated with their own lags and each other) underpin each bivariate VAR-for-VaR. It is important to note that the assumption of uncorrelated impulses is likely to be violated. There is, for example, a higher probability of a run of large consecutive shocks in the history than is typical for an uncorrelated case. Only the first structural shock contemporaneously impacts the first variable, while both structural shocks may affect the second variable. This implies a Cholesky decomposition of the covariance matrix of returns.

More recently, Chavleishvili and Manganelli (2017) suggest a modification to this identification approach to reduce the number of highly correlated variables in the VAR. This specification introduces restrictions on the cross effects included in the VAR-for-VaR specification. In a bivariate case, only one cross effect parameter is estimated. Hence, the parameter on the Spanish or Italian absolute return a_{21} in the equation for the German conditional VaR is the only cross effect permitted. This greatly tightens the standard errors of the impulse response functions with little loss in richness of the permitted dynamics. Specifically, we estimate the following VAR-for-VaR model:

$$\begin{aligned} VaR_{i,t} &= c_1 + a_1|y_{i,t-1}| + b_1 VaR_{i,t-1}, && i = \{ES, IT\} \\ VaR_{DE,t} &= c_2 + a_{21}|y_{i,t-1}| + a_{22}|y_{DE,t-1}| + b_2 VaR_{DE,t-1}, && (1) \end{aligned}$$

where $VaR_{i,t}$ is the time-varying quantile (Value-at-Risk) of the returns of Spanish (ES) and Italian (IT) benchmark bonds, $VaR_{DE,t}$ is the VaR of the German benchmark bond returns, while $|y_{i,t}|$ and $|y_{DE,t}|$ are absolute returns of, respectively, country i and Germany. Following Engle and Manganelli (2004), for a given confidence interval $\theta \in [0, 1]$, a generic quantile VaR_t of the series of the sovereign bond returns is defined as:

$$Pr\left[y_t \leq VaR_t | I_{t-1}\right] = \theta, \tag{2}$$

where I_{t-1} is the information set at time $t-1$. Our characterisation of the VAR-for-VaR is also in line with an important assumption, namely that the quantile of the market return affects (or "causes") the idiosyncratic return, but not the other way round. In fact, the VAR-for-VaR we specify above implies that either the Italian or the Spanish return is the market, while the German is the idiosyncratic return. Therefore, we assume that the Italian or Spanish sovereign bond market is the initial source of shocks. The use of high frequency data makes this identification assumption relatively innocuous in the presence of some simultaneity.

Marginal Expected Shortfall

The Marginal Expected Shortfall (see Brownlees and Engle (2017)) is complementary to the VAR-for-VaR in two ways. First, it takes account of the joint distribution of the standardised returns (i.e. returns divided by their estimated GARCH standard deviations) of the responding-asset and that of the market (or whatever is assumed to be the causal variable). Second, it also takes account of the expectation of responding-asset returns, conditional on a tail event in the causal variable. The correlation between returns in the joint density of the observations therefore plays a vital role in determining the Marginal Expected Shortfall. However, tail-specific correlation is also important. More precisely, the Marginal Expected Shortfall of the German return is given by:

$$MES_{DE,t-1}(C) = E_{t-1}\left(r_{DE,t} | r_{i,t} < C\right), \tag{3}$$

which can be standardised to obtain:

$$
\begin{aligned}
&E_{t-1}\left(r_{DE,t}|r_{i,t} < C\right) = \\
&\sigma_{DE,t}\rho_{DE,t}E_{t-1}\left(\varepsilon_{i,t}|\varepsilon_{i,t} < C/\sigma_{i,t}\right) + \quad \sigma_{DE,t}\sqrt{1-\rho^2_{DE,t}}E_{t-1}\left(\xi_{DE,t}|\varepsilon_{i,t} < C/\sigma_{i,t}\right),
\end{aligned} \tag{4}
$$

where, as before, $i = \{ES, IT\}$. Following Scaillet (2005), we measure the conditional tail expectations of the components using a kernel estimation method as follows:

$$
E_{t-1}(\epsilon_{i,t}|\epsilon_{i,t} < C/\sigma_{i,t}) = \frac{\sum\limits_{t=1}^{T} \epsilon_{i,t}\Phi(\frac{c-\epsilon_{i,t}}{h})}{\sum\limits_{t=1}^{T} \Phi(\frac{c-\epsilon_{i,t}}{h})};
$$

$$
E_{t-1}(\xi_{DE,t}|\epsilon_{DE,t} < C/\sigma_{DE,t}) = \frac{\sum\limits_{t=1}^{T} \xi_{DE,t}\Phi(\frac{c-\epsilon_{DE,t}}{h})}{\sum\limits_{t=1}^{T} \Phi(\frac{c-\epsilon_{DE,t}}{h})}.
$$

where Φ denotes the application of the cumulative normal density function that produces probability-based weightings on observations where the weights are greatest for the most extreme standardised market return observations, $c = VaR(\epsilon_{i,t})$ is the constant empirical 1% VaR of market returns, standardised using volatility estimates. We use Silverman's "rule of thumb" method to determine the bandwidth h for the kernel (see, Silverman (1986)). The conditional volatilities and correlation are estimated using an asymmetric DCC-GJR-GARCH process (see, Glosten et al. (1993)).[13] We test the adequacy of the GJR-GARCH specification by testing for autocorrelation in squared standardised returns.

[13] A generic GARCH model is defined as: $r_t = \mu_t + a_t$, $a_t = H_t^{1/2} z_t$, in which $\mu_t = E\left[r_t|I_{t-1}\right]$ is the conditional mean, a_t are mean zero serially uncorrelated innovations, H_t is their covariance matrix and z_t are standardised iid innovations. A *dynamic* conditional correlation (DCC) GARCH model assumes that $H_t = D_t R_t D_t$, where D_t is the conditional standard deviation matrix and R_t is the conditional correlation matrix. A *constant* conditional correlation (CCC) GARCH instead imposes $H_t = D_t R D_t$.

Tail risk and liquidity interdependencies

An important part of our analysis is the feedback loop between liquidity and estimated tail risks. To investigate this channel, we employ two different approaches. We first assess the extent to which estimated tail risks affect liquidity using a VAR-X model:

$$Y_t = A_0 + \sum_{k=1}^{K} A_k Y_{t-k} + BX_t + U_t, \tag{5}$$

where the vector of endogenous variables Y_t contains the liquidity index (described above) for Spanish (or Italian) and 10-year German benchmark bonds, the vector of exogenous variables X_t includes the 1st quantile of Spanish or Italian returns and the 99th quantile of the German Bund returns, while U_t is a vector of iid disturbances.

We estimate the time-varying quantiles of the German Bund returns through a CAViaR (Engle and Manganelli, 2004), the univariate counterpart of the VAR-for-VaR.[14] We identify shocks through a standard Cholesky factorization of the variance-covariance matrix of the residuals. Importantly, the estimation of the conditional tail quantile as a function of its past implies that it is a *pre-determined* variable at time 't'. The estimated coefficients in matrix B, therefore, reveal the extent to which our liquidity measures are associated with a *given* value of the tail risk. We address concerns over serial correlation by adding lags until the Ljung-Box test indicates that residuals are uncorrelated.[15]

We then assess the opposite relation, the effect of ex-ante changes in liquidity on tail risk, by estimating the following VAR-for-VaR:

[14] Although the quantiles obtained with the CAViaR do not differ substantially from those computed with the VAR-for-VaR, the univariate version does not rely on any assumption regarding the origination of the shock.

[15] The Standard AIC criterion suggests the number of lags should be quite large. To ensure parsimony, we opted to use the smaller number of lags suggested by the Ljung-Box test. The results of the AIC and Ljung-Box tests are available upon request.

$$1\%VaR_{i,t} = \gamma_1 + \beta_1|y_{i,t-1}| + \delta_1\ 1\%VaR_{i,t-1}, \qquad i = \{ES, IT\}$$

$$1\%\ q^{Liq}_{i,t} = \gamma_2 + \beta_{21}|y_{i,t-1}| + \beta_{22}|Liquidity_{i,t-1}| + \delta_2\ 1\%\ q^{Liq}_{i,t-1}, \tag{6}$$

where $Liquidity_{i,t}$ is our liquidity index at a generic time t (with $i = \{ES, IT\}$) and $1\%q^{Liq}_{i,t}$ is its 1% time-varying quantile.[16]

5 Results

We first present the conditional 1% VaRs of the Italian and Spanish bond returns, along with the MES of the German Bund returns in each case. The left panel of Figure 3 contains the results for the 2011-12 sample, with the results for the 2018 period contained in the right panel. It is immediately clear that market tensions surrounding the early-summer 2018 political tensions saw a large fall in the Italian and Spanish benchmark bond returns 1% VaR (top-right panel). For Italy, the 1% VaR was temporarily more negative than recorded during the height of the 2011-12 sovereign debt crisis (top-left panel). Despite some noticeable spikes, the fall in the Spanish benchmark bond returns 1% VaR was less extreme than during 2011-12. The German MES in both periods (lower panel) clearly displays safe haven properties, becoming positive when the Italian and Spanish VaRs fall. However, there is a qualitative difference between the MES for German benchmark bonds depending on whether the tail event is Italian or Spanish. The MES is generally more positive when the systemic expected shortfall is related to Italian tail events. This suggests that the Italian market was a more prominent source of systemic events, particularly during 2018.

[16] As an additional experiment, we estimated an OLS regression $X_t = \sum_{j=1}^{J} C_j \hat{U}_{t-j} + V_t$, where $\hat{U}_{t-j}$ are the residuals obtained from the model 5 and V_t is a vector of iid disturbances. In this setup, these residuals represent instruments for liquidity. The results of this exercise suggest that our instrumented liquidity measures are, as a whole, statistically significant and therefore also indicative of the presence of the "feedback loop" described above. The R-squared of the regression, however, is very small. The results are available upon request.

Conditional correlations and volatilities

We next examine the conditional correlations and volatilities of Italian and Spanish 10-year benchmark bond returns to German returns during the European sovereign debt crisis (2011-12). The upper panel of Figure 4 displays the ratio between the conditional volatilities of Spanish and German returns, computed using CCC and DCC GARCH models. The middle panel contains the same variables for the Italian returns. Holding the conditional correlation constant naturally leads to wider conditional volatility estimates. These provide an indication of the high risks that dealers often face in the Italian and Spanish sovereign bond markets, with this result broadly in line with the risks identified using the VAR-for-VaR model.

The bottom panel Figure 4 displays correlations of both Spanish and Italian returns with the German benchmark bond returns, derived from Dynamic Conditional Correlation GARCH models. The results show little evidence of large and persistent changes in the conditional correlations. This is consistent with the results of Caporin et al. (2018), who argue that the absence of structural change in the relations between euro area national sovereign markets during the crisis implies no contagion. Instead, they believe that all sovereigns were experiencing similar bouts of volatility, rather than spillovers of country-specific shocks.

An alternative interpretation is that the low average values of the conditional correlations indicates that the periphery was already disconnected from the core during the crisis period, implying difficulties in hedging and the absence of pricing externalities due to information linkages. Christiansen (2014) finds that yearly country-level sovereign bond market integration estimates (based on daily data) fell sharply between 2007 and 2012 for peripheral Eurozone countries. The results in Cronin et al. (2019) show that euro area sovereign bond yield correlations were also frequently very high and positive during the pre-crisis period. Therefore, it could be the case that any structural break that occurred during the crisis is simply not captured by the 2011-12 crisis-period sample.

Our 2018 sample provides an opportunity to test for the presence of such a structural break. This was the year during which the relative post-crisis calm between the second half of 2012 and the end of 2017 was persistently disturbed by political developments in Italy.[17] Figure 5 displays the intra-day and daily moving averages of quoted depth and DCC GARCH-implied dynamic correlation with the German benchmark bond returns for the Spanish (upper panel) and Italian (middle panel) benchmark bond returns. The bottom panel displays the *difference* between the dynamic conditional correlations of Spanish and Italian returns respectively with the German benchmark bond returns. We find a strong relationship between our measure of liquidity and conditional correlation. Unstable and/or low correlations make cross-market hedging less viable and reduces the informativeness of one market for another. This is consistent with aspects of the analysis in Dunne (2019) and Cespa and Foucault (2014). For both Italy and Spain, we see that quoted depth declines when the conditional correlation falls. However, the change in correlation for Italy appears to be a structural break and the effect on depth is far more persistent than it is for Spain.

Figure 6 displays DCC GARCH-implied conditional correlation and Marginal Expected Shortfall of Spanish benchmark bond returns in 2011-12 (upper panel) and 2018 (bottom panel), using the Italian benchmark bond as the market asset. The MES is negative in both periods, implying that the Spanish sovereign bond market is expected to experience stress (i.e. a fall in returns) when the Italian market is experiencing a negative tail event. The dynamic conditional correlation generally fluctuates around 0.5 (although it occasional becomes negative), which is opposite in sign and much larger than the Italian and Spanish correlations with German Bunds. The large variability in the conditional correlation implies that Italian benchmark sovereign bonds are not a stable hedge for temporary inventory positions incurred by dealers who are providing liquidity to the Spanish sovereign bond market. Our estimated correlation suggests that a relatively large hedge ratio would be required.

The relationship between conditional correlation and liquidity in the Italian and Spanish

[17] There were several temporary disturbances in euro area national sovereign bond markets, such as during the Greek referendum on the Third Financial Assistance Programme (July 2015) and the Brexit referendum (June 2016). However, these were relatively short-lived disturbances.

sovereign bond markets is confirmed by the results in Table 3. This details a test of whether a constant conditional correlation model is sufficient to fit the variance relations (Engle and Sheppard, 2001). Conditional correlations are computed with respect to the German benchmark bond returns, assuming that Italian and Spanish returns are "market" returns. Our results indicate that the dynamic conditional correlation model is a significantly better fit than the constant conditional correlation model for Italian and Spanish sovereign bond markets in 2018. This provides further evidence of a recent structural break in correlations. This could lead to a drop in liquidity based on weaker hedging opportunities and fewer information externalities. It could also be considered as evidence of contagion in the Italian and Spanish sovereign bond markets, following Caporin et al. (2018)'s definition of the term.

Quantile impulse responses

We now turn our attention to the *dynamics* of cross-market relations, by estimating the 1% quantile impulse response functions from unitary shocks to Spanish (top row) and Italian (bottom row) 10-year benchmark sovereign bond absolute returns. Figure 7 contains the results for the 2011-12 period, while the 2018 results are presented in Figure 8. We also display the estimated standard error bands (two standard deviations above and below the point estimate), computed using the process developed by White et al. (2015). We find that the response of the German 1%VaR is significantly smaller than the Spanish and Italian 1%VaR in both samples. This is further evidence of the safe-haven status of the German Bund. The response of the Spanish VaR is far larger during the crisis period than in 2018. In contrast, the Italian response is much larger, although less persistent, in 2018 than during the crisis. This highlights the disruptive nature of the recent Italian political crisis.

The European sovereign debt crisis resulted in many changes to the euro area policy response and institutional architecture. Examples of these changes include the creation of a permanent crisis resolution fund, the European Stability Mechanism, an enhanced framework for fiscal surveillance and the expansion of the ECB's toolkit to counteract developments on financial markets that hampered the monetary policy transmission mechanism. We assess if these changes had a material effect on the dynamic responses from shocks to Italian and Spanish sovereign bond absolute returns. Figure 9 displays the 1% quantile impulse response functions for unitary shocks to the Spanish (upper row) and Italian (bottom row) absolute returns *before* and *after* Draghi's speech declaring the ECB would do "whatever it takes to preserve the euro" in July 2012.[18] This is the most identifiable date for the numerous policy and institutional developments that took place during the crisis, and given its unexpected nature is less susceptible to anticipation effects that could bias our estimates. The dampening effect of these changes is very evident, with a smaller decrease in the Italian and Spanish 1%VaR in response to similar-sized shocks in the latter part of 2012. Indeed, after Draghi's speech, the impulse responses are rarely statistically significant.

Whether these changes continue to have a dampening effect in 2018 is more open to debate. On the one hand, the impulse response to a sovereign bond absolute return shock is larger in 2018 for the Italian 1% VaR, although the effect is much more temporary (bottom-right panel, Figure 8). However, this lack of persistence could be due to the more benign low-rate environment and the ECB's quantitative easing programme. We provide a rough assessment of this issue by estimating VAR-for-VaR models over shorter (two-month) subsamples and plotting these results against the average daily yield during each period.

Figure 10 shows a scatter plot of average daily within-sample yield (y-axis) and the initial own-response of the 1% VaR (x-axis) for unitary Italian absolute return shocks, estimated across bi-monthly sub-samples. There is substantial variability in the magnitude of the tail quantile responses, with the most negative (i.e. those furtherest to the left) occurring during periods of heightened redenomination risk (April-May 2012) and political turmoil in Italy (May-June 2018). Apart from the (small) tail-quantile responses in the months

[18]This speech was followed by the announcement of the Outright Monetary Transactions (OMT) programme, allowing the purchase of euro area national sovereign bonds conditional on adherence to an ESM programme.

immediately following Draghi's speech, the absolute size of the initial 1%VaR response *rises* with the magnitude of the within-sample average yield. This positive relation is consistent with tail-quantile responses amplifying (and being amplified by) the economic fundamentals that largely determine sovereign bond yields. The results in Figure 10 also provide some tentative evidence that the ECB's quantitative easing programme has dampened the initial tail-quantile responses. Despite the low yields and the presence of quantitative easing, there is a very large response during the May-June 2018 period. This suggests that the rise in market tensions during this period could have had a much larger effect if quantitative easing had already ended and if yield levels were nearer their historical levels.

Liquidity and tail-risk: structural interdependencies

In our final analysis, we assess the *structural* relationship between liquidity and tail risks. We begin with the results from our VAR-X estimation, with our liquidity indices as the dependent variables and the VaRs as exogenous variables. From Table 4 we can see that our liquidity indices are significantly associated with the most extreme quantiles (i.e. the Italian and Spanish 1%VaR and the German 99%VaR). The coefficient signs are as expected, indicating the presence of a feedback loop: liquidity tends to be lower the more negative is the Italian and Spanish 1%VaR and the more positive is the 99%VaR of the German Bund. The model fit (R^2) improves substantially in 2018 compared to 2011-12, indicating that this feedback loop between liquidity and tail risk is still very much present in the Italian and Spanish sovereign bond markets. The negative coefficient on the German 99%VaR indicates that the Bund's safe haven status amplifies this interdependency.

We next present the estimated impulse responses from our VAR-X model. Figure 11 demonstrates that for a given value of own-market tail risk, liquidity contractions in the Spanish and Italian sovereign bond markets spilled over into decreased liquidity in the German market during the European sovereign debt crisis. These spillovers, however, did not occur in the post-crisis sample, indicating that the impact of increased tail risks in national markets was amplified during the crisis, possibly due to fears of a euro break up.

Finally, we estimate quantile impulse responses from a VAR-for-VaR model that includes our liquidity indices. This allows us to assess the effect of changes in liquidity on the estimated 1% value-at-risk of both the return distribution and the liquidity distribution. The results for Spain and Italy are contained in Figures 12 and 13 respectively. Overall, we find clear evidence that contractions in liquidity result in increased tail risk (i.e. decreased VaR). Our earlier results demonstrated that larger tail risks reduce liquidity, and therefore we conclude that a self-reinforcing feedback loop between liquidity and tail risk exists in three of the largest European sovereign bond markets.

6 Conclusion

Although there is some evidence that market reactions during the crisis were larger than implied by developments in economic fundamentals, there is little *direct* empirical evidence documenting the transmission channels through which non-fundamental shocks amplify sovereign bond market tensions. We aim to fill this gap in the literature by documenting the interdependencies between liquidity and tail risk, and how these can have severe own- and cross-market effects.

Using intra-day data from the MTS trading platform, Europe's leading electronic fixed-income trading platform, we provide empirical evidence for own- and cross-market linkages between liquidity provision and tail risks in the German, Italian and Spanish sovereign bond markets. Specifically, we show that the variation in Italian and Spanish tail risks, represented by movements in conditional quantiles derived using the VAR-for-VaR approach (White et al., 2015), are significantly associated with liquidity measures. These results are consistent with theoretical models that explain the depth of the limit order book in relation to adverse selection risk and inventory holding costs. In terms of cross-market effects, we find that reductions in the Italian and Spanish VaR (i.e. greater potential losses) are related to contemporaneous *increases* in the German 99% VaR (i.e. lower potential losses) and German Bund positive expected returns. This shows the role that the safe-haven German Bund, as the benchmark bond for the euro area, can have in amplifying the effect from liquidity and tail risk interdependencies.

We also find that the strength of the reaction of conditional tail quantiles to significant (although not necessarily extreme) movements in absolute bond market returns has changed in the *post-crisis* period. This dampening effect is at least partially due to different euro area policy and institutional reform efforts. However, the relationship between extreme tail quantiles of returns and measures of liquidity provision is always highly significant and involves cross-market effects. Our results suggest that in the absence of a low interest rate environment and the ECBs asset purchase programme, the 2018 rise in Italian political risk could have had much more severe effects. This implies further changes to the euro area institutional architecture are required to improve the resilience of euro area sovereign bond markets.

Our analysis has several important policy implications. First, we highlight that despite improvements in the euro area policy and institutional architecture, national sovereign bond markets remain susceptible to non-fundamental shocks. Our study also contributes to a wider consideration of what it means to have "market access". Establishing at what point liquidity contraction is endogenous rather than fundamentally driven is therefore crucial to assessing whether a given market response is due to solvency or liquidity concerns. Finally, the time series methods we employ are also useful in understanding the efficacy of introducing benchmarks in emerging economy bond markets to improve liquidity conditions and reduce liquidity risk premia.

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Tables

Table 1: **Benchmark bonds: 10-year maturity**

ISIN	**Period**
Germany	
DE0001135440	01/06/2011 - 23/08/2011
DE0001135457	24/08/2011 - 22/11/2011
DE0001135465	23/11/2011 - 10/04/2012
DE0001135473	11/04/2012 - 04/09/2012
DE0001135499	05/09/2012 - 31/12/2012
DE0001102416	02/01/2018 - 09/01/2018
DE0001102440	10/01/2018 - 31/12/2018
Spain	
ES00000123C7	01/06/2011 - 16/11/2011
ES00000123K0	17/11/2011 - 31/12/2012
ES0000012A89	02/01/2018 - 23/01/2018
ES0000012B39	24/01/2018 - 26/06/2018
ES0000012B88	27/06/2018 - 31/12/2018
Italy	
IT0004695075	01/06/2011 - 25/08/2011
IT0004759673	26/06/2011 - 23/02/2012
IT0004801541	24/02/2012 - 27/08/2012
IT0004848831	28/08/2012 - 31/12/2012
IT0005045270	01/01/2018 - 31/12/2018

Notes: This table lists the ISINs we classify as benchmark bonds in our samples and the period during which they were benchmarks. See Section 3 for details on our benchmark selection process.

Table 2: **Benchmark bonds: Summary statistics**

DE

	2011-12		*2018*	
	Relative spread	**Quoted depth**	**Relative spread**	**Quoted depth**
Mean	0.09	16.18	0.08	17.07
St.dev.	0.07	7.54	0.05	8.00
Median	0.08	15.00	0.08	15.00
1st perc.	0.03	5.00	0.03	10.00
99th perc.	0.40	40.00	0.20	55.00

ES

	2011-12		*2018*	
	Relative spread	**Quoted depth**	**Relative spread**	**Quoted depth**
Mean	0.99	12.21	0.22	34.98
St.dev.	2.62	6.49	0.54	15.86
Median	0.64	12.00	0.14	33.00
1st perc.	0.16	4.00	0.06	2.00
99th perc.	5.91	30.00	2.06	74.00

IT

	2011-12		*2018*	
	Relative spread	**Quoted depth**	**Relative spread**	**Quoted depth**
Mean	0.30	14.08	0.16	48.15
St.dev.	0.36	8.27	0.34	19.38
Median	0.20	12.50	0.11	48.00
1st perc.	0.06	4.00	0.04	10.00
99th perc.	1.76	41.00	1.68	98.00

Note: This table reports the mean, standard deviation, median, 1st and 99th percentiles of the relative bid-ask spread and quoted depth for German (DE), Spanish (ES) and Italian (IT) 10-year benchmark sovereign bonds. We define the relative bid-ask spread as the bid-ask spread divided by the mid price: $100((A_t - B_t)/M_t)$, with A_t and B_t representing, respectively, the ask and bid price; quoted depth is the sum of the quantity at best bid and the quantity at best ask, divided by 100. The relative bid-ask spread is expressed in percentage points, whereas quoted depth is in millions of euro. *2011-12* sample: 01/06/2011 - 31/12/2012 (14219 obs.). *2018* sample: 01/01/2018 - 31/12/2018 (7157 obs.).

Table 3: **Non-conditional correlation test**

	ES - DE					
	2011-12			*2018*		
Lags	**1**	**2**	**3**	**1**	**2**	**3**
Test statistic	0.192	0.242	0.332	25.061	27.573	28.493
P-value	0.965	0.970	0.988	0.000	0.000	0.000

	IT - DE					
	2011-12			*2018*		
Lags	**1**	**2**	**3**	**1**	**2**	**3**
Test statistic	1.276	3.196	3.564	14.590	15.263	16.053
P-value	0.528	0.362	0.468	0.001	0.002	0.003

	IT - ES					
	2011-12			*2018*		
Lags	**1**	**2**	**3**	**1**	**2**	**3**
Test statistic	0.062	0.075	0.491	2.210	4.668	6.292
P-value	0.969	0.979	0.974	0.331	0.198	0.178

Note: This table displays the results from a test for the presence of conditional correlation (Engle and Sheppard, 2001). The test effectively involves the estimation of a multivariate dataset using the CCC-GARCH model and an assessment of whether the standardised residuals (standardised by the symmetric square root decomposition of the estimated constant correlation matrix) are i.i.d. and have a covariance equal to the identity matrix. Testing for this can be done using a series of artificial regressions on the outer and lagged product of these residuals and a constant. DE: Germany; ES: Spain; IT: Italy. *2011-12* sample: 01/06/2011 - 31/12/2012 (14219 obs.). *2018* sample: 01/01/2018 - 31/12/2018 (7157 obs.).

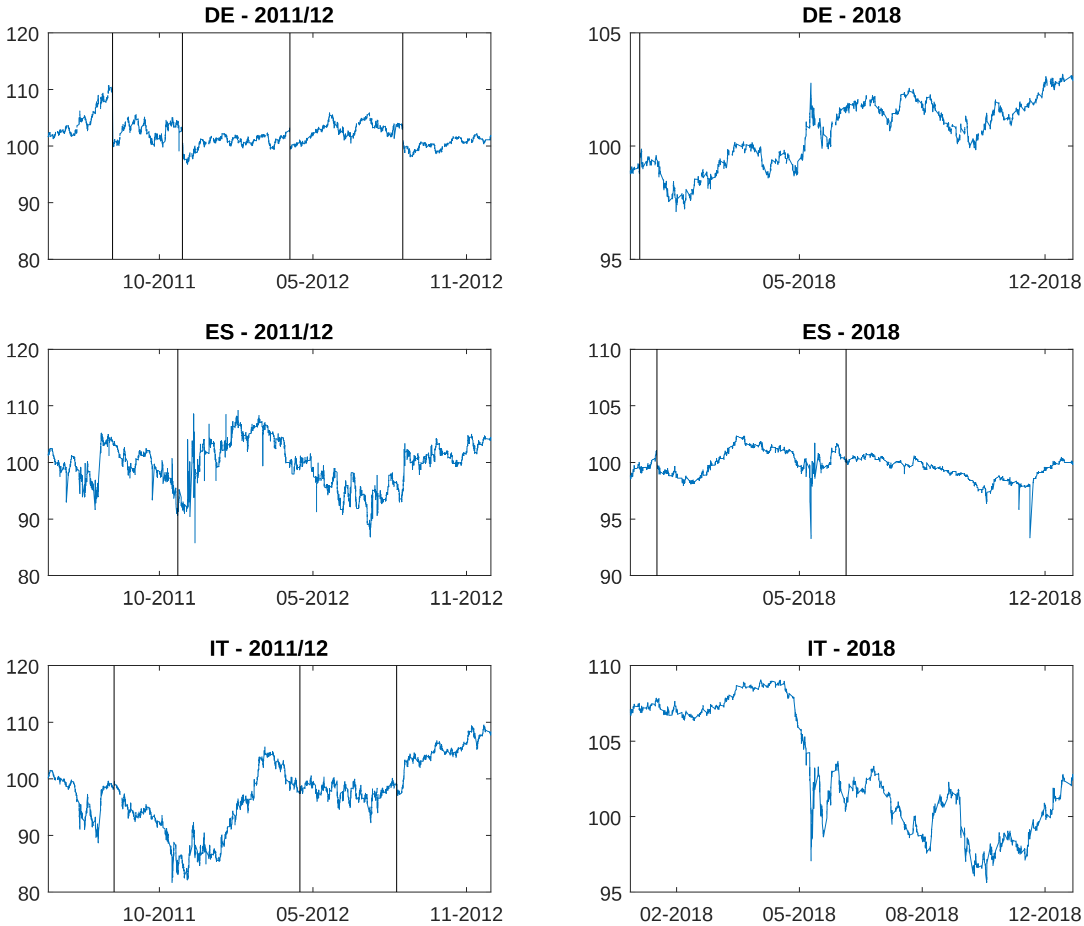
Table 4: **Liquidity and tail risk interdependencies: VAR-X coefficients**

	2011-12		***2018***	
	$Liquidity_t$ **ES**	$Liquidity_t$ **IT**	$Liquidity_t$ **ES**	$Liquidity_t$ **IT**
1% VaR_t^{ES}	0.0270^{***}		0.1348^{*}	
	(0.0055)		(0.0770)	
1% VaR_t^{IT}		0.2918^{***}		0.3272^{**}
		(0.0274)		(0.1558)
99% VaR_t^{DE}	-0.2834^{***}	-0.8337^{***}	-3.1383^{***}	-2.3674^{***}
	(0.0203)	(0.0955)	(0.6166)	(1.1123)
R-squared (%)	45.25	53.88	39.61	76.50
F-test	YES	YES	YES	YES
Obs.	14215	14215	7153	7153

Note: This table reports the coefficients estimated using the VAR-X model 5. In this model, each equation is estimated via OLS. Heteroskedasticity-robust standard errors are reported in parenthesis. The penultimate row displays whether the F-statistic is statistically significant (if "YES") or not ("NO"). DE: Germany; ES: Spain; IT: Italy; *Liquidity*: liquidity index, see Section 4 for details; 1%VaR: quantile computed using CaViar (Engle and Manganelli, 2004) at $\theta = 1\%$ significance level. *2011-12* sample: 01/06/2011 - 31/12/2012. *2018* sample: 01/01/2018 - 31/12/2018. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

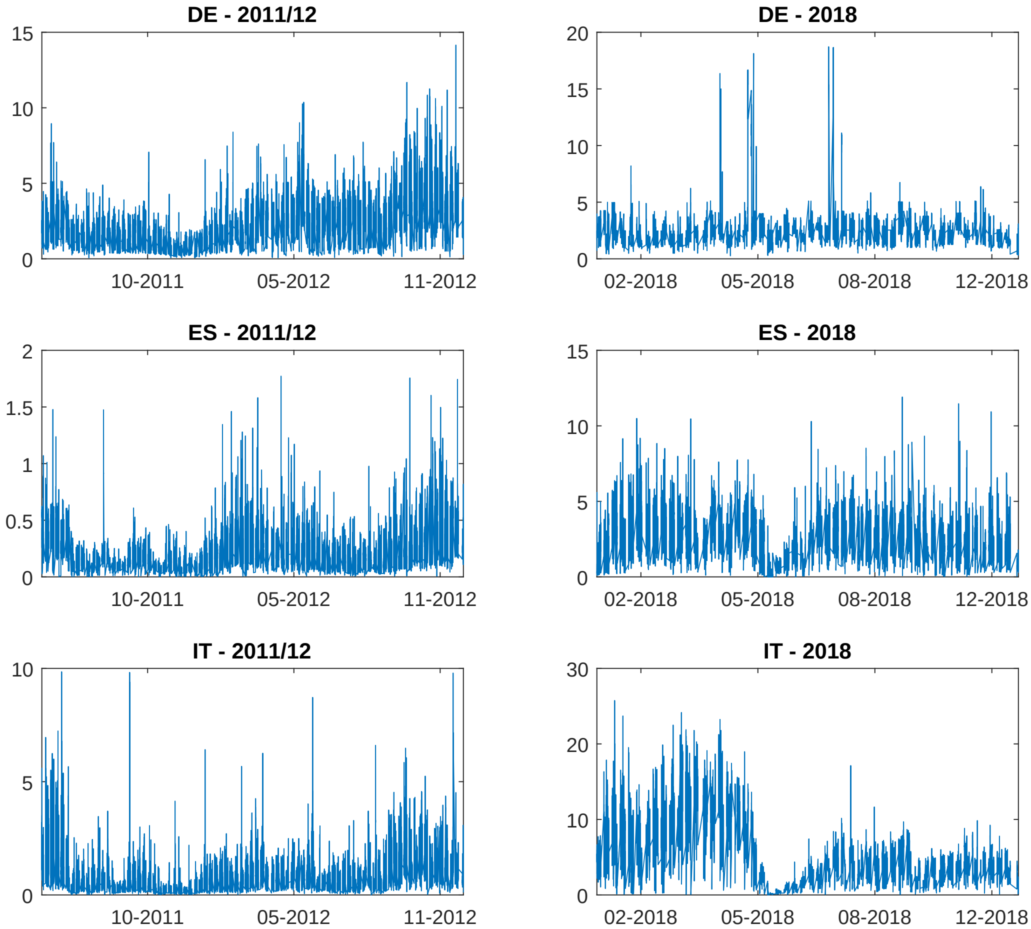
Figures

Figure 1: **10-year benchmark bonds: mid prices**



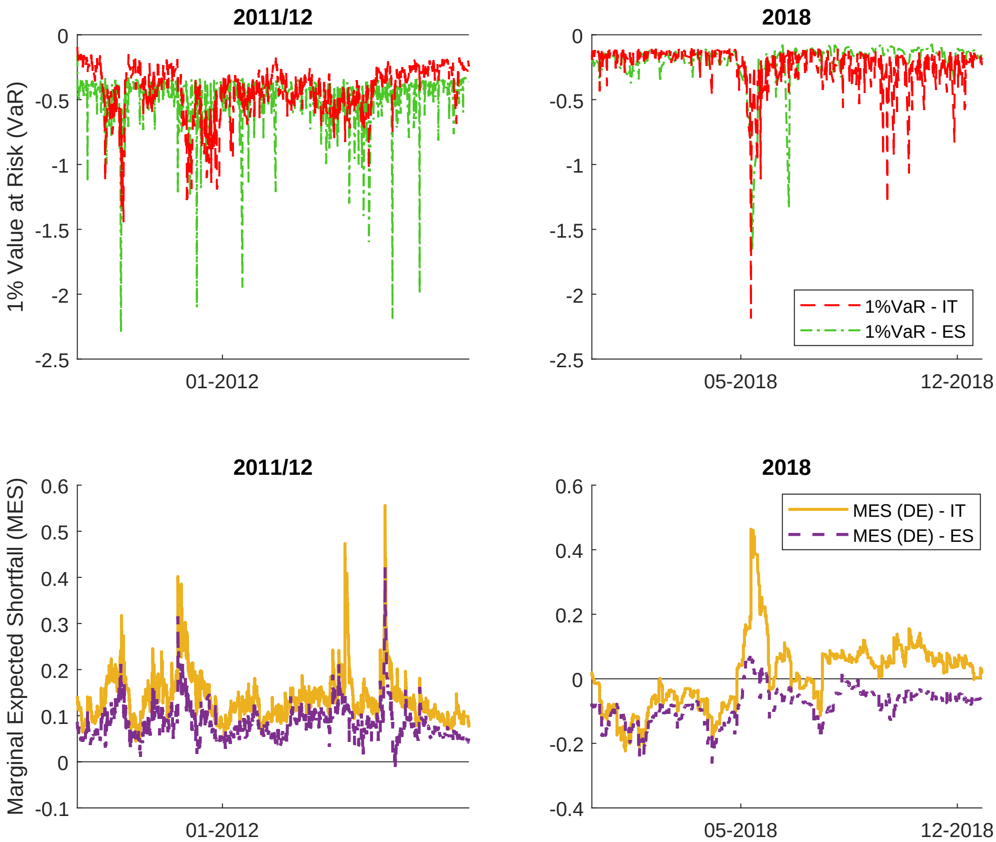
Note: This figure displays intra-day (15-minute interval) mid prices of German (DE), Spanish (ES) and Italian (IT) benchmark bonds in the 2011-12 and 2018 samples. Vertical lines represent days of changes in the benchmark bond. *2011-12* sample: 01/06/2011 - 31/12/2012 (14220 obs.). *2018* sample: 01/01/2018 - 31/12/2018 (7159 obs.).

Figure 2: **10-year benchmark bonds: liquidity indices**



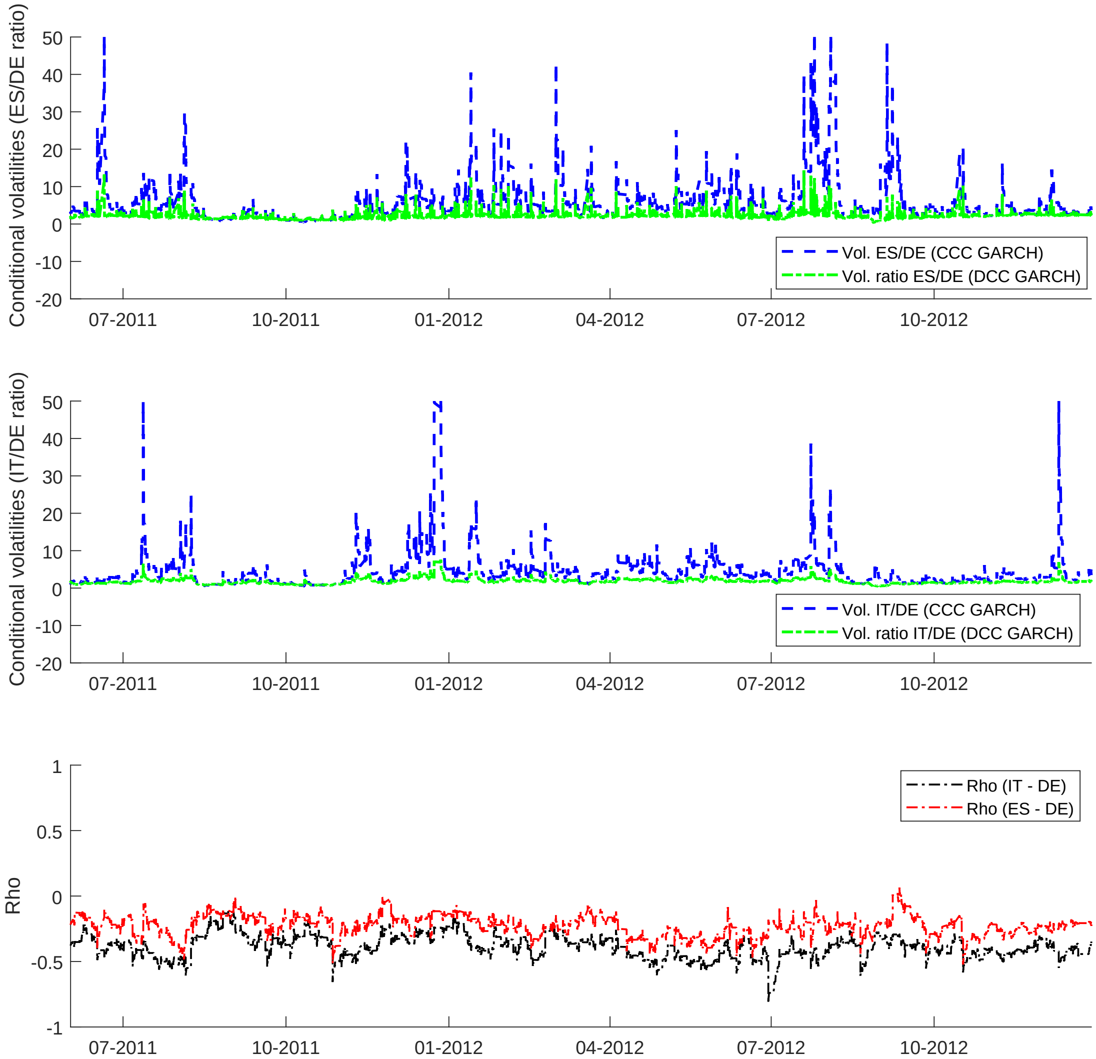
Note: This figure displays the intra-day (15-minute interval) liquidity indices of German (DE), Spanish (ES) and Italian (IT) 10-year benchmark bonds in the 2011-12 and 2018 samples. The liquidity indices are defined as quoted depth divided by the relative bid-ask spread, multiplied by 100. *2011-12* sample: 01/06/2011 - 31/12/2012 (14220 obs.). *2018* sample: 01/01/2018 - 31/12/2018 (7159 obs.).

Figure 3: **Estimated 1% VaR and Marginal Expected Shortfall**



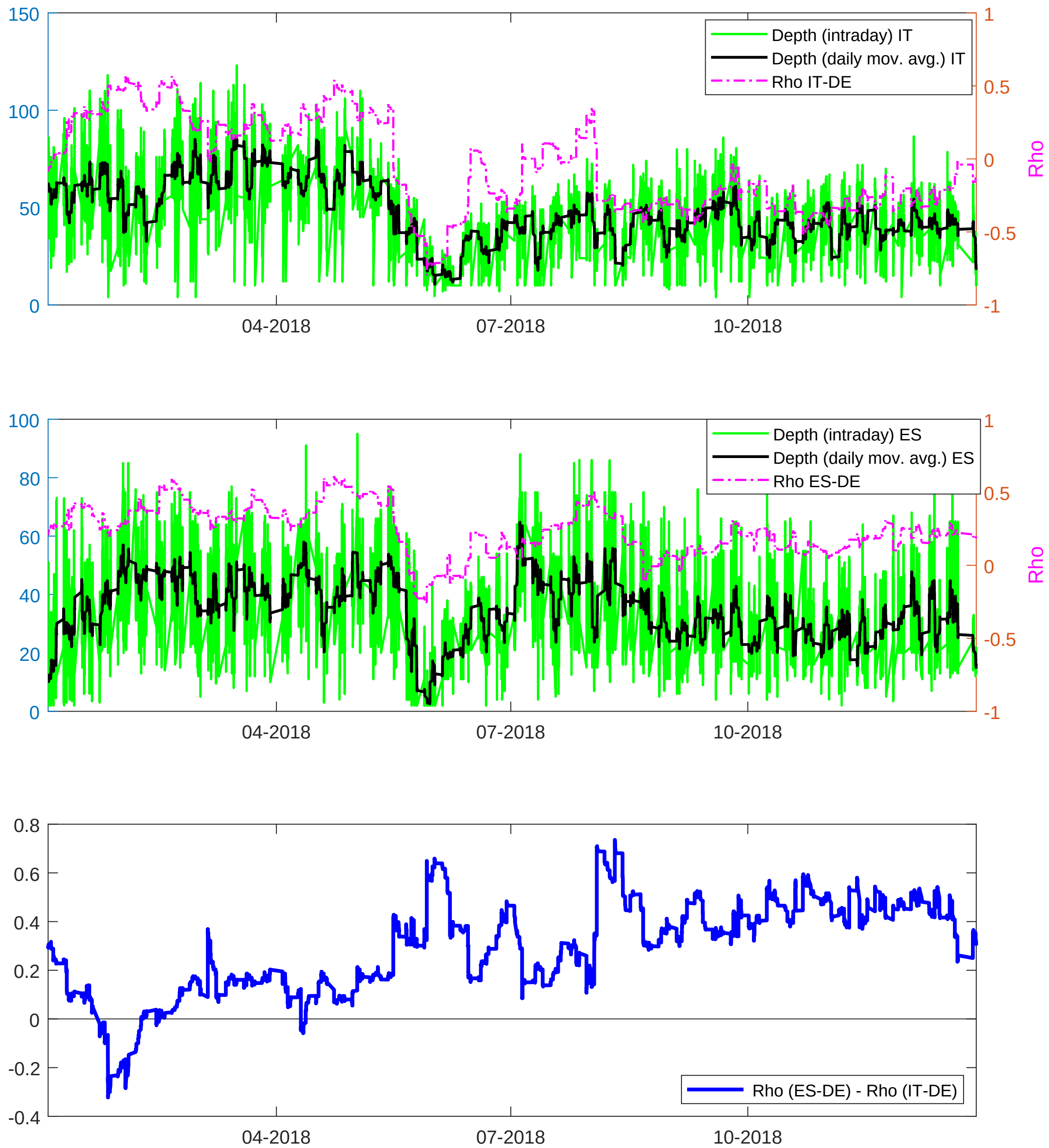
Note: This figure shows the 1% VaR (first row) of Spanish (ES) and Italian (IT) 10-year benchmark bond returns and the Marginal Expected Shortfall (MES) of 10-year benchmark German (DE) Bund returns (second row). We compute the 1% VaR metrics by estimating two separate VAR-for-VaR models, in which the Spanish and the Italian benchmark bonds are assumed to be the "market" assets and the German benchmark bonds are "idiosyncratic". We obtain the MES by using conditional volatilities and correlations estimated with a DCC GARCH, assuming that the market returns are at the 1% quantiles. See Section 4 for more details on the empirical methodologies we employ. *2011-12* sample: 01/06/2011 - 31/12/2012 (14220 obs.). *2018* sample: 01/01/2018 - 31/12/2018 (7159 obs.).

Figure 4: **Conditional correlations and volatilities (2011-12)**



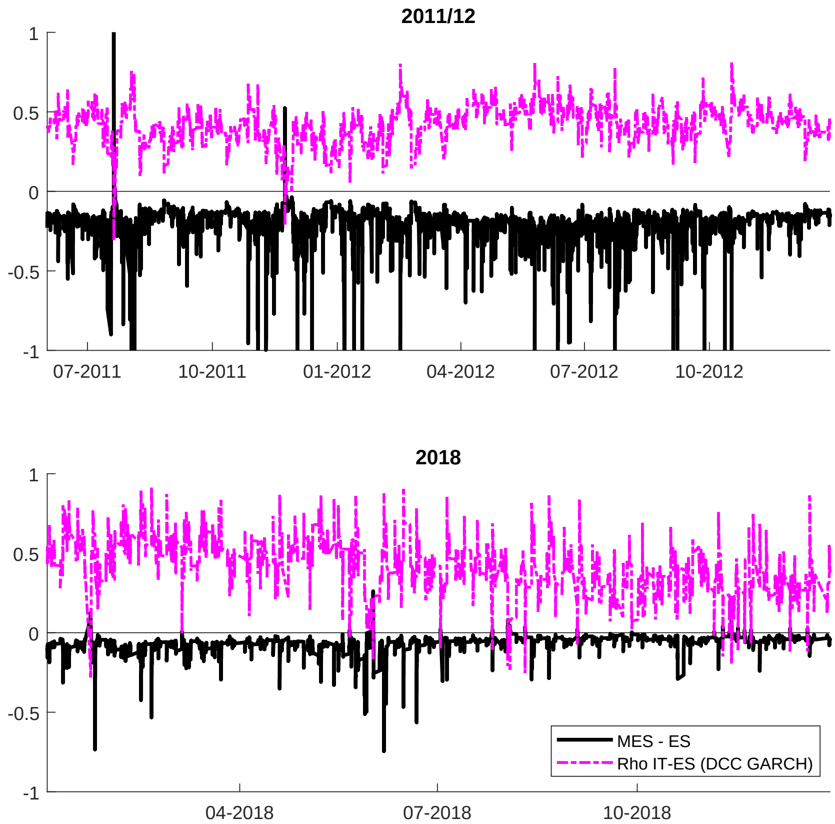
Note: The upper panel displays the ratio between the conditional volatilities of Spanish (ES) and German (DE) benchmark bond returns, computed using CCC and DCC GARCH models. The middle panel displays the same variables for the Italian (IT) benchmark bond returns. The bottom panel displays the DCC GARCH-implied dynamic conditional correlations of both the Spanish and Italian benchmark returns with the German benchmark bond returns. Sample: 01/06/2011 - 31/12/2012 (14220 obs.).

Figure 5: **Conditional correlations and quoted depth (2018)**



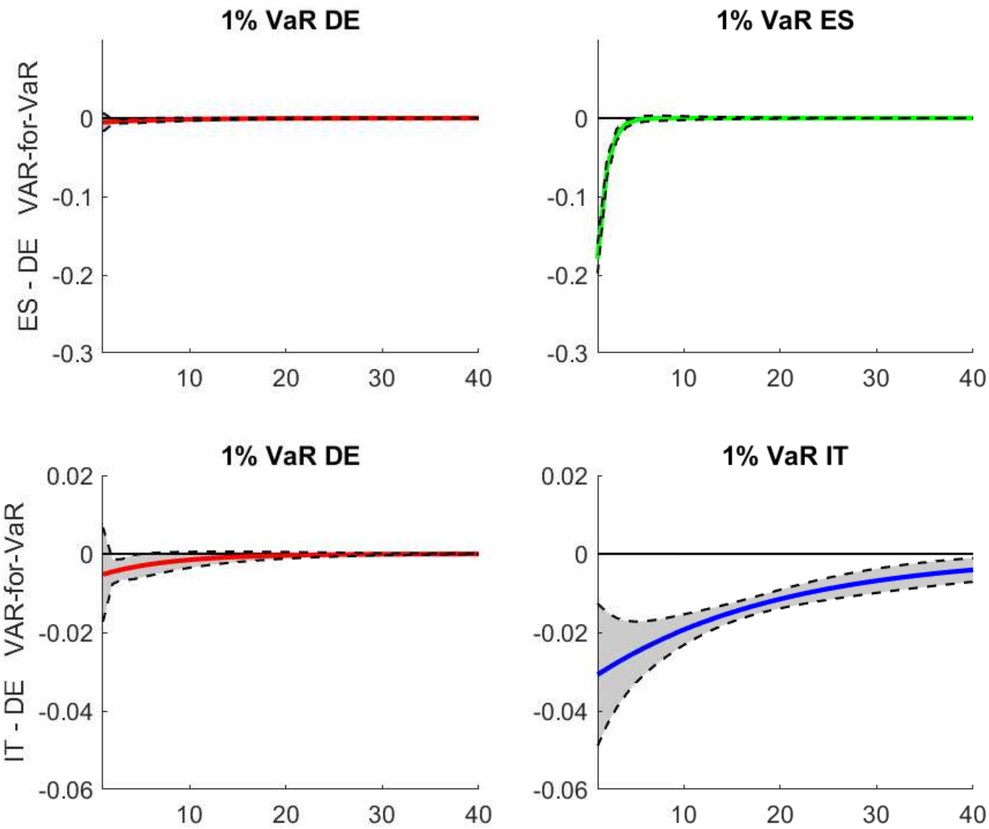
Note: This figure displays intra-day and daily moving average quoted depth and DCC GARCH-implied dynamic conditional correlation (with German Bund returns) for the Spanish (upper panel) and Italian (middle panel) benchmark bond returns. The bottom panel displays the difference between the dynamic conditional correlations of Italian (IT) and Spanish (ES) returns (with the German (DE) returns). Sample: 01/01/2018 - 31/12/2018 (7159 obs.).

Figure 6: **MES and DCC GARCH-implied conditional correlation**



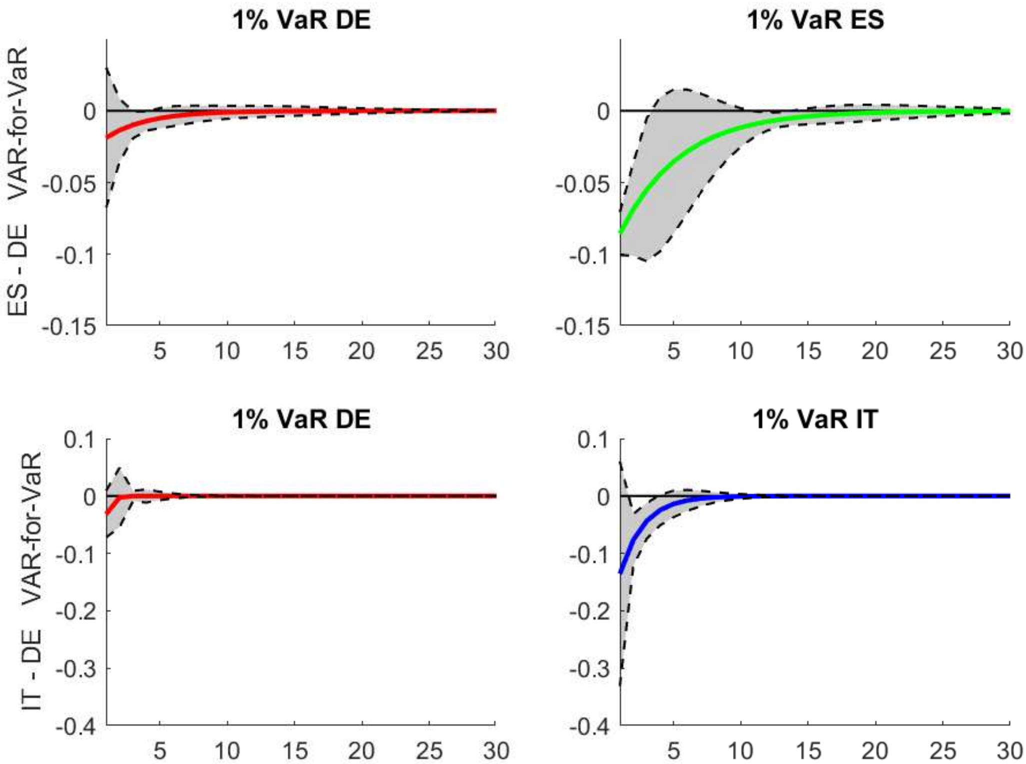
Note: This figure displays the DCC GARCH-implied conditional correlation and Marginal Expected Shortfall of the Spanish returns in the 2011-12 (upper panel) and 2018 (lower panel) samples. We compute these measures under the assumption that the Italian benchmark bond is the market asset, whereas the Spanish benchmark bond is idiosyncratic. *2011-12* sample: 01/06/2011 - 31/12/2012 (14220 obs.). *2018* sample: 01/01/2018 - 31/12/2018 (7159 obs.).

Figure 7: **Quantile-IRFs (2011-12)**



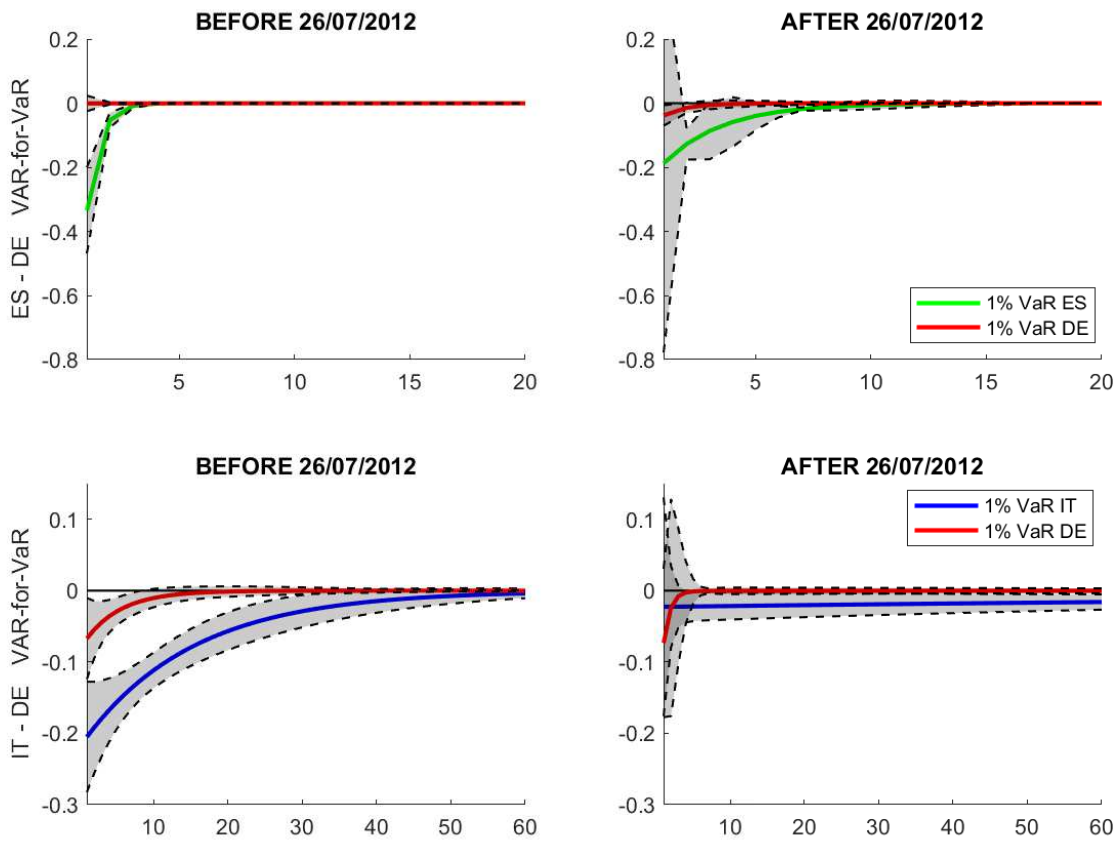
Note: This figure displays quantile impulse response functions for a unitary shock to the Spanish (first row) and Italian (second row) absolute returns in the 2011-12 sample. Standard error bands are computed as in White et al. (2015). Sample: 01/06/2011 - 31/12/2012 (14220 obs.).

Figure 8: **Quantile-IRFs (2018)**



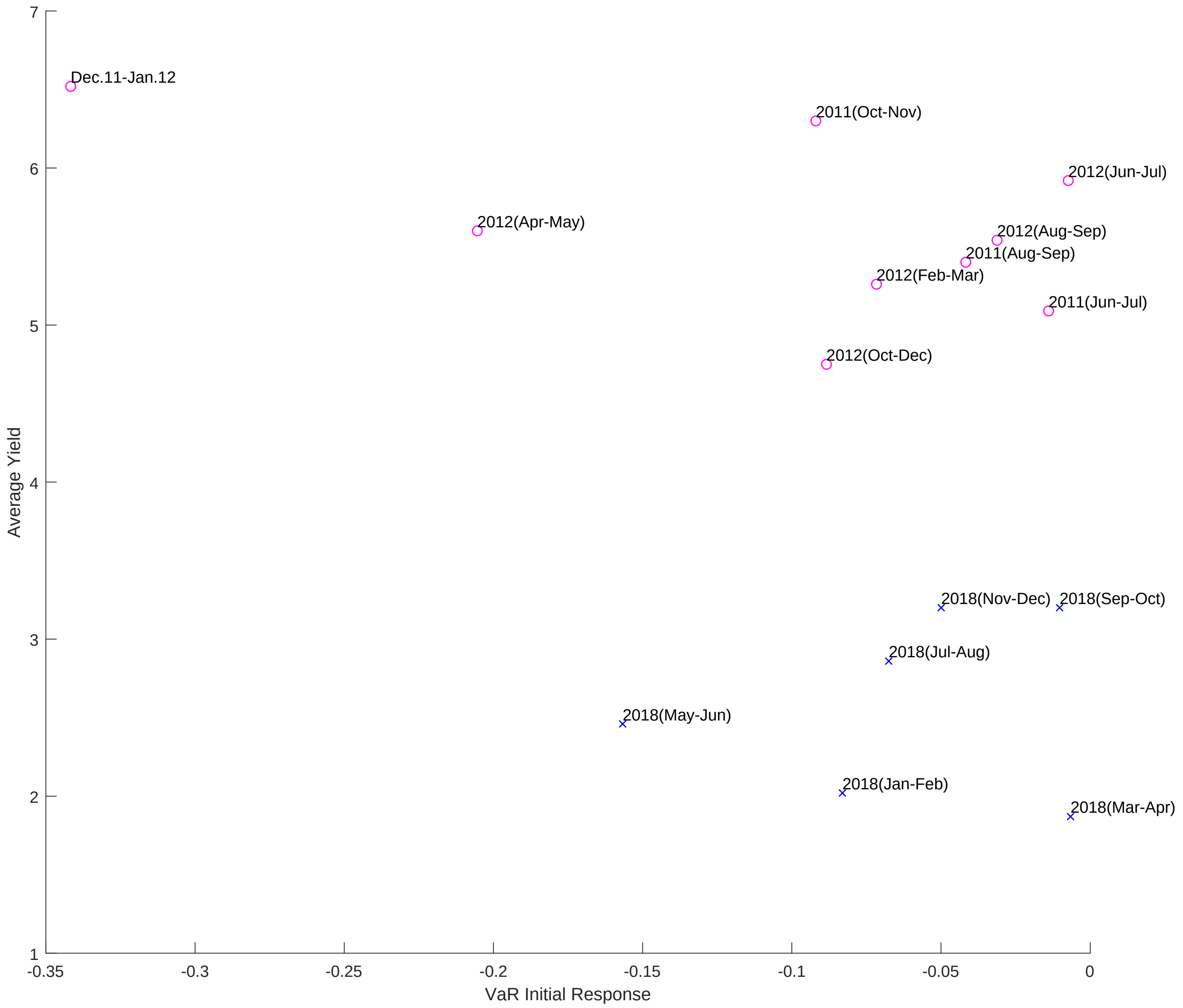
Note: This figure displays quantile impulse response functions for a unitary shock to the Spanish (first row) and Italian (second row) absolute returns in the 2018 sample. Standard error bands are computed as in White et al. (2015). Sample: 01/01/2018 - 31/12/2018 (7159 obs.).

Figure 9: **Quantile-IRFs: Before and after "whatever it takes"**



Note: This figure displays quantile impulse response functions for a unitary shock to the Spanish (first row) and Italian (second row) absolute returns in the 2018 sample. Standard error bands are computed as in White et al. (2015). "Before" sample: 01/01/2012 - 25/07/2012; "After" sample: 27/07/2012 - 31/12/2012.

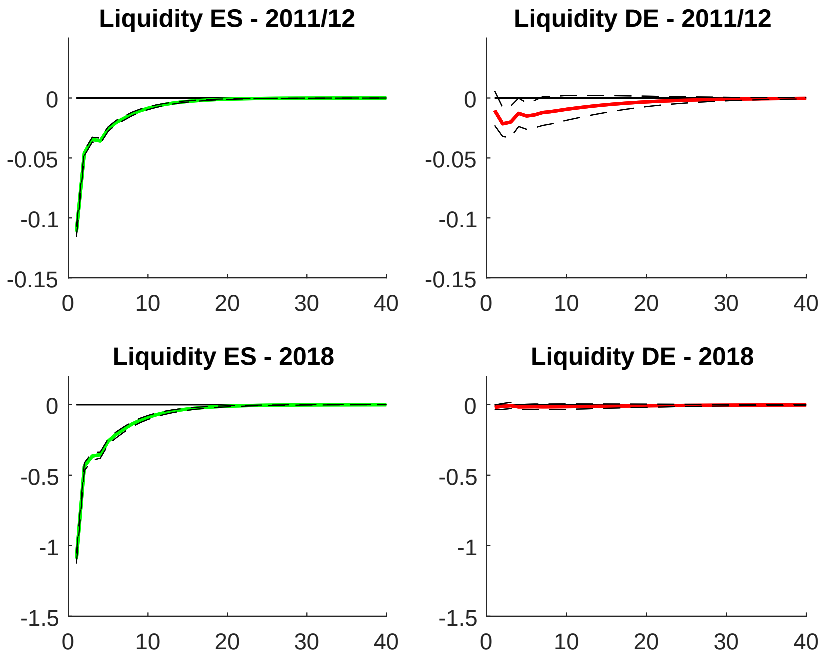
Figure 10: **VAR-for-VaR estimated responses at differing yield levels**



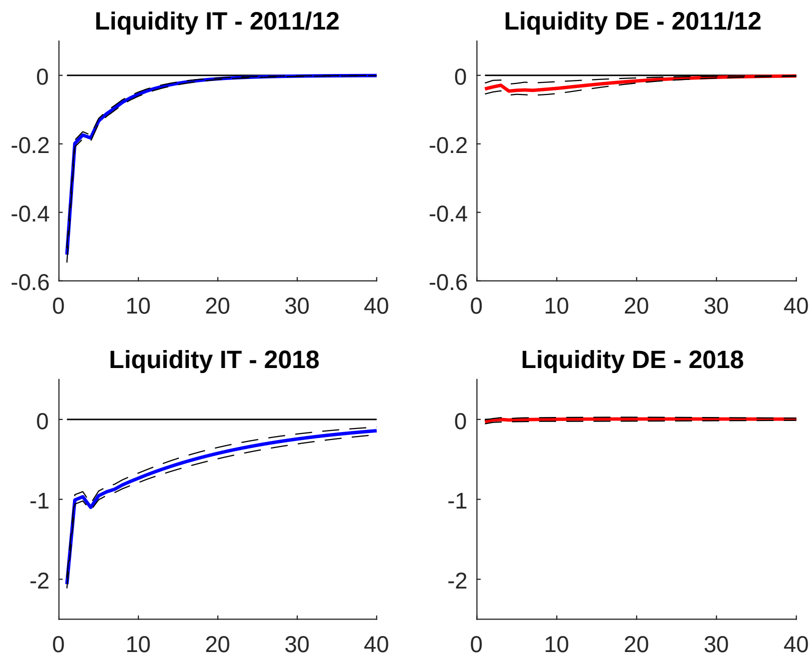
Note: This figure plots bimonthly estimated (impact) responses of the 1% VaR of Italian 10-year benchmark bond returns (x-axis) versus the average daily yield level during those months (y-axis). The circles relate to months in the 2011/12 sample, while the crosses are months in the 2018 sample. Straight lines represent least-squares regression lines for the 2011/12 sample (in magenta) and the 2018 sample (in blue).

Figure 11: **VAR-X impulse response functions**.

(a) $i = ES$

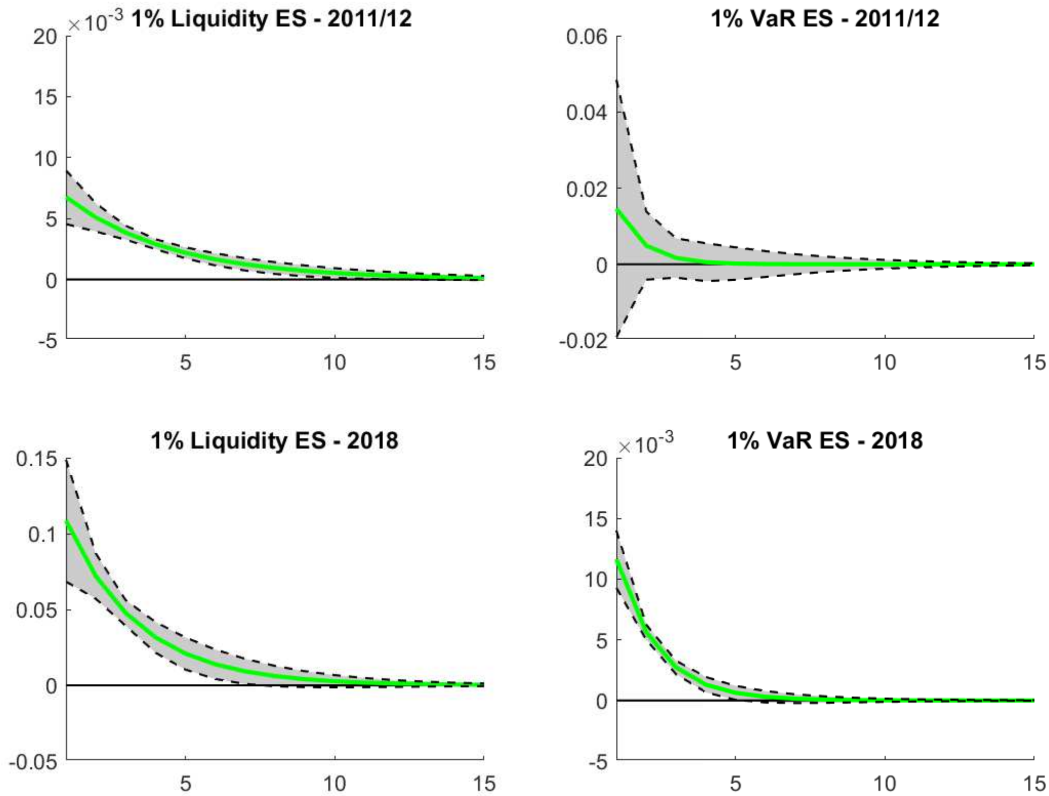


(b) $i = IT$.



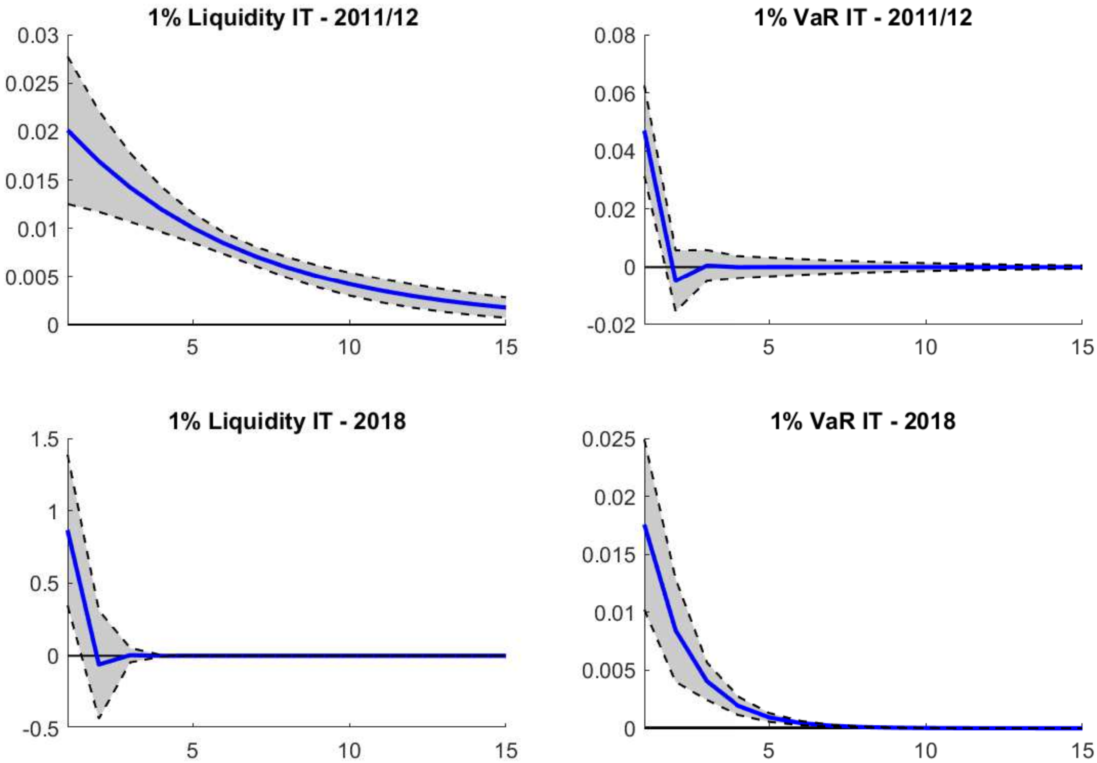
Note: This figure displays the impulse response functions to a shock to the Spanish (panel a) and Italian (panel b) liquidity indices, estimated using the VAR-X model. We estimate the VAR-X models with $k = 3$ lags of the endogenous variable. We use bootstrap (1000 draws) to construct 95% confidence bands. *2011-12* sample: 01/06/2011 - 31/12/2012 (14215 obs.) . *2018* sample: 01/01/2018 - 31/12/2018 (7153 obs.).

Figure 12: **Liquidity and tail-risk feedback dynamics: Spain**



Note: This figure displays the quantile impulse response functions, estimated using a VAR-for-VaR model, for a unitary shock to the Spanish liquidity index in the 2011/12 sample (first row) and the 2018 sample (second row). The liquidity index is defined as quoted depth divided by relative bid-ask spread, multiplied by 100. Standard error bands are computed as in White et al. (2015). *2011-12* sample: 01/06/2011 - 31/12/2012 (14215 obs.). *2018* sample: 01/01/2018 - 31/12/2018 (7153 obs.).

Figure 13: **Liquidity and tail-risk feedback dynamics: Italy**



This figure displays the quantile impulse response functions, estimated using a VAR-for-VaR model, for a unitary shock to the Italian liquidity index in the 2011/12 sample (first row) and the 2018 sample (second row). The liquidity index is defined as quoted depth divided by relative bid-ask spread, multiplied by 100. Standard error bands are computed as in White et al. (2015). *2011-12* sample: 01/06/2011 - 31/12/2012. *2018* sample: 01/01/2018 - 31/12/2018.

Appendices

We report *diagnostic* test results from our analyses using intra-day data in Appendix A. In Appendix B, we provide the results from the replication of our empirical analyses using *daily* data. In Appendix C, we assess if our results are robust to different benchmark bond *maturities*.

Appendix A Intra-day model diagnostics

All the exercises in the main paper use the estimated VAR-for-VaR with $\theta = 1\%$. The second row of the upper panel of Table 5 provides the results of the DQ test (Engle and Manganelli, 2004), which reveals the extent to which our model is capable of effectively computing time-varying quantiles.[19] The insignificance of the estimated p-values indicates that the 1% VAR-for-VaR is reliably estimated. The third and fourth rows reports the results of joint significance tests of the parameters capturing estimated cross effects. The statistical insignificance of these tests demonstrates the presence of substantial cross effects at the 1% VaR.

The lower panel of Table 5 reports the results of diagnostic tests for an estimated VAR-for-VaR with $\theta = 5\%$. These tests are statistically significant, with one exception, and therefore the 5% VAR-for-VaR is not reliably estimated. For this reason we only include the estimated 1% VAR-for-VaR in the experiments reported in the main paper.

Table 6 details the results of a diagnostic test for the GARCH model. The test is a version of a Lagrange multiplier test, adapted to assess the significance of ARCH effects in the series of returns (Engle, 1982). A statistically significant result indicates the presence of autocorrelation in the residuals, and therefore the GARCH model is not an appropriate model to fit returns data. Our results show the GARCH model is particularly suitable for Italy, with the evidence for Germany and Spain more mixed.

[19]The DQ test assesses whether quantile exceedances are independent and identically distributed. A statistically significant p-value indicates a rejection of the iid assumption. See Engle and Manganelli (2004) for more details on the DQ test.

Appendix B Analysis using daily data

We repeat our experiments from the main paper (that used intra-day data) using data at the daily frequency. This helps us to ascertain if there is a value added from using higher-frequency intraday data.

We construct daily data by computing moving averages over roughly 35 intraday observations (i.e. from each 15-minute interval).[20] As a first comparison, Figure 14 plots the intraday and daily moving average of our liquidity measures, the relative bid-ask spread and quoted depth. The daily moving averages are significantly less volatile than intraday data. By way of example, the Italian political crisis that occurred at the end of May 2018 resulted in an increase of the relative bid-ask spread as large as 12 percentage points, three times as large as the increase observed using daily moving averages. This difference is vital for our purposes, since we are investigating the propagation effects of large shocks that affect the *tails* of the distribution of returns. Use of daily moving averages, with less volatile series, could bias our results downwards and indicate a substantially smaller propagation effect.

We next estimate the VAR-for-VaR (with $\theta = 1\%$) and the DCC-GARCH model of the relation between German and Italian benchmark bond returns with daily frequency (i.e. moving averages) data.[21] Overall, Figure 15 shows that the estimated series of the Italian 1%VaR and the German MES are very similar to those obtained with intraday data (see Figure 3 in the main paper). However, there are important differences in the estimation of the dynamic correlation. While the DCC-GARCH still displays a marked reduction in late-May 2018 when using daily data, it deviates from the intraday estimation by reverting back to a higher level (see Figure 15). Therefore, the structural break in the dynamic

[20]Since the 15-minute intervals are computed between 9.00am - 5.30pm each trading day, there is *on average* 35 observation for each day. However, the removal of missing observations (see Section 3 for details) means that the number of observations in each day is variable. Note that the resulting observations are different from end-of-the day data, i.e. the values reported at the end of each trading day.

[21]We only report the estimation results of the relationship between German and Italian returns using daily moving average data. Similar results (available from the authors upon request) arise from the estimation of German and Spanish returns using lower-frequency daily data.

correlation occurring around the time of the Italian political crisis is only captured using intraday data.

Finally, Table 7 displays the results from the VAR-X model examining the own- and cross-market effects of Italian (1%) and German (99%) VaRs on our Italian liquidity index using daily data. Crucially, the relation between our liquidity measure and conditional tail risk is considerably weaker than the results using intra-day data documented in the paper (see Table 4).

Overall, our results using data at the daily frequency underline the need to use intra-day data in order to investigate the interdependencies between liquidity and tail returns in sovereign bond markets.

Appendix C Analysis using different maturities

Bocola and Dovis (2019) use the maturity structure of Italian government debt to indirectly infer the relative size of the role played by non-fundamental risk during the European sovereign debt crisis. We therefore examine whether our results showing an amplification resulting from the interdependence between liquidity and tail risk hold at shorter maturities. We identify benchmark bonds at the 2-year and 5-year maturities using the same approach as for the 10-year maturities (see Section 3 for details). To save space, we restrict our analysis to the Italy and its interaction with the German market. Table 8 lists the ISINs identified as benchmarks in our 2011-12 and 2018 samples, with the mid-prices of Italian 2-year and 5-year bonds plotted in Figure 16. The mid-price movements closely match those of the 10-year benchmark bonds (see Figure 1).

Figure 17 demonstrates that the results from our empirical analysis hold when we consider bonds of different maturities. The large and sudden drop in the Italian 1% VaR during May 2018 is also very apparent at the 2- and 5-year maturities, while the German MES also re-enters positive territory. The breakdown in correlations and the contraction in liquidity (quoted depth) also closely resembles our results using 10-year maturities.

Table 5: **VAR-for-VaR model diagnostics**

$\theta = 1\%$

	IT - DE		ES - DE		IT - ES	
	2011-12	*2018*	*2011-12*	*2018*	*2011-12*	*2018*
RQ crit.	0.0108	0.0068	0.0126	0.0061	0.0157	0.0081
DQ test	0.9446	0.8749	0.9921	0.9647	0.8246	0.8677
Joint eff. (t-stat.)	2.6217	0.8345	0.6719	1.4423	0.0035	0.0037
Joint eff. (p-val.)	0.2696	0.6589	0.7147	0.4862	0.9983	0.9981
Cross-eff. a_{21} **(est.)**	0.0210	-0.2620	-0.0016	-0.1998	-0.5505	-0.0798
Cross-eff. a_{21} **(s.e.)**	0.0086	0.1991	0.0418	0.5223	0.0669	0.1751

$\theta = 5\%$

	IT - DE		ES - DE		IT - ES	
	2011-12	*2018*	*2011-12*	*2018*	*2011-12*	*2018*
RQ crit.	0.0287	0.0157	0.0327	0.0148	0.0000	0.0192
DQ test	0.0000	0.0013	0.0050	0.6224	0.0000	0.0113
Joint eff. (t-stat)	1.8378	9.5236	2.2667	26.4548	0.0387	2.8725
Joint eff. (p-val.)	0.3990	0.0086	0.3220	0.0000	0.9808	0.2378
Cross-eff. a_{21} **(est.)**	-0.0012	-0.0725	-0.0010	-0.1221	-0.1839	0.0656
Cross-eff. a_{21} **(s.e.)**	0.0060	0.0081	0.0942	0.0187	0.0459	0.1377

Note: This table contains VAR-for-VaR estimates at the $\theta = 1\%$ (upper panel) and $\theta = 5\%$ (lower panel) confidence intervals. The first row reports the regression quantile (RQ) criterion (Koenker and Bassett, 1978). The second row reports the p-value for the DQ test (Engle and Manganelli, 2004). A test statistic for the joint significance of the cross-effect parameters and the associated p-values are provided on the third and fourth rows. The fifth and sixth rows report, respectively, the estimate and the standard error of the cross-effect coefficient a_{21}. DE: Germany; ES: Spain; IT: Italy. *2011-12* sample: 01/06/2011 - 31/12/2012 (14219 obs.). *2018* sample: 01/01/2018 - 31/12/2018 (7157 obs.).

Table 6: **GARCH model diagnostics**

	ES		
Lags	**1**	**2**	**3**
2011-12	0.0571	0.0897	0.1007
2018	0.0165	0.0249	0.0407

	DE		
Lags	**1**	**2**	**3**
2011-12	0.6558	0.2662	0.1057
2018	0.0242	0.0628	0.1148

	IT		
Lags	**1**	**2**	**3**
2011-12	0.5867	0.8041	0.9115
2018	0.6408	0.6548	0.4443

Note: This table contains the p-values from Langrange-Multiplier test statistics (robust to heteroscedasticity) developed by Engle (1982), where the null hypothesis is the joint insignificance of autocorrelation in squared standardised residuals from the GARCH models used in the estimation of the MES. The test results for one, two and three lags are included. DE: Germany; ES: Spain; IT: Italy. *2011-12* sample: 01/06/2011 - 31/12/2012 (14219 obs.). *2018* sample: 01/01/2018 - 31/12/2018 (7157 obs.).

Table 7: **VAR-X model using daily data**

	2011-12	***2018***
	$Liquidity_t$ **IT**	$Liquidity_t$ **IT**
1% $\boldsymbol{VaR_t^{IT}}$	0.0435	0.0983
	(0.0330)	(0.1139)
99% $\boldsymbol{VaR_t^{DE}}$	-0.1930^{**}	-1.1543
	(0.0898)	(1.5444)
R-squared (%)	68.92	76.83
F-test	YES	YES
Obs.	399	218

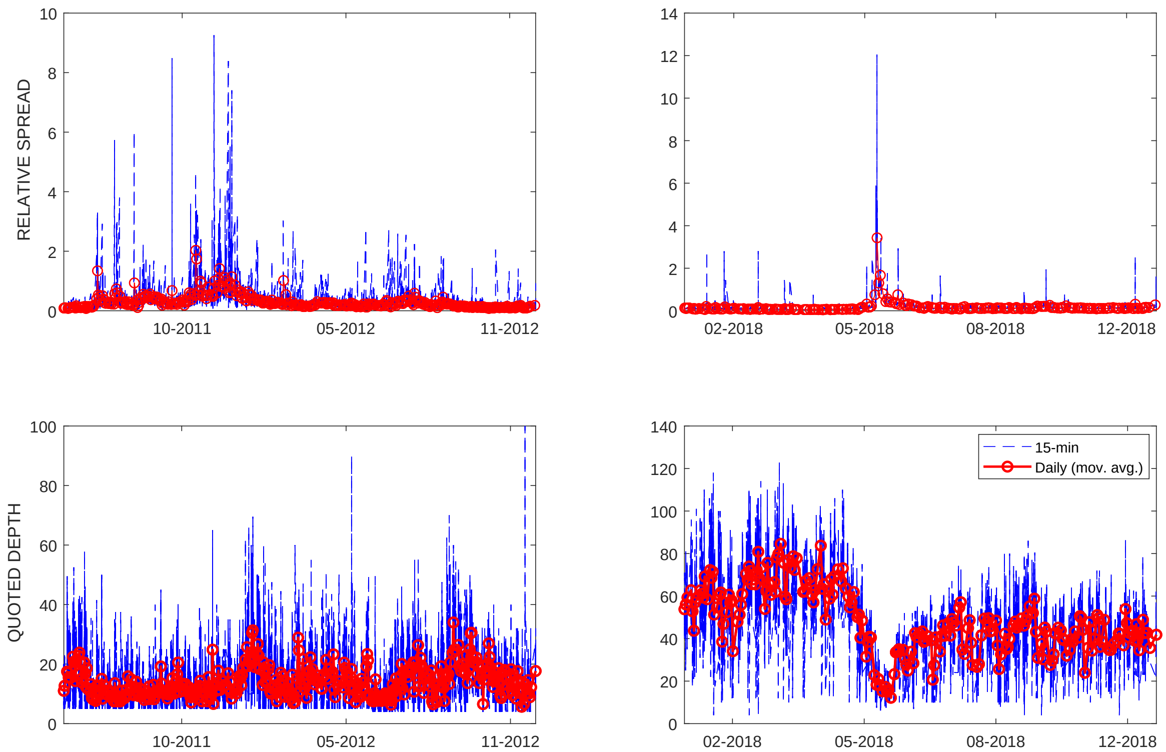
Note: This table reports the results of a VAR-X model examining the own- and cross-market effects of Italian and German tail risks on Italian liquidity. We report heteroskedasticity-robust standard errors in parenthesis. *Liquidity*: liquidity index, as defined in Section 4; DE: Germany; ES: Spain; IT: Italy. The penultimate row displays whether the F-statistic is statistically significant (if "YES") or not ("NO"). *2011-12* sample: 01/06/2011 - 31/12/2012. *2018* sample: 01/01/2018 - 31/12/2018. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table 8: **2-year and 5-year benchmark bonds**

ISIN	**Period**
5-year maturity	
IT0004712748	01/06/2011 - 08/09/2011
IT0004761950	09/09/2011 - 31/12/2012
IT0005277444	02/01/2018 - 22/02/2018
IT0005325946	23/02/2018 - 31/12/2018
DE0001141604	01/06/2011 - 08/05/2012
DE0001141638	09/05/2012 - 31/12/2012
DE0001141760	02/01/2018 - 31/12/2018
2-year maturity	
IT0004716327	01/06/2011 - 22/09/2011
IT0004765183	23/09/2011 - 31/12/2012
IT0005289274	02/01/2018 - 21/03/2018
IT0005329336	22/03/2018 - 31/12/2018
DE0001137347	01/06/2011 - 16/08/2011
DE0001137354	17/08/2011 - 15/11/2011
DE0001137362	16/11/2011 - 31/12/2012
DE0001104701	02/01/2018 - 19/02/2018
DE0001104719	20/02/2018 - 22/05/2018
DE0001104727	23/05/2018 - 31/12/2018

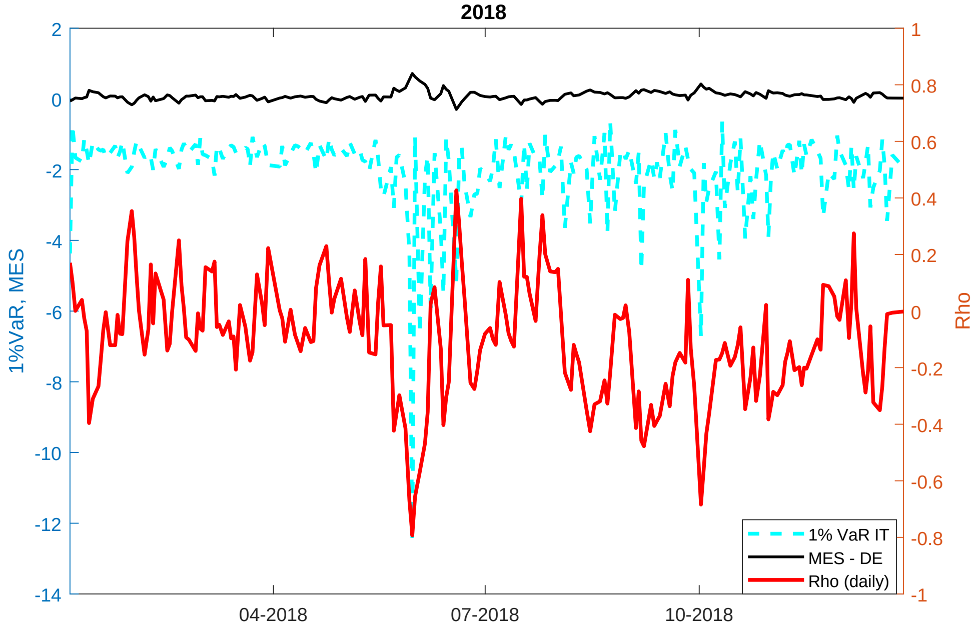
Note: Notes: This table lists the ISINs in our sample we classify as benchmark bonds and the period during which they were benchmarks. See Section 3 for details on our benchmark selection process.

Figure 14: **Italian benchmark bond: Intraday and daily liquidity measures**



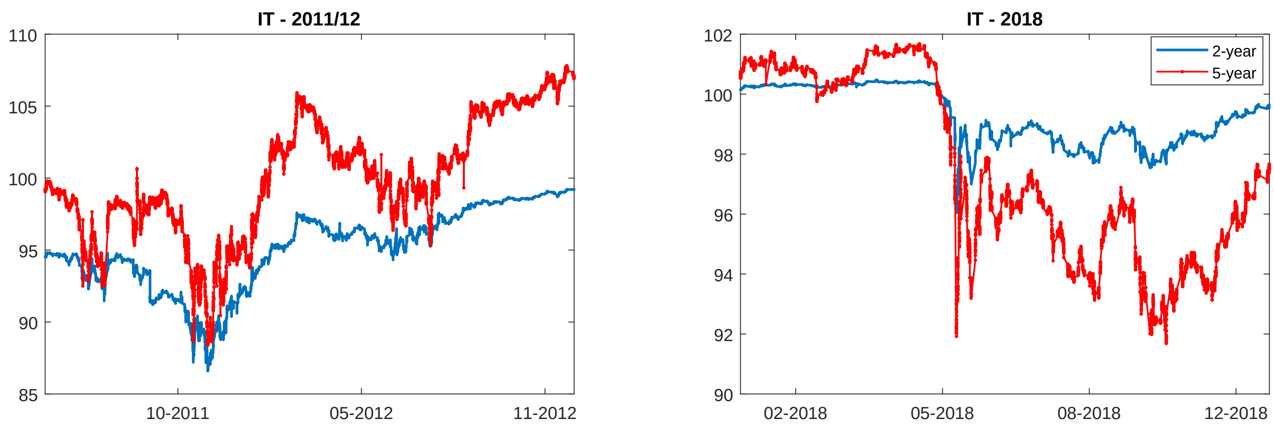
Note: This figure displays the time series of the relative spread (first row) and quoted depth (second row) for the Italian benchmark bond in the 2011/12 and the 2018 samples. Each panel reports the intraday (15-minute interval) series (blue line) and the daily moving average series (red circled line), computed by taking the moving average (with number of leads equal to the number of lags) with daily frequency.

Figure 15: **Model estimation results using daily data**



Note: This figure displays the 1% VaR of Italian benchmark bond returns, the MES of German bond returns and the dynamic conditional correlation between Italian and German benchmark bond returns. The dynamic conditional correlation and the MES are both obtained by estimating the DCC GARCH.

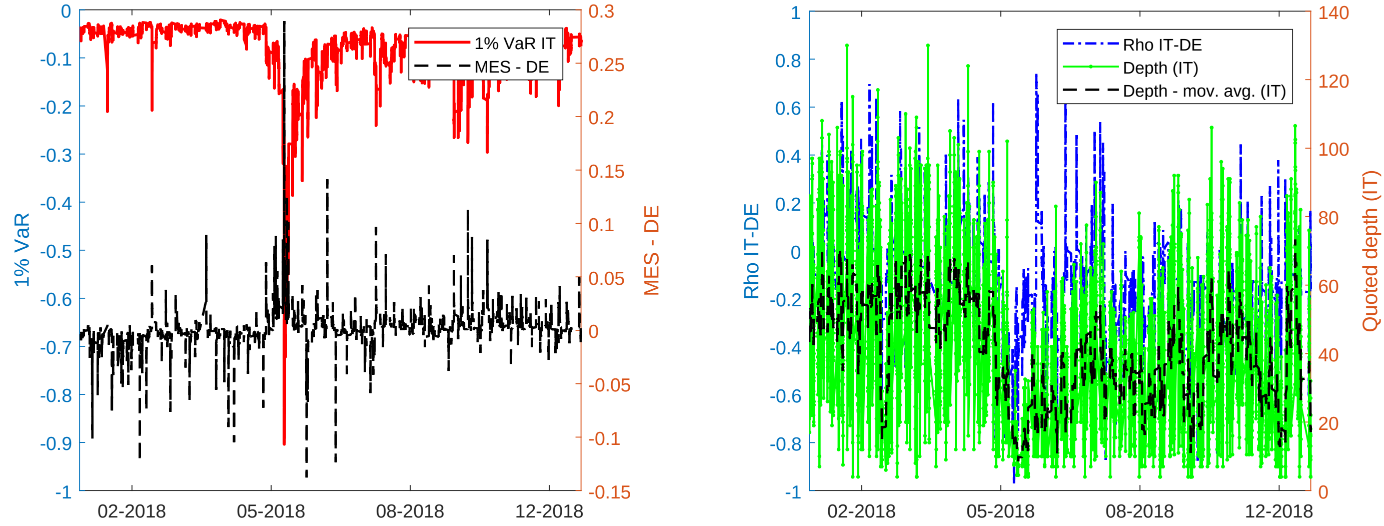
Figure 16: **Mid prices of 2- and 5-year Italian benchmark bonds**



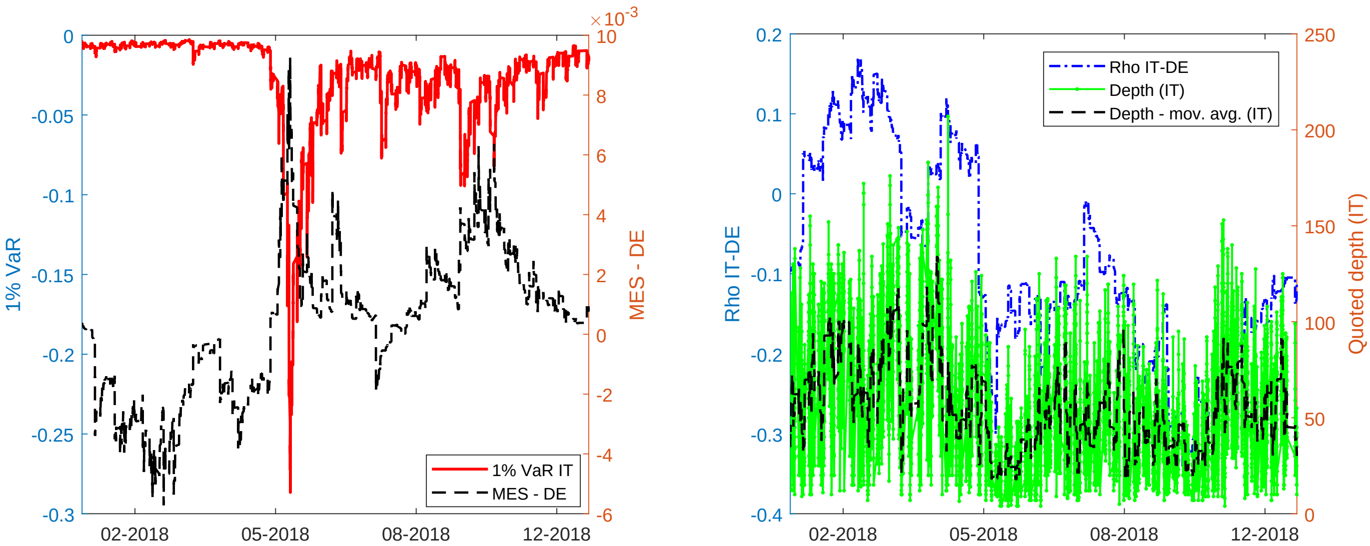
This figure displays intra-day (15-minute interval) mid prices of Italian (IT) benchmark bonds in the 2011-12 and 2018 samples.

Figure 17: **Italian VaR, Depth and German MES with 2-year and 5-year benchmark bonds**.

(a) **5-year maturity**



(b) **2-year maturity**



Note: This figure displays 1% VaR of the Italian benchmark returns (left), the MES of the German returns (left), the DCC GARCH-implied conditional correlation (right) and the quoted depth (both at intraday and daily frequency; right) computed with 2-year (panel a) and 5-year (panel b) benchmark bonds in the 2018 sample.

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