J. Int. Financ. Markets Inst. Money 90 (2024) 101892

Contents lists available at ScienceDirect

Journal of International Financial Markets, Institutions & Money

journal homepage: www.elsevier.com/locate/intfin

# New insights into liquidity resiliency[☆]

Conall O'Sullivan [a,1], Vassilios G. Papavassiliou [a,*,1,2], Ronald Wekesa Wafula [a,1], Sabri Boubaker [b,3,4]

[a] University College Dublin, Ireland
[b] EM Normandie Business School, Métis Lab, France

ARTICLE INFO

*JEL classification:*
C5
G01
G10
G15

*Keywords:*
Resiliency
Liquidity
Sovereign bond markets
LASSO
High-frequency data
Market microstructure

ABSTRACT

In this study we offer fresh insights into liquidity resiliency. We empirically study the resiliency of the euro area sovereign bond market across the maturity spectrum. We measure resiliency using a standard Ordinary Least Squares regression approach, along with the least absolute shrinkage and selection operator (LASSO) machine learning approach. We find both spread-based and depth-based resiliency are negatively correlated with spreads and positively correlated with depths. Moreover, we study the interrelationships among resiliency, volatility, returns, and credit default swap (CDS) spreads. Lastly, we document strong commonalities in resiliency for core and periphery euro area markets in both calm and turbulent periods.

## 1. Introduction

The importance of market liquidity as a characteristic and as a risk factor in international financial markets is well known to academics and practitioners and has been highlighted in numerous studies over the years. Liquidity is an elusive concept and is loosely defined as the ease with which transactions occur in the marketplace with little impact on prices. Market liquidity is multidimensional thus it needs to be approached and measured carefully using appropriate methods and tools.

Borio (2000) argues that liquidity has four separate dimensions. *Tightness*, denotes the difference between buy and sell prices and is widely represented by the bid–ask spread. *Depth* relates to the quantity/size of transactions in financial markets. *Immediacy* refers to the speed with which transactions are executed. Finally, *resiliency* refers to the ease with which prices revert to their normal levels

☆ We are grateful to the Editor, Professor Jonathan Batten, and two anonymous referees for their constructive comments and suggestions. We would like to thank Botao Wu, Sebeom Oh, and conference participants at the Annual Financial Market Liquidity Conference 2022 in Budapest, Hungary, and at the First Annual Meeting of the International Society for the Advancement of Financial Economics (ISAFE-2022) in Ho Chi Minh City, Vietnam. O'Sullivan would like to acknowledge the support of New York University (NYU) Tandon's Finance and Risk Engineering department for granting access to the Markit database. Papavassiliou would like to acknowledge the support of University College Dublin, Ireland for financial assistance under grant numbers SF1258 and R18254. All errors remain our own.

* Corresponding author.

*E-mail addresses:* conall.osullivan@ucd.ie (C. O'Sullivan), vassilios.papavassiliou@ucd.ie (V.G. Papavassiliou), ronald.wafula@ucdconnect.ie (R.W. Wafula), sboubaker@em-normandie.fr (S. Boubaker).

[1] UCD Michael Smurfit Graduate Business School, Carysfort Avenue, Blackrock, Co Dublin, Ireland.
[2] UCD Geary Institute for Public Policy.
[3] International School, Vietnam National University, Hanoi, Vietnam.
[4] Swansea University, Swansea, United Kingdom.

https://doi.org/10.1016/j.intfin.2023.101892
Received 8 February 2023; Accepted 23 November 2023
Available online 25 November 2023

after temporary order imbalances (a discussion on the measurement of the multi-faceted dimension of liquidity in financial markets is provided by Diaz and Escribano (2020). Although we know enough about the first three dimensions of liquidity (especially about the tightness and depth dimension), we know very little about resiliency which has been neglected by the academic community. This study is devoted to liquidity resiliency and aims at offering new insights into the features, characteristics, and workings of market liquidity resiliency.

The investigation of resiliency is particularly important during periods of market stress where liquidity can evaporate quickly and can cause adverse contagion effects across different markets and asset classes and thus adversely affect financial stability. Thus, being able to measure the speed at which liquidity can revert to its long term equilibrium value after a financial shock is of paramount importance not only for market participants and investors who face significant execution and price risk, but also for policymakers and regulators who assess the resilience of the economy and financial system and take remedial actions when needed. Understanding resiliency is also important for stock exchanges and trading platforms that need to know the replenishment mechanism of the order book in order to be able to compete for liquidity. As Bhattacharya and Spiegel (1998) argue, the ability of a stock exchange to absorb unusual volatility, which may arise from order imbalances, impending news announcements or other triggers, without closing down should constitute a legitimate metric for liquidity.

Resiliency is directly linked to the notion of liquidity uncertainty. During periods of market stress there is a greater degree of uncertainty and trading volume decreases for a large group of assets, including sovereign bonds (the drop in trading volumes can also be associated with the possibility of "liquidity black holes" discussed by Moorthy (2003)). Easley and O'Hara (2010) use a model of Knightian uncertainty proposed by Bewley (2002)to explain the "uncertainty bid–ask spread" that allows traders to improve their rank-ordering of alternative portfolios in the light of uncertainty. Similar explanations are provided by Routledge and Zin (2009) and Ozsoylev and Werner (2011) who suggest a widening of bid–ask spreads in the face of uncertainty would take place to reduce the likelihood of trading. That is, whenever an asset's trading volume drops it is expected that traders will strive to widen the bid–ask spread following an increase in uncertainty.

Rehse et al. (2019) provide empirical support to those theoretical predictions concluding that gains from trading drop during periods of uncertainty and the overall welfare lowers amid wider bid–ask spreads, i.e. lower liquidity. The authors argue that uncertainty can be seen as a determinant of liquidity commonality as studied by Karolyi et al. (2012), among others. This argument is confirmed by Chung and Chuwonganant (2014) who show that market uncertainty exerts a large market-wide impact on liquidity, which gives rise to co-movements in individual asset liquidity. Vayanos (2004) and Brunnermeier and Pedersen (2009) argue that liquidity can dry-up as a result of flight-to-quality effects, during which liquidity providers become more risk averse and rebalance their positions towards assets with low levels of uncertainty. The aforementioned studies indicate that resiliency as a stand-alone liquidity dimension is affected by market uncertainty justifying the choice of our selection to use the European sovereign debt crisis period for our experiments.

Our study contributes to the literature in a number of ways. First, we empirically study the resiliency of the euro area sovereign bond market. Previous studies have mainly focused on stock markets (for instance, Bhattacharya and Spiegel, 1998 study the resiliency of the NYSE stock market, Coppejans et al. (2004) investigate the resiliency of the Swedish stock index futures market, and Degryse et al. (2005) study the resiliency of the Paris Bourse) whilst bond markets remain unexplored with regard to liquidity resiliency. Given the different features of bonds compared to those of stocks, it remains to be seen whether findings from stock markets carry over to the bond market. Generally speaking, bond market investors are characterized by higher sensitivity to downside risk than stock market investors, and thus a liquidity premium would be required as compensation (Bai et al., 2016; Kinateder and Papavassiliou, 2019). The euro area bond market although integrated due to participation in the Economic and Monetary Union (EMU) is a market that consists of countries with different credit risk characteristics, thus liquidity is dispersed and the study of resiliency becomes even more important than in other bond markets, such as the U.S. Treasury market.[5]

Second, we define resiliency as the rate of mean reversion in liquidity and measure it using two different methodological approaches: the first being an Ordinary Least Squares regression (OLS) approach, while the second being a combination of an OLS approach and the least absolute shrinkage and selection operator (LASSO) machine learning approach. Our definition of resiliency is in line with the works of Kyle (1985), Harris (2002), Degryse et al. (2005), and Large (2007), among others. Our empirical approach to measure resiliency as the rate of mean reversion in liquidity is in agreement with previous works by Dong et al. (2007) who employ a pricing-error process to estimate resiliency and Kempf et al. (2015) who study the resiliency of the electronic order book of the London Stock Exchange. The LASSO approach has been previously used as a variable selection technique in applications that range from statistical arbitrage to corporate bankruptcy forecasts and asset pricing (Tian et al., 2015; Huck, 2019; Chinco et al., 2019; Freyberger et al., 2020; Feng et al., 2020). We separately estimate and compare spread-based resiliency constructed using relative spread liquidity proxies and depth-based resiliency constructed using quoted depth liquidity proxies. Our findings provide evidence that the two aforementioned methods can be used interchangeably in the measurement of market resiliency regardless of whether resiliency is estimated in terms of spreads or depths.

[5] The euro area sovereign bond market is one of the world's largest capital markets. According to the Association for Financial Markets in Europe (AFME), the total quarterly issuance in Europe (EU member states, UK and EU commission) was EUR 814 billion during Q4 2022. The average daily trading volume in the eurozone (bonds and bills) during 2022 was EUR 107 billion. The total traded notional value by EU sovereign issuer in 2022 reached 29% for Germany, 28% for Italy, 22% for France, 8% for Spain, and 3% for the Netherlands (International Capital Market Association (ICMA), Secondary Market Practices Committee, European Secondary Bond Market Data, 2022). Due to the bond market's sheer size and importance, this study will provide enlightening insights on the workings of bond market liquidity resiliency.

Third, we focus our empirical analysis on a detailed high-frequency dataset from the MTS markets, in contrast to earlier studies that have used datasets of lower sampling frequencies, such as daily or monthly (Bhattacharya and Spiegel, 1998). The advantages of using high-frequency data have been highlighted in the related literature and extend from statistical gains to higher predictive accuracy, among other things (see Gargano et al., 2019 for a discussion). Moreover, the use of high-frequency data enables the construction of more accurate microstructure-based liquidity measures (as well as more accurate return and volatility measures) that are able to capture multiple liquidity dimensions, and thus of paramount importance for the study of liquidity resiliency.

Fourth, we investigate liquidity resiliency in core (Germany and the Netherlands) and periphery (Italy and Spain) euro area bond markets during both tranquil and crisis periods. During the euro area sovereign debt crisis, the liquidity of periphery bond markets was significantly impaired as opposed to liquidity levels of core euro area countries (see discussions by Beetsma et al., 2013; Pelizzon et al., 2016; Schneider et al., 2016; O'Sullivan and Papavassiliou, 2020). Therefore it is very important to gain insights on resiliency across core and periphery countries and during crisis and calm periods, as resiliency's behaviour depends on the state of the economy (see Ali Nasir, 2022 for a discussion of the impact of financial crises on European financial markets).[6] As an example, Félez-Vinas (2019) highlights the adverse effects on resiliency as a result of episodes of liquidity dry-ups during times of stress which is increasingly relevant for regulators and policymakers. We also condition for time-to-maturity as resiliency levels may differ across the various segments of the yield curve. Along these lines we employ benchmark securities of 2-, 5-, 10-, and 30-year maturity thus capturing the full maturity spectrum of the euro area yield curve. Fifth, we explore the intertemporal associations among resiliency, volatility, returns, and credit default swap (CDS) spreads for the first time in the literature using Granger causalities and impulse response functions. Finally, our paper investigates the presence of common factors in liquidity resiliency of the euro area sovereign bond market offering interesting new insights.

Our main findings can be summarized as follows. We find that quoted depth resiliency increases (to a larger extent than relative spread resiliency) as we move from short-term to long-term maturity bonds, especially in the pre-crisis period. Previous findings show that the liquidity premium increases with maturity which is in line with our findings that spreads widen and depths fall as we move up the maturity spectrum. However, the fact that long-term maturity bonds have higher quoted depth resiliency means that this overlooked dimension of liquidity actually improves with maturity. Both spread-based and depth-based resiliency is negatively correlated with spreads and positively correlated with depths, confirming previous findings from the stock market (Kempf et al., 2015). Correlations among spread, depth, and resiliency liquidity measures are very small in absolute terms indicating that the information contained in resiliency is unique, thus rendering resiliency nearly independent from the other two liquidity dimensions. The magnitude of these correlations does not dramatically change during the crisis period indicating that resiliency remains relatively stable regardless of the state of the economy.

We also document strong bidirectional causalities between resiliency and sovereign credit risk, volatility, and sovereign bond returns, providing evidence that liquidity resiliency is a priced variable. Lastly, we document strong commonalities in spread-based and depth-based resiliency in both pre-crisis and crisis periods. Commonality of core countries is lower than that of periphery countries during the crisis period. Commonality slightly increases for core countries in the crisis whilst it declines for periphery countries. Interestingly, commonality in spread-based resiliency is stronger than commonality in depth-based resiliency in both core and periphery countries and during calm and crisis periods.

The rest of the paper is organized as follows. Section 2 presents the related literature. Section 3 discusses the methods used to empirically estimate resiliency. Section 4 describes the dataset. Section 5 presents and discusses our empirical findings. Finally, Section 6 concludes the paper.

## 2. Related literature

The topic of financial market liquidity resiliency has been neglected in the empirical literature. The seminal paper of Garbade (1982) defines resiliency as the order replenishment process through which new orders arrive into the market in response to temporary order imbalances. Kyle (1985) argues that market liquidity encompasses a number of transactional properties of market, i.e. tightness, depth, and resiliency. He defines the latter as the speed with which prices recover from a random uninformative shock. This interpretation is more recently used by Obizhaeva and Wang (2013) who define market resiliency as the speed at which supply or demand (proxied by price of assets) in the markets converge or recover to their new steady state.

Bhattacharya and Spiegel (1998) investigate market resiliency around stock exchange suspensions and find that, on the one hand, there is great substitutability among the various liquidity dimensions, and on the other hand, the resiliency of an exchange can be improved following regulatory changes that would enable an exchange to absorb large and unusual volatility shocks over time. Harris (2002) defines resiliency as the process through which prices revert to former levels after a shock in response to large order flows. He argues that a market is resilient when it is impossible for uninformed traders to substantially affect market prices.

[6] Although the sovereign debt crisis of 2009/12 was the most severe crisis in Europe and it offers a perfect laboratory to study the unique properties and features of liquidity resiliency, we also experimented with the Brexit, Russian-Ukraine war, and COVID-19 stress episodes. Brexit's impact on euro area sovereign bond markets was negligible. The euro area bond market's initial response to Russia's invasion was swift and government yield curves shifted upward, however, the duration of the financial shock was much shorter and of a much lower magnitude than that of the sovereign debt crisis. Also, the liquidity deterioration during the COVID-19 outbreak was not as severe as the liquidity deterioration during the euro area sovereign debt crisis period. The ECB's response was speedy and sizable as, building on the experiences from the sovereign debt crisis of 2009/12, Europe was better prepared to deal with a new crisis. We find that resiliency measures, on average, exhibit the same properties as those reported in Tables 1–4, however, the level of deterioration of resiliency was much smaller than that of the sovereign debt crisis.

**Table 1**
Descriptive statistics.

| Panel A: OLS-based resiliency | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Relative Spread Resiliency | | | | Relative Spreads (bps) | | | |
| Maturity | Period | DE | NL | IT | ES | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.211 | 0.215 | 0.259 | 0.236 | 8.310 | 7.975 | 7.364 | 18.012 |
| | Crisis | 0.203 | 0.239 | 0.188 | 0.210 | 5.480 | 5.682 | 24.668 | 47.313 |
| 5-Year | Pre-crisis | 0.246 | 0.244 | 0.224 | 0.237 | 9.401 | 15.622 | 19.868 | 29.024 |
| | Crisis | 0.225 | 0.261 | 0.257 | 0.251 | 7.580 | 14.283 | 36.466 | 74.672 |
| 10-Year | Pre-crisis | 0.280 | 0.250 | 0.265 | 0.267 | 11.661 | 18.973 | 23.826 | 34.497 |
| | Crisis | 0.243 | 0.285 | 0.316 | 0.283 | 8.651 | 15.523 | 31.656 | 58.319 |
| 30-Year | Pre-crisis | 0.247 | 0.255 | 0.294 | 0.292 | 57.830 | 58.023 | 60.577 | 77.113 |
| | Crisis | 0.243 | 0.301 | 0.275 | 0.281 | 41.820 | 34.141 | 86.710 | 158.132 |
| Panel B: LASSO-based resiliency | | | | | | | | | |
| | | Relative Spread Resiliency | | | | Relative Spreads (bps) | | | |
| Maturity | Period | DE | NL | IT | ES | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.269 | 0.646 | 0.535 | 0.557 | 8.310 | 7.975 | 7.364 | 18.012 |
| | Crisis | 0.264 | 0.695 | 0.534 | 0.479 | 5.480 | 5.682 | 24.668 | 47.313 |
| 5-Year | Pre-crisis | 0.287 | 0.636 | 0.474 | 0.581 | 9.401 | 15.622 | 19.868 | 29.024 |
| | Crisis | 0.250 | 0.686 | 0.489 | 0.516 | 7.580 | 14.283 | 36.466 | 74.672 |
| 10-Year | Pre-crisis | 0.294 | 0.641 | 0.440 | 0.563 | 11.661 | 18.973 | 23.826 | 34.497 |
| | Crisis | 0.280 | 0.692 | 0.486 | 0.511 | 8.651 | 15.523 | 31.656 | 58.319 |
| 30-Year | Pre-crisis | 0.264 | 0.643 | 0.492 | 0.571 | 57.830 | 58.023 | 60.577 | 77.113 |
| | Crisis | 0.283 | 0.694 | 0.504 | 0.515 | 41.820 | 34.141 | 86.710 | 158.132 |

*Notes*: Panel A shows the mean OLS-based relative spread resiliency along with relative spreads (in basis points) for Germany (DE), Netherlands (NL), Italy (IT), and Spain (ES). Relative spread is defined as the best bid–ask spread divided by the midpoint of the bid and ask quotes. The OLS-based relative spread resiliency is estimated according to Eq. (2). The pre-crisis period spans the dates from January 2008 to October 2009 whilst the crisis period extends from November 2009 to December 2013. We use benchmark securities across four maturity segments, i.e. 2-, 5-, 10-, and 30-year maturity. Panel B shows the corresponding statistics for the LASSO-based relative spread resiliency which is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The liquidity measures have been winsorized by 95% in order to avoid extreme values in the resiliency estimates.

Coppejans et al. (2004) use a dataset from the Swedish stock index futures market and show that shocks to liquidity dissipate quickly, indicating a high degree of resiliency. Degryse et al. (2005) define resiliency as the speed of recovery of the market after a shock, defined as a trade that increases the bid–ask spread. They relate resiliency to the state of the market and firm attributes such as tick size and market capitalization.

In a theoretical study, Foucault et al. (2005) propose conditions under which resiliency is high. They find that liquidity resiliency increases with the increase in patient traders and reduces on the reduction of tick size. Dong et al. (2007) rely on Kalman-filter estimation techniques to empirically estimate resiliency for a selection of 100 NYSE stocks. They show that resiliency is determined by trading activity, information asymmetry, tick size, and intraday volatility and these attributes exhibit the expected sign in relation to resiliency. Large (2007) measures resiliency using a dynamic model of the limit order book activity which takes the form of a multivariate continuous time point process with an adapted intensity. It actually categorizes event types following Biais et al. (1995), in order to distinguish resiliency events and the shocks that precede them from other orders. Using a London Stock Exchange electronic limit order book, the author manages to quantify the resiliency of the limit order book in three respects: its magnitude, delay, and trade direction.

Kempf et al. (2015) find that resiliency increases with the proportion of patient traders, decreases with the order arrival rate, and increases with tick size, supporting the theoretical predictions of Foucault et al. (2005). They also show that high-frequency trading can lead to higher market resiliency, however, in times of high volatility the beneficial effects of high-frequency trading on resiliency are lowered. Gomber et al. (2015) employ intraday event study methods to study how liquidity shocks affect the cost of a roundtrip trade of given size which they call Exchange Liquidity Measure (XLM). They find that resiliency is higher after large transactions as opposed to being lower after smaller transactions. That is, when resiliency is high, liquidity reverts back to normal levels more quickly than when resiliency is low.

Bessembinder et al. (2016) consider the role of market resiliency in extending the theory of strategic trading around a predictable liquidation. Empirical evidence implies that traders prefer to supply liquidity in resilient markets rather than exploit predictable trades. Danielson et al. (2018) measure resiliency using the idea of the Threshold Exceedance Duration (TED), defined as the length of time between the point at which liquidity deviates from a specified threshold and the first point in time at which it reverts back to at least that level. Félez-Vinas (2019) analyses the impact of market fragmentation on resiliency, which she defines as the speed of recovery of the market, in normal conditions and in times of stress. The author finds that fragmentation has a positive effect on resiliency as it increases the market's ability to converge towards its long-run liquidity levels. Kim and Kim (2019) use the Beveridge–Nelson decomposition and the spectral analysis in the frequency domain to measure the resiliency of the stocks listed on the NYSE, AMEX and NASDAQ stock exchanges during the period 1964 to 2013.

Griffith and Roseman (2019) and Ibikunle et al. (2021) also measure resiliency as an asymmetric mean-reversion process in an effort to examine the effects of an increase in the minimum price variation on limit order book liquidity in NASDAQ-listed stocks, as well as the effects of dark trading restrictions on liquidity and informational efficiency. Hua et al. (2020) propose a resiliency covariance-based measure that encompasses both the price impact of a liquidity shock and its persistence. Lower values of such resiliency measure are associated with higher expected returns. Clapham et al. (2020) measure order book resiliency using a regression approach which relates post-event changes in spreads and depth to the specific net liquidity provision of groups of traders following a market impact event. Their results show that spread-based resiliency is accomplished by high-frequency traders who are able to replenish the top of the order book within 5 seconds after the market impact event. Roşu (2020) finds that informed trading in limit order markets improves liquidity resiliency and the bid–ask spread. Broto and Lamas (2020) propose a new approach to analyse resiliency which is based on liquidity volatility. Liquidity resiliency has deteriorated after the global financial crisis and spillovers from liquidity volatility to returns volatility have intensified.

Batten et al. (2022) use the aggregate liquidity proxy of Pástor and Stambaugh (2003) to estimate the resiliency of the S&P 500 index from 1990 to 2018. This measures the speed with which prices recover from a previous day's order flow shock. Fishe et al. (2022) examine market resiliency of E-mini futures by focusing on the timing of new order decisions after an execution removes quantity from the order book. Tang et al. (2022) find that financial market and institution development, as well as the depth of financial markets are beneficial to the improvement of resiliency.

Most of this literature examines liquidity resiliency from a theoretical perspective with empirical applications in stock or futures markets. In contrast to these papers, our study focuses on the empirical estimation of liquidity resiliency in the euro area government bond market. Along with extending the measurement of liquidity resiliency to another asset class, this also allows us to measure how resiliency is affected by extreme market uncertainty as our data period includes the euro area sovereign debt crisis. Our work also complements the literature on the use of machine learning applied to market microstructure research. Given the recent advances in financial technology (FinTech) market microstructure needs to evolve and machine learning techniques can play an important role in that evolution (Easley et al., 2021). Our proposed methodological approach has enabled us to provide a comparison of resiliency across countries with different credit risk characteristics and during normal and stressed time periods, thus offering useful insights for policy.[7] Also, our study complements previous literature on central limit order book markets (Degryse et al., 2005; Kempf et al., 2015; Danielson et al., 2018), those with a similar structure to that of MTS bond markets, in which trading is anonymous and primary dealers play an important role in specifying prices and quantities and in promoting liquidity.

## 3. Methods

In this paper we define resiliency as the rate of mean reversion in liquidity. We use the two main liquidity dimensions to measure resiliency, tightness and depth. That is, we measure the extent of deviations of liquidity, either spread-based or depth-based, from its long-term value that is eventually offset by net liquidity flows over the next time period. The long-run equilibrium liquidity is proxied by a time-varying average level of liquidity and resiliency is the rate of mean reversion around this level of liquidity. We consider the relative spread and the quoted depth measures to proxy for liquidity of all benchmark bonds in our sample, following O'Sullivan and Papavassiliou (2019, 2020).

We take two separate methodological approaches to empirically estimate resiliency. Our first approach is similar to that of Kempf et al. (2015). We model the relationship between past liquidity levels $L_{t-1}$ and current liquidity flows $\Delta L_t = L_t - L_{t-1}$ as a mean reversion model of the form:

$$\Delta L_t = \kappa \left(\varphi - L_{t-1}\right) + \varepsilon_t \tag{1}$$

where $\varphi$ denotes liquidity's long-run value, $\kappa$ is the speed of adjustment to liquidity's long-run value which measures the level of resiliency, and $\varepsilon_t$ is a normally distributed white noise error term. Other things being equal, the higher the speed of adjustment $\kappa$ the higher the resiliency, which translates into liquidity improvements.

Empirically, liquidity is persistent (Chordia et al., 2000; Hasbrouck and Seppi, 2001). To account for serial correlation in the residuals we include past liquidity changes as additional explanatory variables in the model. Using the Akaike information criterion (AIC) we find that the inclusion of three lags is adequate to remove serial correlation in the model's residuals. In doing so, we eliminate possible bias in the estimation of resiliency as denoted by parameter $\kappa$. For each country's benchmark bonds we estimate the following model for each trading day using 5-min frequency liquidity data:

$$\Delta L_{i,t}^{S/D} = \alpha_{i,T}^{S/D} - \kappa_{i,T}^{S/D} L_{i,t-1}^{S/D} + \sum_{\tau=1}^{3} \psi_{i,t-\tau}^{S/D} \Delta L_{i,t-\tau}^{S/D} + \varepsilon_{i,t}^{S/D} \tag{2}$$

where $S/D$ indicates whether liquidity is proxied via the relative spread $(S)$ or the quoted depth $(D)$, and $t$ denotes the time index of day $T$.

[7] An interesting discussion of the impact of crisis periods on the sovereign bond market is provided by Ali Nasir et al. (2023).

Our second methodological approach to measuring liquidity resiliency is a two-stage regression approach that uses the LASSO model. To the best of our knowledge this is the first attempt in the related literature to empirically estimate resiliency using the LASSO method. The LASSO is a machine learning modelling technique that has become quite popular in recent years further to advances in financial technology (FinTech) applications. It was first introduced by Tibshirani (1996) and since then it has been used as an attractive technique for regularization and variable selection for high-dimensional data (see papers by Fan and Peng, 2004 and Bickel et al., 2009 for a discussion on the LASSO's theoretical properties).

Estimating the regression coefficients in a linear regression model using the LASSO, involves minimizing an objective function that includes a $L^1$ regularization term that tends to shrink the number of features. LASSO is used as a variable selection method as it penalizes the sum of the absolute values of the regression coefficients, forcing the shrinkage of certain coefficients and thus acting as a variable selection process.

Consider data of the form $\left(X^i, y_i\right)$, $i = 1, 2, \ldots, N$, where $X^i = \left(x_{i1}, \ldots, x_{ip}\right)^T$ are the predictor variables and $y_i$ are the response variables for the $i$th observation. Assuming that the observations are independent as in standard regression models, we standardize the $x_{i,j}$ by subtracting the mean and dividing by the standard deviation. Denoting $\hat{\beta} = \left(\hat{\beta}_1, \ldots, \hat{\beta}_p\right)^T$ the LASSO estimate $\left(\hat{\alpha}, \hat{\beta}\right)$ is defined by:

$$\left(\hat{\alpha}, \hat{\beta}\right) = arg\ min\left\{\sum_{i=1}^{N}\left(y_i - \alpha - \sum_j \beta_j x_{ij}\right)^2\right\} \tag{3}$$

subject to $\sum_j \left|\beta_j\right| \le t$. The term $t \ge 0$ is a tuning parameter that controls the amount of shrinkage that is applied to the estimates. Let $t_0 = \sum \left|\hat{\beta}_j^o\right|$ where $\hat{\beta}_j^o$ denotes the full least squares estimates. Values of $t < t_0$ will cause shrinkage of the solutions towards 0 with some coefficients taking on 0 values, thus being able to select and use a smaller subset of predictors from a larger pool of predictors that exhibit the strongest effects.

We take a two-step process to measuring liquidity resiliency. In the first step, we use the LASSO as a purification tool that enables us to get more refined relative spread and quoted depth liquidity measures. We run the LASSO model for all four maturity segments (2-, 5, 10-, and 30-year benchmark bonds) for the period running from January 2008 to December 2013. We use the following regressors in the LASSO model: 5-min relative spreads, 5-min quoted depths, 5-min returns, and 5-min squared returns (variances) with 3 lags each. The 5-min intervals are artificially constructed using linear interpolation methods. In total, we use 48 regressors (4 regressors across 4 maturities with 3 lags each) whilst we use either relative spreads or quoted depths from a single bond as the dependent variable. We use lags of spreads and depths as regressors in order to account for autoregressive effects in liquidity. We use returns and squared returns as regressors due to the strong bi-directional causalities that exist between them and liquidity. Previous studies show that the effects of liquidity on asset prices are statistically and economically significant (Amihud et al., 2005). The relationship between liquidity and volatility is also well documented. The higher the liquidity, the lower the price volatility, others things being equal (Bessembinder and Kaufman, 1997; Chordia et al., 2001, 2002). In our case, the 5-min squared returns proxy for volatility (variance) following the realized volatility literature (Andersen and Bollerslev, 1998).

We use the LASSO's residuals as filtered relative spread and quoted depth liquidity measures that are used as model inputs in the second step to estimate resiliency. The residuals from the LASSO relative spread and quoted depth measures are orthogonalized to lagged independent variables that the LASSO deems to be important in predicting the liquidity measures at the 5-min horizon. These residuals then represent the unpredictable changes in the liquidity measures.

In a second step, the LASSO's residuals are fed into Eq. (2) and recursive regressions are run for each trading day within our sample, yielding daily spread-based and depth-based liquidity resiliency measures across all four maturity segments for all countries. That is, the LASSO is not directly used to measure resiliency, but instead is used as a useful purification tool that yields more refined spread-based and depth-based liquidity proxies. In the sections that follow we analyse and compare the two resiliency measures, showing that they can be used interchangeably in the measurement of liquidity resiliency regardless of whether they are constructed in terms of spreads or depths.

## 4. Data

We employ a rich high-frequency dataset provided by MTS (Mercato dei Titoli di Stato), Europe's premier interdealer electronic fixed-income market for euro-denominated government bonds. MTS group counts to over 500 counterparties and 2,000 traders trading an average trading volume exceeding EUR 130 billion across all MTS platforms. Our dataset spans the dates from January 2008 to December 2013 and includes a tranquil period (January 2008 to October 2009) and a crisis period (November 2009 to December 2013).[8] It consists of the following core and periphery countries: Austria, Belgium, Finland, France, Germany, Greece,

[8] The U.S. global crisis did not have a significant impact on euro area sovereign bond markets, as discussed in Dellas and Tavlas (2013) and O'Sullivan and Papavassiliou (2020), justifying our selection to use the period January 2008 until October 2009 as the pre-crisis sample. We consider November 2009 as the beginning of the European sovereign debt crisis in line with Claeys and Vašíček (2014), De Santis (2014), and O'Sullivan and Papavassiliou (2020). It is a well-known fact that the crisis peaked between 2010 and 2012 and it took more than two years for the crisis to subside in 2013. It was a lengthy and severe financial crisis that exacerbated investor anxiety due to Europe's failure to act decisively during the crisis.

Ireland, Italy, Netherlands, Portugal, and Spain. It contains the three best bid and ask quotations throughout each trading day, time-stamped to the nearest second.

We focus on benchmark fixed coupon-bearing government bonds from the domestic MTS markets across four time-to-maturity segments: 2-, 5-, 10-, and 30-year, similar to O'Sullivan and Papavassiliou (2020, 2021). We have discarded quotes recorded outside regular trading hours, i.e. from 8:15 am to 5:30 pm CET, as well as pre-sessional and end-of-day quotations and quotes with zero and negative bid–ask spreads.

We artificially construct relative spread and quoted depth liquidity measures following O'Sullivan and Papavassiliou (2020): relative spread is defined as the best bid–ask spread divided by the midpoint of the bid and ask quotes, whilst quoted depth is defined as best bid size plus best ask size, where size denotes the quantity of securities bid or offered for sale at the posted bid and ask prices. We prefer to use midpoints of bid–ask quotes instead of transaction prices in order to avoid bid–ask bounce effects (Bandi and Russell, 2006). We also winsorize our liquidity measures by 95 percent in order to weed out the morning and afternoon spikes and thus avoid extreme values in our resiliency estimates.[9] We also impose a non-negativity truncation on the resiliency measurements to avoid resiliency taking on negative values.

We construct 5-min returns from the midpoint of the continuously recorded bid and ask quotes and daily realized volatility measures for each benchmark security by the summation of squared 5-min intraday returns (Andersen and Bollerslev, 1998; Andersen et al., 2001). Our empirical analysis places emphasis on Germany (DE) and the Netherlands (NL) as two representative markets from the core eurozone region, and Italy (IT) and Spain (ES) as the two most liquid markets in the periphery euro area region. We also obtain sovereign credit default swap (CDS) spreads for all countries in our sample at all four maturities from Markit.

## 5. Empirical findings and discussion

In Section 5.1 we present and discuss descriptive statistics of the OLS and LASSO-based resiliency measures. In Section 5.2 we use Vector Autoregression Analysis (VAR) to study the joint dynamics among resiliency, volatility, returns, and credit default swap (CDS) spreads, while in Section 5.3 we study commonality in resiliency.

### *5.1. Descriptive statistics*

Table 1 displays the mean relative spread resiliency for Germany (DE), Netherlands (NL), Italy (IT), and Spain (ES) across the 2-, 5-, 10-, and 30-year maturity segments during both pre-crisis (January 2008 until October 2009) and crisis periods (November 2009 until December 2013). Panel A of Table 1 shows the OLS-based relative spread resiliency estimates, whilst Panel B shows the corresponding estimates using the combined approach that includes the LASSO model. The table also displays the mean values of the conventional relative spread liquidity measures in order to facilitate discussion. The following observations are apparent. First, with regard to resiliency, there is a clear liquidity deterioration for Germany in the crisis, as both resiliency estimates drop from their pre-crisis levels, however, conventional relative spreads for Germany are lower in the crisis relative to their pre-crisis values indicating that liquidity is improved for German bonds as they benefit from their safe haven status.

The results concerning Dutch resiliency are more clear-cut as resiliency clearly increases in the crisis across both ends of the yield curve, indicating that liquidity improved for the Dutch market. This finding is in agreement with the drop in Dutch relative spreads during the euro area crisis which denotes increases in liquidity. Relative spreads for Italy and Spain increase significantly during the crisis confirming previous findings that periphery countries experienced major liquidity dry-ups due to flight-to-liquidity and flight-to-quality effects (O'Sullivan and Papavassiliou, 2020). It appears that resiliency for Spain drops consistently across the maturity spectrum in the crisis, especially for the LASSO-based resiliency, confirming the drop in relative spreads. Results for Italy are mixed, as it appears that the short 2-year and the longer term 30-year benchmarks were more vulnerable than their 5- and 10-year counterparts as their liquidity resiliency was adversely affected during the crisis. Fig. 1 provides a visual illustration of the LASSO-based relative spread resiliency for all four countries.

Table 2 displays the mean quoted depth resiliency along with conventional quoted depth liquidity measures. There is clear evidence of resiliency deterioration during the crisis for Germany and Spain, which is also reflected in the lower quoted depth liquidity for all maturities. Results for the Netherlands and Italy are less clear-cut. Resiliency levels clearly increase for the Dutch market for all benchmarks although quoted depth drops for the medium-term bonds. On the other hand, the Italian medium-term bonds exhibit higher resiliency in the crisis than the 2- and 30-year bonds, however, the 30-year bond resiliency levels remain unchanged in the crisis commensurate with the Italian 30-year benchmark being the most informative and liquid in the eurozone (Dufour and Nguyen, 2013; Papavassiliou and Kinateder, 2021).

Tables 3–4 depict a more detailed one-on-one comparison between OLS and LASSO-based liquidity resiliency. In Table 3, we first note that the mean values of LASSO-based relative spread resiliency are higher than the corresponding values of OLS-based resiliency, regardless of the bonds' maturities. LASSO-based spread resiliency takes on higher maximum and minimum values than those of the OLS-based resiliency. The standard deviation of the OLS-based relative spread resiliency is lower than that of the LASSO-based resiliency in most cases, regardless of maturity and country of origin, showing that OLS estimates yield a less volatile and noisy resiliency measure. OLS-based resiliency is also less serially correlated than the LASSO-based resiliency in most cases, as

[9] We also experimented with a 99% winsorization threshold as well as with no winsorization. Tables A.1–A.4 show descriptive statistics that use these alternative specifications. Our empirical findings do not change dramatically when these alternative specifications are used.

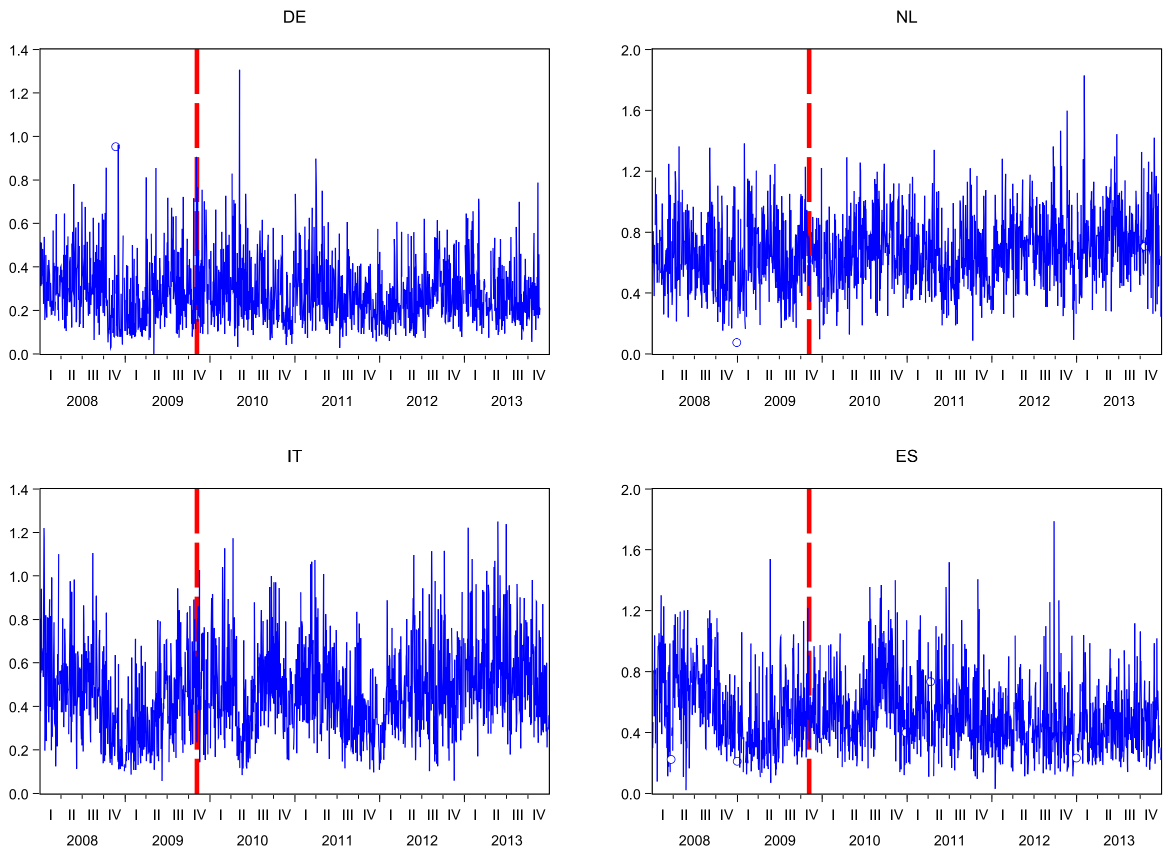


**Fig. 1.** Plotted is LASSO-based relative spread resiliency for the period spanning the dates from January 2008 to December 2013 for the 10-year benchmark bond of the following countries: Germany (DE), Netherlands (NL), Italy (IT), and Spain (ES). Vertical dashed red lines correspond to the start of the crisis period, i.e. November 2009. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

evidenced by Ljung–Box Q tests up to the 12th order. In most cases the Jarque–Bera statistic takes on much smaller values for the LASSO than for the OLS-based resiliency, indicating that the purified LASSO-based resiliency measure is closer to being normally distributed. According to standard ADF unit root tests, all liquidity series are clearly level stationary.

The results shown in Table 4 are mixed, however, we still get liquidity resiliency measures that are highly autocorrelated and stationary at level. Quoted depth resiliency increases as we move from the 2-year shorter term benchmark to the 30-year longer term benchmark, albeit more consistently than relative spread resiliency, especially in the pre-crisis period. Related research by Dick-Nielsen et al. (2012) shows that the liquidity premium increases with maturity, in fact, it can double for long maturity bonds compared to short maturity ones. This liquidity premium compensates investors for bearing securities with higher bid–ask spreads and lower quoted depths. However, it is interesting to note that liquidity resiliency improves with maturity thereby making investments in longer maturity bonds safer when viewed from this dimension of liquidity.

In order to better understand the relationship among spreads, depth, spread resiliency, and depth resiliency we calculate the mean correlations of those measures during calm and crisis periods presented in Table 5.[10] Spreads and depths are negatively correlated with each other as expected, showing that when liquidity improves in the marketplace depth proxies become larger and spreads contract. Spread and depth resiliency, regardless of whether it is estimated using OLS or LASSO-based methods, is negatively correlated with spreads and positively correlated with depths in most cases, as expected. This finding indicates that resiliency becomes higher when the tightness (price) and depth (quantity) dimensions of liquidity are high. These correlations among spread, depth, and resiliency are quite small and hardly exceed 14 percent in absolute terms. This is actually great news for our resiliency measures as it indicates that the information contained in resiliency is unique and cannot be captured by the spread and depth liquidity dimensions.

Correlations between the OLS-based and LASSO-based resiliency measures are also very small and hardly exceed 7 percent in absolute terms, showing that the information contained in each of those measures is unique and is not reflected in the other.

[10] For the sake of space we report correlations of the German 10-year benchmark only, as the correlations of remaining maturities do not differ dramatically from those of the 10-year benchmark. The full set of correlations is available from the authors upon request.

**Table 2**
Descriptive statistics.

| Panel A: OLS-based resiliency | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Quoted Depth Resiliency | | | | Quoted Depth (million €) | | | |
| Maturity | Period | DE | NL | IT | ES | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.333 | 0.435 | 0.469 | 0.453 | 23.134 | 28.044 | 21.636 | 26.924 |
| | Crisis | 0.356 | 0.443 | 0.399 | 0.394 | 18.527 | 28.405 | 20.933 | 22.005 |
| 5-Year | Pre-crisis | 0.441 | 0.497 | 0.507 | 0.561 | 22.513 | 29.788 | 23.850 | 25.619 |
| | Crisis | 0.410 | 0.549 | 0.526 | 0.523 | 19.028 | 26.048 | 24.041 | 19.981 |
| 10-Year | Pre-crisis | 0.413 | 0.482 | 0.524 | 0.555 | 22.898 | 28.338 | 23.251 | 23.908 |
| | Crisis | 0.377 | 0.557 | 0.535 | 0.450 | 18.605 | 23.273 | 19.036 | 16.403 |
| 30-Year | Pre-crisis | 0.428 | 0.636 | 0.504 | 0.587 | 8.804 | 10.767 | 8.716 | 10.201 |
| | Crisis | 0.428 | 0.672 | 0.504 | 0.499 | 7.473 | 11.102 | 11.094 | 9.692 |
| **Panel B: LASSO-based resiliency** | | | | | | | | | |
| | | Quoted Depth Resiliency | | | | Quoted Depth (million €) | | | |
| Maturity | Period | DE | NL | IT | ES | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.318 | 0.508 | 0.483 | 0.442 | 23.134 | 28.044 | 21.636 | 26.924 |
| | Crisis | 0.315 | 0.517 | 0.444 | 0.441 | 18.527 | 28.405 | 20.933 | 22.005 |
| 5-Year | Pre-crisis | 0.337 | 0.563 | 0.515 | 0.533 | 22.513 | 29.788 | 23.850 | 25.619 |
| | Crisis | 0.329 | 0.627 | 0.549 | 0.549 | 19.028 | 26.048 | 24.041 | 19.981 |
| 10-Year | Pre-crisis | 0.356 | 0.539 | 0.521 | 0.527 | 22.898 | 28.338 | 23.251 | 23.908 |
| | Crisis | 0.325 | 0.621 | 0.534 | 0.491 | 18.605 | 23.273 | 19.036 | 16.403 |
| 30-Year | Pre-crisis | 0.331 | 0.651 | 0.506 | 0.623 | 8.804 | 10.767 | 8.716 | 10.201 |
| | Crisis | 0.324 | 0.679 | 0.506 | 0.534 | 7.473 | 11.102 | 11.094 | 9.692 |

*Notes:* Panel A shows the mean OLS-based quoted depth resiliency along with quoted depths (in million €) for Germany (DE), Netherlands (NL), Italy (IT), and Spain (ES). Quoted depth is defined as best bid size plus best ask size, where size denotes the quantity of securities bid or offered for sale at the posted bid and ask prices. The OLS-based quoted depth resiliency is estimated according to Eq. (2). The pre-crisis period spans the dates from January 2008 to October 2009 whilst the crisis period extends from November 2009 to December 2013. We use benchmark securities across four maturity segments, i.e. 2-, 5-, 10-, and 30-year maturity. Panel B shows the corresponding statistics for the LASSO-based quoted depth resiliency which is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The liquidity measures have been winsorized by 95% in order to avoid extreme values in the resiliency estimates.

Interestingly, the magnitude of correlations does not differ substantially between the pre-crisis and the crisis period, indicating that market resiliency is relatively stable over time (also apparent from Tables 1–4). This finding can have important policy implications especially with regard to the speed required for liquidity to revert back to its long-term value after various financial shocks that occur in turbulent periods. The above findings are in agreement with those recorded by Kempf et al. (2015) from the stock market who document a similar relationship among resiliency, spreads, and depths.

### *5.2. Vector Autoregression Analysis*

In this section we use Vector Autoregression Analysis (VAR) to study the joint dynamics and explore the intertemporal associations among resiliency, volatility, returns, and credit default swap (CDS) spreads. It would be of substantial interest to determine the multivariate relationships between resiliency and the latter three variables which have not been explored in earlier literature. Judging from previous research that focused on the spread and depth liquidity dimensions, there is good reason to expect either unidirectional or bidirectional causalities between those measures. Previous research has shown that there is an inverse relationship between liquidity and volatility, that is, during periods of liquidity improvements price volatility decreases, other things being equal (Harris, 1994; Chordia et al., 2001, 2002). Along these lines, Benston and Hagerman (1974) and Duffie et al. (2007) document bidirectional causalities between liquidity and volatility, confirming their inverse relationship which can be due to increased inventory risk.

The relationship between asset prices and liquidity is well documented. Amihud and Mendelson (1986) find bidirectional causalities between liquidity and returns. Liquidity is priced in the marketplace and the effects of liquidity on asset prices are significant from a statistical and economical point of view (Amihud et al., 2005). Liquidity is also closely related to sovereign credit risk especially during periods of stress (Augustin, 2018). It remains to be seen whether the aforementioned relationships carry over to liquidity resiliency.

**Table 3**
Descriptive statistics.

| Panel A: Pre-crisis | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) |
| Mean | 0.269 | 0.211 | 0.646 | 0.215 | 0.535 | 0.259 | 0.557 | 0.236 |
| Max. | 1.365 | 1.305 | 1.406 | 1.108 | 1.242 | 1.110 | 1.330 | 1.144 |
| Min. | 0.020 | 0.001 | 0.113 | 0.001 | 0.092 | 0.001 | 0.019 | 0.001 |
| SD | 0.159 | 0.191 | 0.250 | 0.158 | 0.203 | 0.162 | 0.274 | 0.194 |
| Skew. | 1.410 | 1.788 | 0.324 | 1.874 | 0.437 | 1.491 | 0.441 | 1.481 |
| Kurt. | 7.943 | 7.374 | 2.705 | 8.815 | 3.054 | 6.452 | 2.465 | 5.358 |
| Jarque–Bera | 620.60 | 617.26 | 9.43 | 925.32 | 14.69 | 402.31 | 19.69 | 277.09 |
| Q(12) | 87.10 | 185.91 | 40.67 | 33.84 | 52.64 | 95.81 | 318.54 | 28.03 |
| ADF | −17.83 | −6.41 | −17.07 | −19.78 | −16.95 | −12.58 | −8.39 | −19.47 |
| | 5-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) |
| Mean | 0.287 | 0.246 | 0.636 | 0.244 | 0.474 | 0.224 | 0.580 | 0.237 |
| Max. | 1.630 | 0.945 | 1.368 | 1.255 | 1.242 | 1.084 | 1.633 | 1.063 |
| Min. | 0.019 | 0.002 | 0.121 | 0.001 | 0.027 | 0.012 | 0.064 | 0.001 |
| SD | 0.174 | 0.179 | 0.242 | 0.177 | 0.208 | 0.146 | 0.285 | 0.170 |
| Skew. | 1.949 | 1.297 | 0.241 | 1.908 | 0.447 | 1.627 | 0.507 | 1.664 |
| Kurt. | 11.641 | 4.578 | 2.590 | 8.932 | 3.035 | 7.167 | 2.739 | 7.171 |
| Jarque–Bera | 1729.71 | 178.25 | 7.441 | 961.91 | 15.31 | 540.52 | 20.33 | 550.46 |
| Q(12) | 101.07 | 28.91 | 50.62 | 39.21 | 236.15 | 192.45 | 235.02 | 24.27 |
| ADF | −8.12 | −19.21 | −17.33 | −9.64 | −7.94 | −10.79 | −8.99 | −18.38 |
| | 10-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) |
| Mean | 0.294 | 0.280 | 0.641 | 0.250 | 0.440 | 0.265 | 0.563 | 0.267 |
| Max. | 0.961 | 0.947 | 1.383 | 1.463 | 1.218 | 0.803 | 1.540 | 1.174 |
| Min. | 0.001 | 0.008 | 0.076 | 0.001 | 0.057 | 0.040 | 0.024 | 0.001 |
| SD | 0.157 | 0.162 | 0.246 | 0.159 | 0.210 | 0.143 | 0.271 | 0.186 |
| Skew. | 1.037 | 0.998 | 0.336 | 1.749 | 0.588 | 1.075 | 0.468 | 1.778 |
| Kurt. | 4.596 | 3.905 | 2.685 | 10.592 | 3.194 | 4.043 | 2.655 | 7.783 |
| Jarque–Bera | 131.86 | 92.81 | 10.22 | 1351.06 | 27.17 | 110.46 | 18.45 | 686.90 |
| Q(12) | 54.07 | 23.66 | 47.27 | 54.99 | 348.82 | 221.02 | 269.10 | 12.78 |
| ADF | −9.13 | −19.53 | −17.43 | −19.76 | −7.61 | −5.97 | −8.73 | −19.54 |
| | 30-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) |
| Mean | 0.264 | 0.247 | 0.643 | 0.255 | 0.492 | 0.294 | 0.571 | 0.292 |
| Max. | 0.912 | 1.255 | 1.370 | 1.036 | 1.244 | 0.805 | 1.503 | 0.958 |
| Min. | 0.032 | 0.001 | 0.095 | 0.001 | 0.061 | 0.002 | 0.008 | 0.001 |
| SD | 0.146 | 0.143 | 0.250 | 0.150 | 0.217 | 0.138 | 0.277 | 0.171 |
| Skew. | 1.050 | 1.554 | 0.343 | 1.098 | 0.463 | 0.778 | 0.452 | 1.009 |
| Kurt. | 4.436 | 8.632 | 2.718 | 4.756 | 3.011 | 3.578 | 2.663 | 4.271 |
| Jarque–Bera | 124.26 | 800.21 | 10.24 | 152.87 | 16.37 | 53.28 | 17.27 | 110.01 |
| Q(12) | 63.92 | 60.04 | 53.46 | 17.58 | 135.62 | 30.81 | 248.57 | 36.31 |
| ADF | −12.13 | −20.14 | −17.02 | −19.63 | −15.96 | −11.93 | −8.77 | −19.55 |

(*continued on next page*)

 

**Table 3** (*continued*).

Panel B: Crisis

| | 2-Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | DE | | NL | | IT | | ES | |
| | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) |
| Mean | 0.264 | 0.203 | 0.695 | 0.239 | 0.534 | 0.188 | 0.479 | 0.210 |
| Max. | 0.955 | 1.262 | 1.776 | 0.985 | 1.416 | 0.856 | 1.273 | 0.928 |
| Min. | 0.023 | 0.001 | 0.087 | 0.001 | 0.034 | 0.001 | 0.036 | 0.001 |
| SD | 0.141 | 0.150 | 0.234 | 0.131 | 0.217 | 0.114 | 0.222 | 0.137 |
| Skew. | 1.128 | 1.719 | 0.381 | 1.209 | 0.732 | 1.275 | 0.823 | 1.454 |
| Kurt. | 4.541 | 7.535 | 3.414 | 5.263 | 3.638 | 5.689 | 3.558 | 6.198 |
| Jarque–Bera | 320.94 | 1431.97 | 32.74 | 484.71 | 111.06 | 607.26 | 129.98 | 826.08 |
| Q(12) | 56.37 | 74.30 | 136.06 | 97.28 | 101.94 | 211.91 | 345.58 | 101.08 |
| ADF | −29.14 | −28.99 | −28.32 | −18.63 | −29.56 | −14.29 | −9.88 | −14.41 |
| | 5-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) |
| Mean | 0.251 | 0.225 | 0.686 | 0.261 | 0.489 | 0.257 | 0.516 | 0.251 |
| Max. | 1.018 | 1.207 | 1.812 | 1.004 | 1.313 | 0.942 | 1.790 | 0.921 |
| Min. | 0.021 | 0.001 | 0.081 | 0.001 | 0.035 | 0.001 | 0.018 | 0.001 |
| SD | 0.135 | 0.166 | 0.234 | 0.146 | 0.218 | 0.138 | 0.244 | 0.145 |
| Skew. | 1.309 | 1.811 | 0.398 | 1.157 | 0.737 | 0.999 | 1.048 | 1.286 |
| Kurt. | 5.871 | 8.016 | 3.533 | 4.976 | 3.661 | 4.268 | 4.748 | 5.278 |
| Jarque–Bera | 649.04 | 1692.28 | 39.99 | 409.51 | 113.77 | 247.54 | 320.27 | 521.84 |
| Q(12) | 90.46 | 30.66 | 147.36 | 187.33 | 367.58 | 711.83 | 203.87 | 113.43 |
| ADF | −17.78 | −30.41 | −13.99 | −9.75 | −8.37 | −3.72 | −10.84 | −29.06 |
| | 10-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) |
| Mean | 0.280 | 0.243 | 0.692 | 0.285 | 0.486 | 0.316 | 0.511 | 0.283 |
| Max. | 1.306 | 1.096 | 1.829 | 1.201 | 1.250 | 0.922 | 1.786 | 1.136 |
| Min. | 0.026 | 0.001 | 0.088 | 0.001 | 0.058 | 0.001 | 0.030 | 0.001 |
| SD | 0.145 | 0.159 | 0.234 | 0.151 | 0.208 | 0.152 | 0.238 | 0.157 |
| Skew. | 1.328 | 1.688 | 0.394 | 1.089 | 0.705 | 0.930 | 1.013 | 1.212 |
| Kurt. | 6.347 | 7.302 | 3.488 | 4.865 | 3.389 | 4.008 | 4.561 | 5.756 |
| Jarque–Bera | 785.05 | 1322.10 | 37.44 | 363.49 | 93.19 | 198.03 | 281.06 | 595.29 |
| Q(12) | 74.04 | 14.38 | 122.38 | 141.40 | 297.14 | 96.05 | 217.14 | 87.72 |
| ADF | −28.63 | −30.62 | −28.46 | −19.40 | −12.66 | −28.42 | −10.84 | −28.11 |
| | 30-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) | RS (LASSO) | RS (OLS) |
| Mean | 0.283 | 0.243 | 0.694 | 0.301 | 0.504 | 0.275 | 0.515 | 0.281 |
| Max. | 1.315 | 1.236 | 1.702 | 0.971 | 1.330 | 1.000 | 1.836 | 1.298 |
| Min. | 0.026 | 0.001 | 0.091 | 0.001 | 0.044 | 0.001 | 0.002 | 0.001 |
| SD | 0.157 | 0.147 | 0.237 | 0.156 | 0.222 | 0.147 | 0.240 | 0.162 |
| Skew. | 1.501 | 1.386 | 0.318 | 0.997 | 0.540 | 1.087 | 1.002 | 1.374 |
| Kurt. | 7.377 | 6.438 | 3.333 | 4.225 | 3.217 | 4.836 | 4.571 | 6.625 |
| Jarque–Bera | 1212.83 | 862.08 | 22.51 | 242.01 | 52.94 | 357.93 | 278.89 | 914.65 |
| Q(12) | 106.66 | 9.103 | 124.57 | 112.31 | 534.41 | 190.30 | 209.85 | 85.78 |
| ADF | −26.85 | −30.08 | −27.94 | −19.08 | −11.42 | −17.88 | −8.95 | −28.36 |

*Notes:* Panel A shows the Mean, Maximum, Minimum, Standard Deviation, Skewness and Kurtosis values, Jarque–Bera test for normality, the Ljung–Box portmanteau test for up to the 12th order Q(12), and the Augmented Dickey–Fuller (ADF) unit root test for the LASSO-based and the OLS-based relative spread resiliency (RS) for Germany (DE), Netherlands (NL), Italy (IT), and Spain (ES). Relative spread is defined as the best bid–ask spread divided by the midpoint of the bid and ask quotes. The OLS-based relative spread resiliency is estimated according to Eq. (2), while the LASSO-based relative spread resiliency is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The pre-crisis period spans the dates from January 2008 to October 2009. All statistics are presented for benchmark securities across four maturity segments, i.e. 2-, 5-, 10-, and 30-year. Panel B of the table shows the corresponding statistics for the crisis period which extends from November 2009 to December 2013. The liquidity measures have been winsorized by 95% in order to avoid extreme values in the resiliency estimates.

**Table 4**
Descriptive statistics.

Panel A: Pre-crisis

| | 2-Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | DE | | NL | | IT | | ES | |
| | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) |
| Mean | 0.318 | 0.333 | 0.508 | 0.435 | 0.483 | 0.469 | 0.442 | 0.453 |
| Max. | 1.053 | 1.044 | 1.454 | 1.392 | 1.193 | 1.432 | 1.509 | 1.620 |
| Min. | 0.043 | 0.001 | 0.078 | 0.002 | 0.054 | 0.001 | 0.079 | 0.001 |
| SD | 0.166 | 0.233 | 0.202 | 0.198 | 0.217 | 0.223 | 0.201 | 0.260 |
| Skew. | 0.993 | 0.603 | 0.741 | 0.705 | 0.769 | 0.805 | 0.976 | 1.011 |
| Kurt. | 4.325 | 2.858 | 3.892 | 4.645 | 3.621 | 4.212 | 5.125 | 4.253 |
| Jarque–Bera | 109.71 | 28.49 | 55.56 | 90.73 | 52.62 | 78.55 | 154.33 | 109.35 |
| Q(12) | 37.16 | 86.42 | 14.53 | 22.53 | 137.46 | 180.94 | 47.69 | 44.78 |
| ADF | −17.76 | −10.74 | −18.43 | −20.60 | −11.07 | −5.65 | −8.66 | −18.10 |
| | 5-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) |
| Mean | 0.337 | 0.441 | 0.563 | 0.497 | 0.515 | 0.507 | 0.533 | 0.561 |
| Max. | 1.241 | 1.185 | 1.183 | 1.145 | 1.187 | 1.143 | 1.178 | 1.400 |
| Min. | 0.041 | 0.001 | 0.139 | 0.001 | 0.074 | 0.076 | 0.112 | 0.001 |
| SD | 0.188 | 0.219 | 0.179 | 0.181 | 0.168 | 0.169 | 0.196 | 0.249 |
| Skew. | 1.290 | 0.423 | 0.425 | 0.197 | 0.473 | 0.405 | 0.441 | 0.476 |
| Kurt. | 5.968 | 3.403 | 3.123 | 2.954 | 3.330 | 3.091 | 3.182 | 3.089 |
| Jarque–Bera | 297.76 | 16.99 | 13.73 | 3.03 | 19.20 | 12.82 | 15.07 | 17.69 |
| Q(12) | 18.50 | 8.17 | 14.99 | 9.89 | 37.11 | 45.58 | 56.52 | 38.10 |
| ADF | −18.72 | −20.10 | −19.76 | −20.18 | −18.68 | −11.91 | −18.08 | −17.99 |
| | 10-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) |
| Mean | 0.356 | 0.413 | 0.539 | 0.482 | 0.521 | 0.524 | 0.527 | 0.555 |
| Max. | 1.328 | 1.768 | 1.277 | 1.188 | 1.108 | 1.218 | 1.210 | 1.485 |
| Min. | 0.028 | 0.005 | 0.141 | 0.001 | 0.111 | 0.152 | 0.123 | 0.001 |
| SD | 0.183 | 0.199 | 0.192 | 0.197 | 0.186 | 0.189 | 0.212 | 0.252 |
| Skew. | 1.392 | 1.376 | 0.616 | 0.457 | 0.676 | 0.662 | 0.586 | 0.713 |
| Kurt. | 6.043 | 8.161 | 3.434 | 3.251 | 3.336 | 3.348 | 3.195 | 3.637 |
| Jarque–Bera | 327.54 | 661.33 | 31.69 | 17.36 | 37.11 | 36.20 | 26.17 | 47.11 |
| Q(12) | 15.89 | 6.11 | 12.18 | 39.44 | 160.67 | 138.60 | 54.02 | 55.32 |
| ADF | −19.47 | −21.16 | −19.82 | −19.55 | −4.32 | −4.49 | −17.23 | −17.75 |
| | 30-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) |
| Mean | 0.331 | 0.428 | 0.650 | 0.636 | 0.506 | 0.504 | 0.623 | 0.587 |
| Max. | 1.353 | 1.343 | 2.440 | 1.736 | 1.478 | 1.478 | 2.027 | 1.758 |
| Min. | 0.001 | 0.001 | 0.096 | 0.001 | 0.080 | 0.001 | 0.071 | 0.001 |
| SD | 0.183 | 0.243 | 0.305 | 0.288 | 0.226 | 0.227 | 0.334 | 0.317 |
| Skew. | 1.219 | 0.802 | 0.970 | 0.601 | 0.814 | 0.784 | 0.843 | 0.681 |
| Kurt. | 5.958 | 3.598 | 5.386 | 3.385 | 4.060 | 4.026 | 3.798 | 3.187 |
| Jarque–Bera | 282.82 | 56.60 | 175.77 | 30.77 | 72.22 | 67.86 | 64.57 | 36.51 |
| Q(12) | 23.93 | 158.57 | 31.05 | 33.78 | 50.80 | 52.11 | 191.55 | 241.31 |
| ADF | −18.75 | −9.96 | −16.72 | −17.16 | −17.41 | −17.49 | −9.47 | −7.53 |

(*continued on next page*)

**Table 4** (*continued*).

Panel B: Crisis

| | 2-Year | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | DE | | NL | | IT | | ES | |
| | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) |
| Mean | 0.315 | 0.356 | 0.443 | 0.517 | 0.444 | 0.399 | 0.441 | 0.394 |
| Max. | 1.382 | 1.335 | 1.320 | 1.643 | 1.559 | 1.189 | 1.790 | 1.514 |
| Min. | 0.006 | 0.001 | 0.087 | 0.002 | 0.039 | 0.001 | 0.061 | 0.001 |
| SD | 0.162 | 0.252 | 0.192 | 0.202 | 0.192 | 0.185 | 0.193 | 0.199 |
| Skew. | 1.149 | 0.783 | 0.821 | 0.855 | 0.988 | 0.851 | 1.092 | 0.920 |
| Kurt. | 5.427 | 3.365 | 4.153 | 4.319 | 4.824 | 4.180 | 6.101 | 4.776 |
| Jarque–Bera | 480.79 | 114.23 | 178.11 | 203.18 | 315.03 | 189.74 | 618.68 | 289.18 |
| Q(12) | 104.93 | 266.78 | 65.87 | 53.32 | 123.03 | 75.99 | 77.77 | 133.01 |
| ADF | −26.92 | −9.17 | −29.52 | −19.88 | −27.21 | −26.91 | −28.96 | −19.17 |
| | 5-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) |
| Mean | 0.329 | 0.410 | 0.549 | 0.627 | 0.549 | 0.526 | 0.549 | 0.523 |
| Max. | 1.962 | 1.167 | 1.125 | 1.114 | 1.256 | 1.387 | 1.431 | 1.132 |
| Min. | 0.001 | 0.001 | 0.005 | 0.212 | 0.121 | 0.001 | 0.082 | 0.001 |
| SD | 0.172 | 0.198 | 0.175 | 0.165 | 0.182 | 0.184 | 0.187 | 0.205 |
| Skew. | 1.595 | 0.357 | 0.213 | 0.205 | 0.487 | 0.417 | 0.387 | 0.358 |
| Kurt. | 11.280 | 2.850 | 3.184 | 2.994 | 3.135 | 3.339 | 3.345 | 2.818 |
| Jarque–Bera | 3380.51 | 23.50 | 9.56 | 7.31 | 42.15 | 35.80 | 30.93 | 24.17 |
| Q(12) | 46.17 | 128.90 | 187.08 | 180.43 | 412.95 | 619.68 | 159.55 | 302.09 |
| ADF | −28.47 | −26.78 | −28.47 | −9.61 | −8.38 | −3.93 | −17.71 | −9.47 |
| | 10-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) |
| Mean | 0.325 | 0.377 | 0.557 | 0.621 | 0.534 | 0.535 | 0.491 | 0.450 |
| Max. | 1.122 | 1.106 | 1.443 | 1.537 | 1.214 | 1.455 | 1.334 | 1.624 |
| Min. | 0.033 | 0.001 | 0.005 | 0.120 | 0.103 | 0.001 | 0.069 | 0.002 |
| SD | 0.153 | 0.188 | 0.205 | 0.217 | 0.191 | 0.210 | 0.205 | 0.204 |
| Skew. | 1.150 | 0.789 | 0.456 | 0.497 | 0.557 | 0.748 | 0.826 | 0.814 |
| Kurt. | 5.063 | 3.386 | 3.294 | 3.364 | 3.063 | 3.759 | 3.717 | 4.479 |
| Jarque–Bera | 410.73 | 116.76 | 40.64 | 48.92 | 54.18 | 124.41 | 139.52 | 213.68 |
| Q(12) | 35.72 | 60.84 | 62.81 | 51.20 | 67.24 | 90.89 | 50.19 | 78.91 |
| ADF | −29.18 | −29.05 | −29.73 | −28.57 | −12.03 | −12.70 | −28.86 | −27.19 |
| | 30-Year | | | | | | | |
| | DE | | NL | | IT | | ES | |
| | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) | QD (LASSO) | QD (OLS) |
| Mean | 0.324 | 0.428 | 0.672 | 0.679 | 0.506 | 0.504 | 0.534 | 0.499 |
| Max. | 1.595 | 1.512 | 1.818 | 1.819 | 1.640 | 1.645 | 1.765 | 1.677 |
| Min. | 0.002 | 0.001 | 0.002 | 0.027 | 0.029 | 0.001 | 0.002 | 0.001 |
| SD | 0.186 | 0.251 | 0.270 | 0.272 | 0.232 | 0.234 | 0.280 | 0.258 |
| Skew. | 1.556 | 0.949 | 0.541 | 0.566 | 1.044 | 0.990 | 0.947 | 0.905 |
| Kurt. | 7.739 | 3.987 | 3.483 | 3.402 | 4.547 | 4.478 | 4.078 | 4.054 |
| Jarque–Bera | 1382.30 | 202.37 | 62.12 | 62.88 | 294.43 | 269.66 | 204.12 | 193.80 |
| Q(12) | 35.91 | 50.84 | 48.86 | 59.57 | 26.72 | 27.63 | 128.69 | 201.29 |
| ADF | −28.86 | −31.81 | −29.24 | −19.23 | −30.36 | −30.56 | −11.41 | −18.34 |

*Notes:* Panel A shows the Mean, Maximum, Minimum, Standard Deviation, Skewness and Kurtosis values, Jarque–Bera test for normality, the Ljung–Box portmanteau test for up to the 12th order Q(12), and the Augmented Dickey–Fuller (ADF) unit root test for the LASSO-based and the OLS-based quoted depth resiliency (QD) for Germany (DE), Netherlands (NL), Italy (IT), and Spain (ES). Quoted depth is defined as best bid size plus best ask size, where size denotes the quantity of securities bid or offered for sale at the posted bid and ask prices. The OLS-based quoted depth resiliency is estimated according to Eq. (2), while the LASSO-based quoted depth resiliency is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The pre-crisis period spans the dates from January 2008 to October 2009. All statistics are presented for benchmark securities across four maturity segments, i.e. 2-, 5-, 10-, and 30-year. Panel B of the table shows the corresponding statistics for the crisis period which extends from November 2009 to December 2013. The liquidity measures have been winsorized by 95% in order to avoid extreme values in the resiliency estimates.

**Table 5**
Correlation matrix.

| Panel A: Pre-crisis | | | | | | |
|---|---|---|---|---|---|---|
| | RS (LASSO) | QD (LASSO) | RS (OLS) | QD (OLS) | RS | QD |
| RS (LASSO) | 1.000 | | | | | |
| QD (LASSO) | 0.353*** | 1.000 | | | | |
| RS (OLS) | 0.072 | −0.059 | 1.000 | | | |
| QD (OLS) | 0.016 | 0.045 | 0.299*** | 1.000 | | |
| RS | −0.144*** | −0.002 | −0.090* | 0.032 | 1.000 | |
| QD | 0.055 | −0.054 | 0.110** | 0.013 | −0.196*** | 1.000 |
| **Panel B: Crisis** | | | | | | |
| | RS (LASSO) | QD (LASSO) | RS (OLS) | QD (OLS) | RS | QD |
| RS (LASSO) | 1.000 | | | | | |
| QD (LASSO) | 0.290*** | 1.000 | | | | |
| RS (OLS) | 0.062** | −0.007 | 1.000 | | | |
| QD (OLS) | 0.064** | 0.054* | 0.266*** | 1.000 | | |
| RS | −0.064** | −0.013 | −0.113*** | −0.033 | 1.000 | |
| QD | 0.048 | 0.014 | 0.053* | 0.086*** | −0.071** | 1.000 |

*Notes:* The table reports the correlation matrix for relative spread (RS) and quoted depth (QD) resiliency and conventional relative spread and quoted depth liquidity measures. The OLS-based resiliency is estimated according to Eq. (2), while the LASSO-based resiliency is estimated according to Eqs. (2) and (3) following a two-stage regression approach. Relative spread is defined as the best bid–ask spread divided by the midpoint of the bid and ask quotes. Quoted depth is defined as best bid size plus best ask size, where size denotes the quantity of securities bid or offered for sale at the posted bid and ask prices. Correlations of the German 10-year benchmark bond are recorded. Panel A presents the correlations of the pre-crisis period (January 2008–October 2009) while Panel B reports the correlations of the crisis period (November 2009–December 2013). *** Denotes statistical significance at the 1 percent level; ** Denotes statistical significance at the 5 percent level; * Denotes statistical significance at the 10 percent level.

In the analysis that follows, we use a VAR model of the following form:

$$LIQ_t^{S/D} = \beta_0 + \sum_{P=1}^{k} \beta_p LIQ_{t-p}^{S/D} + \sum_{p=1}^{k} \gamma_p RV_{t-p} + \sum_{p=1}^{k} \delta_p RET_{t-p} + \sum_{p=1}^{k} \omega_p CDS_{t-p} + \varepsilon_t \tag{4}$$

$$RV_t = \gamma_0 + \sum_{P=1}^{k} \gamma_p RV_{t-p} + \sum_{p=1}^{k} \delta_p RET_{t-p} + \sum_{p=1}^{k} \omega_p CDS_{t-p} + \sum_{p=1}^{k} \beta_p LIQ_{t-p}^{S/D} + \varepsilon_t \tag{5}$$

$$RET_t = \delta_0 + \sum_{P=1}^{k} \delta_p RET_{t-p} + \sum_{p=1}^{k} \gamma_p RV_{t-p} + \sum_{p=1}^{k} \omega_p CDS_{t-p} + \sum_{p=1}^{k} \beta_p LIQ_{t-p}^{S/D} + \varepsilon_t \tag{6}$$

$$CDS_t = \omega_0 + \sum_{P=1}^{k} \omega_p CDS_{t-p} + \sum_{p=1}^{k} \delta_p RET_{t-p} + \sum_{p=1}^{k} \gamma_p RV_{t-p} + \sum_{p=1}^{k} \beta_p LIQ_{t-p}^{S/D} + \varepsilon_t \tag{7}$$

where $LIQ_t^{S/D}$ denotes liquidity resiliency estimated from spreads (S) or depths (D), $RV_t$ denotes realized volatility, $RET_t$ denotes bond returns, and $CDS_t$ denotes credit default swap spreads. We choose the optimal number of lags in the above equations on the basis of the Akaike information criterion. Similar to Chordia et al. (2005) and Goyenko et al. (2011) we use a VAR variable ordering that places volatility before returns, while liquidity resiliency is placed after returns. In Section 5.2.1. we present pairwise Granger causality tests between the endogenous variables of the VAR. In Section 5.2.2. we offer more robust evidence on the joint dynamics implied by the VAR model using Impulse Response Functions.

### 5.2.1. *Granger causalities*

Tables 6–9 present the Granger causality results. In Table 6 we document more statistically significant causalities for spread-based resiliency than depth-based resiliency for German bonds. We find strong bidirectional causalities between CDS spreads and resiliency for the 2- and 10-year benchmarks, as well as between volatility and resiliency for the 10-year benchmark. The strong association between CDS spreads and resiliency is apparent during both pre-crisis and crisis periods as expected, confirming the importance of sovereign credit risk in driving liquidity. We also document strong unidirectional causalities between resiliency and returns, mainly running from resiliency to returns during the crisis period. This result offers preliminary evidence that liquidity resiliency is a priced variable and is in line with the findings in Goyenko et al. (2011) in their study of the U.S. Treasury market. Statistically significant bidirectional causalities between CDS spreads and resiliency for the Dutch market are also reported in Table 7. One-way causalities are also evident between resiliency, returns, and volatility, regardless of how resiliency is estimated. The presence of strong causalities is also apparent in the Italian market (shown in Table 8) mainly for spread-based resiliency which Granger causes the other three bond attributes across the maturity spectrum.

The picture is more clear-cut for Spanish bonds in Table 9. Strong two-way and one-way causalities are documented between spread-based and depth-based resiliency and the other three bond attributes confirming previous studies that focus on the tightness and depth dimensions of liquidity. Although resiliency exhibits different features from conventional spread and depth liquidity

**Table 6**
Granger causality tests.

Panel A: Relative spread resiliency

| | 2-Year | | | | 5-Year | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.124 | 0.236 | 0.815 | 0.939 | 0.680 | 0.836 | 0.679 | 0.145 |
| RET→RES | 0.564 | 0.658 | 0.766 | 0.953 | 0.789 | 0.406 | 0.618 | 0.360 |
| CDS→RES | **0.011** | **0.010** | 0.235 | 0.897 | **0.000** | 0.258 | 0.847 | **0.087** |
| RES→VOL | 0.537 | 0.133 | **0.009** | 0.967 | 0.739 | 0.270 | 0.930 | 0.311 |
| RES→RET | 0.352 | 0.855 | **0.026** | 0.988 | 0.522 | 0.247 | **0.040** | 0.803 |
| RES→CDS | **0.041** | 0.773 | 0.589 | 0.953 | 0.392 | 0.948 | **0.017** | 0.700 |

| | 10-Year | | | | 30-Year | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | **0.064** | **0.020** | 0.222 | 0.769 | **0.034** | 0.810 | 0.346 | 0.848 |
| RET→RES | 0.637 | 0.349 | 0.518 | 0.960 | 0.813 | 0.284 | 0.339 | 0.629 |
| CDS→RES | **0.000** | **0.014** | 0.124 | 0.347 | **0.000** | 0.158 | 0.813 | **0.020** |
| RES→VOL | 0.588 | 0.361 | 0.149 | 0.707 | **0.095** | 0.757 | 0.704 | 0.142 |
| RES→RET | 0.662 | 0.419 | 0.986 | 0.517 | 0.927 | 0.153 | 0.668 | 0.180 |
| RES→CDS | 0.401 | **0.051** | 0.467 | 0.898 | 0.388 | 0.486 | **0.054** | 0.214 |

Panel B: Quoted depth resiliency

| | 2-Year | | | | 5-Year | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.892 | 0.287 | 0.713 | 0.909 | 0.820 | 0.405 | 0.788 | **0.084** |
| RET→RES | 0.175 | 0.972 | 0.874 | 0.707 | 0.514 | 0.226 | 0.904 | 0.679 |
| CDS→RES | **0.050** | **0.004** | 0.234 | 0.350 | 0.262 | 0.173 | 0.998 | 0.255 |
| RES→VOL | 0.499 | 0.965 | **0.093** | 0.943 | 0.453 | **0.082** | 0.872 | 0.134 |
| RES→RET | 0.466 | 0.325 | 0.250 | 0.824 | 0.184 | 0.882 | 0.402 | **0.014** |
| RES→CDS | **0.016** | 0.588 | 0.246 | 0.927 | 0.776 | 0.750 | 0.347 | **0.019** |

| | 10-Year | | | | 30-Year | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.377 | 0.612 | 0.951 | 0.606 | 0.218 | 0.890 | 0.140 | 0.203 |
| RET→RES | 0.810 | 0.700 | 0.285 | 0.586 | 0.704 | 0.725 | 0.106 | 0.241 |
| CDS→RES | 0.968 | 0.613 | 0.893 | 0.494 | 0.733 | **0.003** | 0.343 | **0.025** |
| RES→VOL | **0.087** | 0.286 | 0.900 | 0.485 | 0.216 | 0.946 | 0.698 | 0.439 |
| RES→RET | 0.586 | 0.573 | 0.859 | 0.639 | 0.897 | 0.399 | 0.303 | 0.614 |
| RES→CDS | 0.762 | 0.382 | 0.415 | 0.386 | 0.506 | 0.798 | **0.066** | 0.324 |

*Notes:* The table presents $p$-values of pairwise Granger causality tests between resiliency, volatility, bond returns, and CDS spreads across four time-to-maturity groups for German benchmark securities. Panel A presents Granger causalities when resiliency is measured using relative spreads, while Panel B presents the corresponding causalities when resiliency is measured using quoted depths. OLS-based resiliency is estimated according to Eq. (2) whilst LASSO-based resiliency is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The pre-crisis period spans the dates from January 2008 to October 2009 whilst the crisis period extends from November 2009 to December 2013. Statistically significant $p$-values are shown in bold.

proxies, it demonstrates strong intertemporal relationships with sovereign credit risk, volatility, and sovereign bond returns. The importance of CDS spreads in causing resiliency is highlighted in the crisis period, with statistically significant two-way Granger causalities being the result of liquidity dry-ups that took place at the time. This finding points to a feedback relationship between CDS spreads and bond liquidity resiliency that can lead to liquidity spirals during crisis periods (Brunnermeier and Pedersen, 2009). We investigate these dynamics further in the next section on Impulse Response Functions.[11]

### 5.2.2. Impulse Response Functions

In this section we employ Impulse Response Functions (IRFs) that may shed further light on the joint dynamics of liquidity resiliency with volatility, returns, and CDS spreads. IRFs make it possible to determine the duration of the effects of innovations from the lags of the endogenous variables on each dependent variable. Following Eqs. (4)–(7), we apply one standard deviation

[11] Despite the popularity of Granger causality, the validity of this framework for inferring causal relationships among time series has remained a topic of continuous debate (Shojaie and Fox, 2022). Although Granger causality can lead to useful insights about interactions among variables observed over time, claims about causality should be treated with caution.

**Table 7**
Granger causality tests.

Panel A: Relative spread resiliency

| | 2-Year | | | | 5-Year | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.213 | **0.056** | 0.111 | 0.492 | 0.995 | 0.269 | **0.022** | **0.029** |
| RET→RES | **0.061** | 0.321 | 0.358 | 0.166 | 0.138 | 0.281 | **0.040** | 0.335 |
| CDS→RES | 0.370 | 0.868 | 0.436 | **0.002** | 0.426 | **0.000** | 0.478 | **0.000** |
| RES→VOL | 0.634 | 0.953 | 0.345 | 0.814 | 0.295 | 0.574 | 0.758 | 0.300 |
| RES→RET | 0.230 | 0.157 | 0.209 | 0.498 | 0.409 | 0.478 | 0.766 | 0.231 |
| RES→CDS | 0.270 | 0.397 | 0.975 | 0.525 | 0.214 | 0.260 | **0.040** | 0.272 |
| | 10-Year | | | | 30-Year | | | |
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.776 | **0.065** | 0.466 | 0.249 | **0.068** | 0.858 | 0.515 | 0.568 |
| RET→RES | 0.539 | 0.233 | 0.445 | 0.576 | 0.187 | 0.634 | 0.436 | 0.618 |
| CDS→RES | 0.766 | **0.000** | 0.737 | **0.001** | 0.377 | 0.532 | 0.303 | 0.105 |
| RES→VOL | 0.458 | 0.287 | 0.417 | 0.465 | 0.983 | 0.619 | 0.139 | 0.830 |
| RES→RET | 0.304 | 0.442 | 0.518 | 0.611 | **0.079** | 0.473 | 0.128 | 0.629 |
| RES→CDS | 0.996 | **0.015** | 0.269 | 0.784 | 0.523 | 0.780 | 0.217 | 0.989 |

Panel B: Quoted depth resiliency

| | 2-Year | | | | 5-Year | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.121 | 0.974 | 0.308 | 0.443 | 0.350 | 0.102 | 0.626 | 0.422 |
| RET→RES | **0.040** | 0.835 | 0.312 | 0.256 | 0.452 | 0.355 | 0.422 | 0.606 |
| CDS→RES | 0.841 | 0.746 | **0.038** | 0.329 | 0.478 | **0.010** | 0.714 | 0.708 |
| RES→VOL | 0.316 | 0.999 | **0.001** | 0.104 | **0.062** | 0.190 | 0.760 | 0.937 |
| RES→RET | 0.168 | 0.131 | **0.005** | 0.107 | **0.077** | 0.681 | 0.761 | 0.872 |
| RES→CDS | 0.368 | **0.086** | **0.036** | 0.510 | 0.207 | 0.528 | 0.331 | 0.374 |
| | 10-Year | | | | 30-Year | | | |
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.578 | 0.633 | 0.127 | 0.425 | 0.147 | 0.116 | 0.112 | 0.100 |
| RET→RES | 0.695 | 0.753 | 0.105 | 0.202 | 0.364 | 0.260 | **0.048** | **0.042** |
| CDS→RES | 0.606 | 0.234 | 0.490 | 0.635 | 0.755 | 0.621 | **0.050** | 0.460 |
| RES→VOL | 0.308 | 0.808 | 0.378 | 0.631 | 0.871 | 0.661 | 0.101 | 0.096 |
| RES→RET | 0.987 | 0.543 | 0.281 | 0.480 | **0.066** | **0.087** | 0.111 | 0.101 |
| RES→CDS | 0.173 | 0.684 | 0.193 | **0.006** | 0.553 | 0.399 | 0.318 | 0.344 |

*Notes*: The table presents *p*-values of pairwise Granger causality tests between resiliency, volatility, bond returns, and CDS spreads across four time-to-maturity groups for Dutch benchmark securities. Panel A presents Granger causalities when resiliency is measured using relative spreads, while Panel B presents the corresponding causalities when resiliency is measured using quoted depths. OLS-based resiliency is estimated according to Eq. (2) whilst LASSO-based resiliency is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The pre-crisis period spans the dates from January 2008 to October 2009 whilst the crisis period extends from November 2009 to December 2013. Statistically significant *p*-values are shown in bold.

unit shock to the error of each VAR model equation and, in a second step, IRFs trace the effects of the shock in the VAR system. For brevity we focus on the LASSO-based resiliency, however, we find similar results for the OLS-based resiliency. We have selected to report IRFs for the 10-year German and Spanish benchmark bonds only, as including all countries and maturity segments would render the analysis overly detailed.

Figs. 2–5 display the IRFs for the German 10-year benchmark. We apply bootstrapped 95 percent confidence intervals with 2500 bootstrap replications to generate the shocks. The plot's centre line is the impulse response function, which traces the shock in the endogenous variables. The outer lines are the 95 percent bootstrapped confidence intervals, which aid in inferring the statistical significance of the shock to the endogenous variables. In Figs. 2(a) and 2(b) spread resiliency increases by roughly 0.16 standard deviations on the first day following a shock to resiliency, and the response fades away after the third day during the pre-crisis period. The effect of resiliency innovations on its own lags is positive and statistically significant for the first two days following the shock. CDS spread innovations significantly increase resiliency by 0.02 standard deviations on day one but this reduces and becomes insignificant on day two after the shock. However, from day four onwards, CDS spread shocks on resiliency take on statistically significant negative values and persist even after ten days, confirming the previous results from the Granger causality analysis. The effect of volatility innovations on resiliency is positive on day one but not significant and from day three onwards it drops to zero. Return innovations initially reduce resiliency by nearly 0.01 standard deviations but the effect is insignificant and takes on zero

**Table 8**
Granger causality tests.

Panel A: Relative spread resiliency

| | 2-Year | | | | 5-Year | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | **0.013** | 0.625 | **0.023** | 0.541 | **0.090** | 0.176 | 0.525 | 0.931 |
| RET→RES | **0.042** | 0.271 | 0.168 | 0.899 | 0.295 | 0.888 | 0.549 | 0.931 |
| CDS→RES | **0.014** | **0.000** | **0.000** | 0.689 | **0.000** | **0.005** | **0.000** | 0.117 |
| RES→VOL | 0.944 | 0.486 | 0.610 | 0.286 | **0.003** | 0.258 | 0.374 | 0.165 |
| RES→RET | 0.824 | 0.204 | 0.872 | 0.250 | 0.831 | 0.704 | 0.719 | 0.207 |
| RES→CDS | 0.735 | **0.026** | 0.468 | 0.608 | 0.309 | 0.596 | 0.800 | 0.474 |

| | 10-Year | | | | 30-Year | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.151 | 0.508 | 0.538 | 0.621 | 0.848 | 0.685 | 0.317 | 0.408 |
| RET→RES | 0.398 | **0.089** | 0.818 | 0.118 | **0.016** | 0.549 | 0.820 | 0.592 |
| CDS→RES | **0.000** | **0.000** | **0.052** | 0.117 | **0.001** | 0.435 | **0.001** | 0.108 |
| RES→VOL | **0.011** | **0.029** | 0.084 | 0.912 | 0.813 | 0.529 | **0.000** | 0.163 |
| RES→RET | 0.808 | 0.696 | 0.722 | 0.327 | 0.522 | 0.433 | **0.012** | 0.725 |
| RES→CDS | 0.744 | 0.279 | 0.955 | 0.948 | 0.168 | 0.417 | 0.151 | 0.386 |

Panel B: Quoted depth resiliency

| | 2-Year | | | | 5-Year | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.140 | **0.043** | 0.385 | 0.548 | 0.368 | 0.746 | 0.795 | 0.503 |
| RET→RES | 0.350 | 0.655 | 0.766 | 0.798 | 0.738 | 0.780 | 0.953 | 0.799 |
| CDS→RES | **0.012** | **0.012** | 0.853 | 0.621 | **0.000** | **0.001** | 0.342 | 0.332 |
| RES→VOL | 0.633 | 0.758 | 0.709 | 0.984 | 0.459 | 0.104 | 0.545 | 0.395 |
| RES→RET | 0.462 | 0.300 | 0.559 | 0.755 | 0.790 | 0.271 | 0.179 | 0.869 |
| RES→CDS | 0.964 | 0.933 | 0.401 | 0.505 | 0.572 | 0.764 | 0.654 | 0.688 |

| | 10-Year | | | | 30-Year | | | |
|---|---|---|---|---|---|---|---|---|
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.501 | 0.259 | 0.798 | 0.784 | 0.765 | 0.801 | **0.063** | **0.046** |
| RET→RES | 0.741 | 0.613 | 0.718 | 0.347 | 0.510 | 0.690 | 0.144 | 0.166 |
| CDS→RES | **0.000** | **0.000** | 0.733 | 0.559 | 0.221 | 0.266 | 0.106 | **0.036** |
| RES→VOL | 0.529 | 0.147 | 0.432 | 0.927 | 0.999 | 0.872 | 0.752 | 0.724 |
| RES→RET | 0.483 | 0.179 | 0.480 | 0.355 | 0.761 | 0.847 | 0.889 | 0.873 |
| RES→CDS | 0.795 | 0.839 | **0.055** | 0.533 | 0.102 | **0.060** | 0.415 | 0.575 |

*Notes*: The table presents $p$-values of pairwise Granger causality tests between resiliency, volatility, bond returns, and CDS spreads across four time-to-maturity groups for Italian benchmark securities. Panel A presents Granger causalities when resiliency is measured using relative spreads, while Panel B presents the corresponding causalities when resiliency is measured using quoted depths. OLS-based resiliency is estimated according to Eq. (2) whilst LASSO-based resiliency is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The pre-crisis period spans the dates from January 2008 to October 2009 whilst the crisis period extends from November 2009 to December 2013. Statistically significant $p$-values are shown in bold.

values from day three onwards. Resiliency shocks increase volatility and CDS spreads and reduce returns but only the impact on CDS spreads is significant at a one day lag.

Figs. 3(a) and 3(b) indicate that shocks to depth-based resiliency significantly impact its own lagged values. However, the effect on the other endogenous variables is statistically negligible. For example, a positive unit standard deviation shock to depth-based resiliency reduces volatility by 0.02 standard deviation units on day one and this impact is marginally significant as it dies-off from day two onwards. Shocks to depth-based resiliency reduce volatility on day one but the impact is marginally significant and fades away after the first day.

Figs. 4(a) and 4(b) present IRFs in the crisis period with similar results to those of the pre-crisis period. Innovations to resiliency increase resiliency by around 0.16 standard deviation units on day one following a shock. This reduces and fades away from day three onwards. Notably, the effect is significant on day one and day two. This finding is in agreement with that of Goyenko et al. (2011) who find that liquidity shocks on their lagged values are significant in the U.S. Treasury market. Innovations to CDS spreads forecast an initial significant increase in resiliency that is followed by a decrease in resiliency that becomes significant from day four onwards. CDS spread shocks have a negative impact on resiliency in the long run as rising CDS spreads indicate higher economic uncertainty with reduced resiliency. The negative effect of CDS spreads on liquidity resiliency is in agreement with previous studies

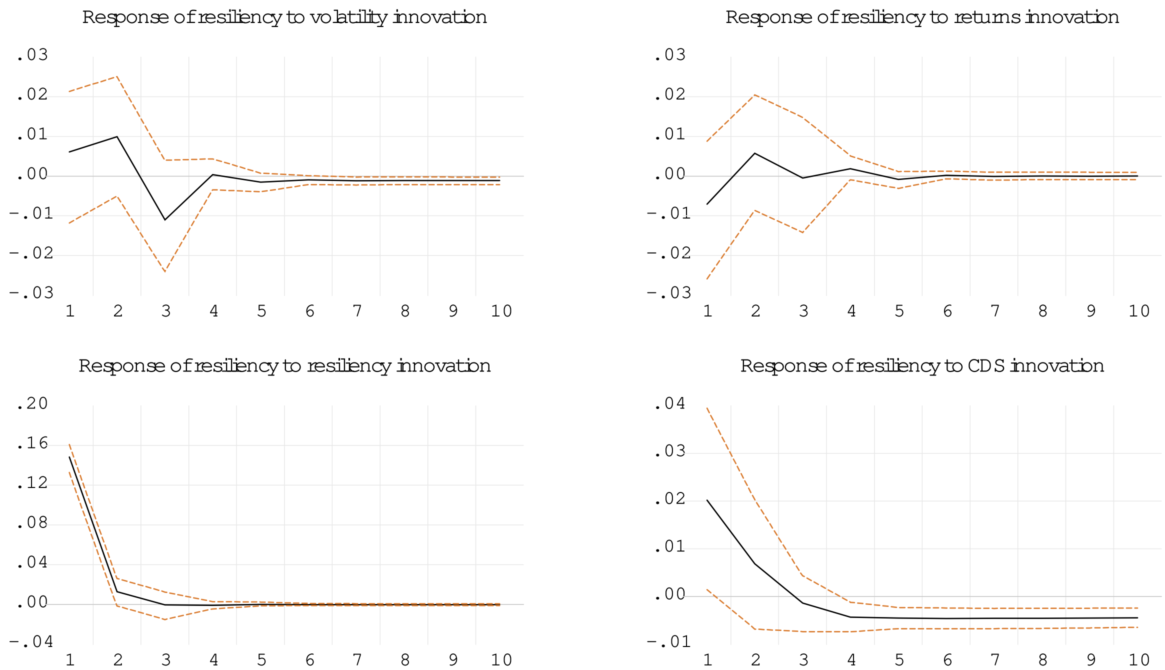


**Fig. 2(a).** Response of LASSO-based relative spread resiliency to the endogenous variables in Germany for the 10-year benchmark. The Impulse Response Functions run during the pre-crisis period in the euro area (January 2008 to October 2009).

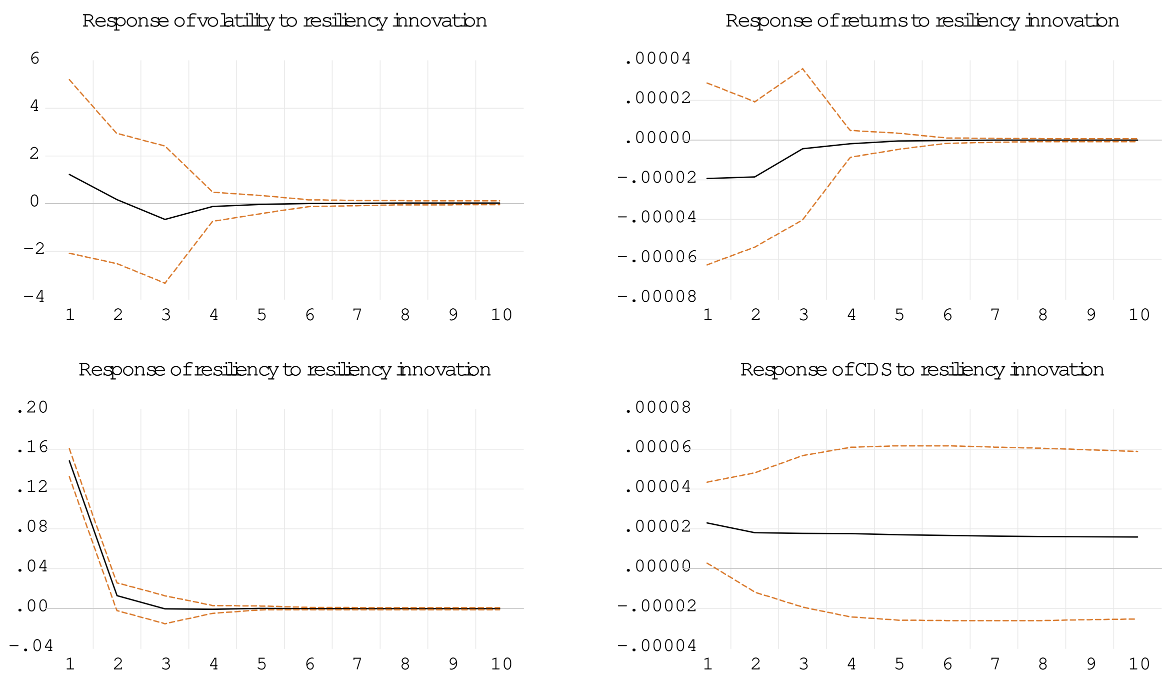


**Fig. 2(b).** Response of the endogenous variables to LASSO-based relative spread resiliency in Germany for the 10-year benchmark. The Impulse Response Functions run during the pre-crisis period in the euro area (January 2008 to October 2009).

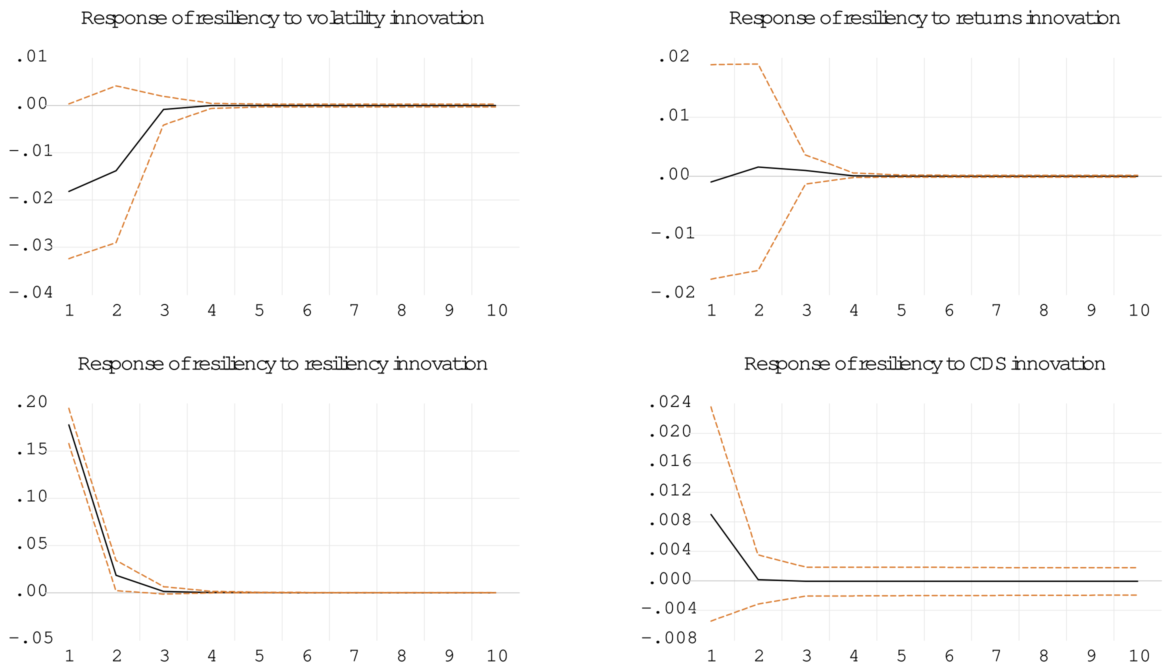


**Fig. 3(a).** Response of LASSO-based quoted depth resiliency to the endogenous variables in Germany for the 10-year benchmark. The Impulse Response Functions run during the pre-crisis period in the euro area (January 2008 to October 2009).

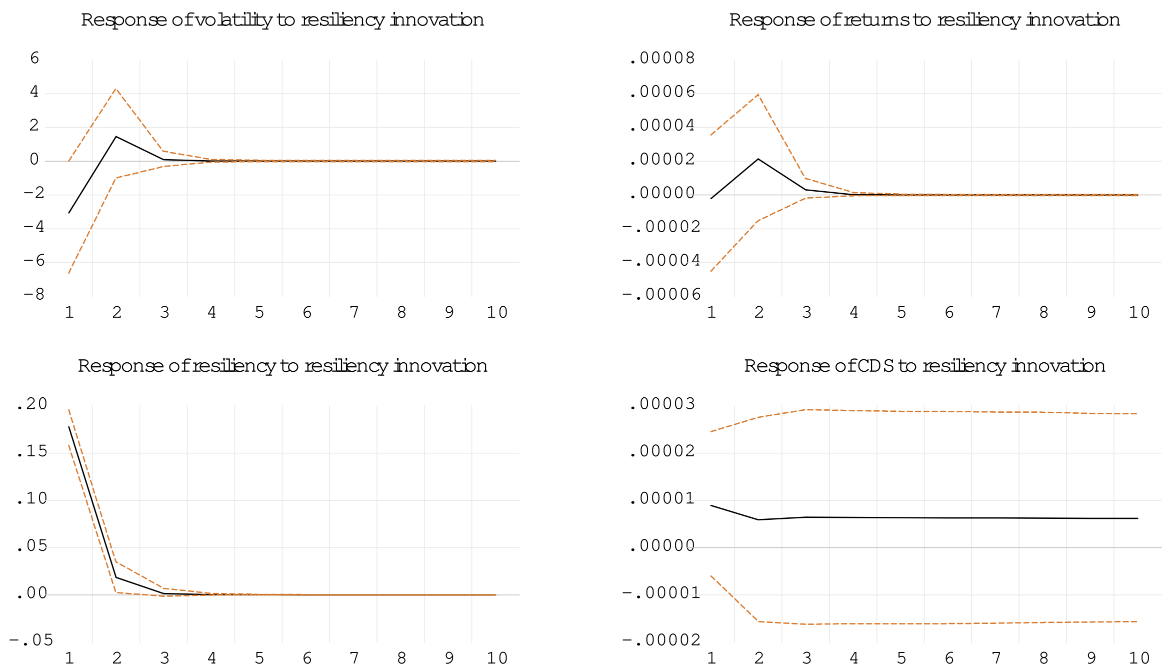


**Fig. 3(b).** Response of the endogenous variables to LASSO-based quoted depth resiliency in Germany for the 10-year benchmark. The Impulse Response Functions run during the pre-crisis period in the euro area (January 2008 to October 2009).

**Table 9**
Granger causality tests.

| Panel A: Relative spread resiliency | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2-Year | | | | 5-Year | | | |
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.178 | 0.325 | 0.853 | 0.449 | 0.141 | 0.574 | 0.561 | 0.128 |
| RET→RES | 0.586 | 0.964 | 0.676 | 0.425 | 0.390 | 0.861 | 0.520 | 0.440 |
| CDS→RES | **0.000** | **0.034** | **0.007** | **0.018** | **0.000** | 0.120 | 0.170 | **0.004** |
| RES→VOL | 0.216 | 0.954 | 0.374 | 0.521 | 0.324 | 0.339 | 0.153 | 0.296 |
| RES→RET | 0.287 | 0.207 | 0.504 | 0.705 | 0.607 | 0.889 | 0.193 | 0.374 |
| RES→CDS | 0.339 | 0.520 | 0.141 | **0.049** | 0.215 | 0.531 | 0.517 | **0.026** |
| | 10-Year | | | | 30-Year | | | |
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.437 | 0.260 | 0.326 | 0.927 | 0.263 | 0.129 | 0.935 | **0.093** |
| RET→RES | 0.366 | 0.561 | 0.404 | 0.748 | **0.020** | **0.030** | 0.484 | 0.951 |
| CDS→RES | **0.000** | **0.019** | **0.009** | **0.016** | **0.000** | **0.000** | 0.111 | **0.000** |
| RES→VOL | 0.142 | 0.685 | 0.217 | 0.659 | 0.795 | **0.006** | 0.662 | 0.573 |
| RES→RET | 0.840 | 0.354 | 0.758 | 0.916 | 0.580 | 0.856 | 0.311 | 0.734 |
| RES→CDS | 0.384 | 0.332 | 0.366 | **0.072** | 0.769 | 0.181 | 0.561 | 0.149 |

| Panel B: Quoted depth resiliency | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 2-Year | | | | 5-Year | | | |
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.577 | 0.424 | **0.014** | **0.080** | 0.108 | 0.649 | 0.107 | 0.125 |
| RET→RES | 0.899 | 0.303 | **0.006** | **0.042** | 0.604 | 0.820 | 0.657 | 0.406 |
| CDS→RES | **0.002** | **0.033** | **0.083** | 0.114 | **0.000** | **0.001** | **0.089** | 0.121 |
| RES→VOL | 0.798 | 0.604 | 0.557 | 0.778 | 0.576 | 0.774 | 0.642 | 0.776 |
| RES→RET | 0.193 | 0.219 | 0.754 | 0.920 | 0.650 | **0.035** | 0.959 | 0.728 |
| RES→CDS | 0.948 | 0.126 | 0.642 | **0.059** | 0.104 | 0.907 | 0.363 | 0.484 |
| | 10-Year | | | | 30-Year | | | |
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | LASSO | OLS | LASSO | OLS | LASSO | OLS | LASSO | OLS |
| VOL→RES | 0.187 | 0.176 | 0.232 | 0.216 | 0.194 | 0.730 | 0.782 | 0.975 |
| RET→RES | 0.957 | 0.666 | 0.707 | 0.970 | **0.012** | **0.023** | 0.168 | 0.371 |
| CDS→RES | 0.145 | **0.014** | **0.001** | **0.000** | **0.000** | **0.000** | 0.472 | 0.105 |
| RES→VOL | 0.563 | 0.867 | 0.511 | 0.779 | 0.395 | 0.335 | 0.718 | 0.735 |
| RES→RET | 0.883 | 0.712 | 0.842 | 0.931 | 0.675 | 0.856 | **0.077** | **0.043** |
| RES→CDS | 0.554 | **0.020** | 0.992 | 0.782 | 0.869 | 0.879 | 0.989 | 0.506 |

*Notes*: The table presents *p*-values of pairwise Granger causality tests between resiliency, volatility, bond returns, and CDS spreads across four time-to-maturity groups for Spanish benchmark securities. Panel A presents Granger causalities when resiliency is measured using relative spreads, while Panel B presents the corresponding causalities when resiliency is measured using quoted depths. OLS-based resiliency is estimated according to Eq. (2) whilst LASSO-based resiliency is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The pre-crisis period spans the dates from January 2008 to October 2009 whilst the crisis period extends from November 2009 to December 2013. Statistically significant *p*-values are shown in bold.

by Das et al. (2014), Calice et al. (2013), Pelizzon et al. (2016), and Czech (2021). Shocks to spread-based resiliency significantly increase CDS spreads on day one but the impact subsequently dies away.

In Fig. 5(a) it is evident that resiliency positively impacts its own lagged innovations up to day three before it fades away. Volatility, returns and CDS shocks negatively impact quoted depth resiliency but only the returns shock impact is significant at the first lag. In Fig. 5(b) we observe that day one shocks to resiliency negatively impact on volatility, returns and CDS spreads, however, the effects are statistically insignificant.

Figs. 6–9 display the IRFs for the Spanish 10-year benchmark. In Figs. 6(a) and 6(b) spread resiliency increases by roughly 0.16 standard deviations on the first day following a resiliency shock, and the response fades away after the third day during the pre-crisis period. Volatility shocks do not impact resiliency significantly but returns shocks positively impact resiliency from the third lag onwards. CDS shocks negatively impact resiliency highlighting the reduction in resiliency when credit conditions deteriorate. Resiliency shocks do not impact volatility, returns or CDS spreads. Figs. 7(a) and 7(b) show that only resiliency shocks impact resiliency when resiliency is measured with quoted depths with shocks to resiliency (other variables) not impacting the other variables (resiliency). Figs. 8(a) and 8(b) depict IRFs for spread resiliency in the crisis period. We observe that resiliency (CDS) shocks positively (negatively) impact resiliency but that resiliency shocks do not impact other variables. These relations remain the same

**Table 10**
PCA periphery countries.

| Panel A: Relative spread resiliency | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LASSO | | | | OLS | | | |
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | Full | Index | Full | Index | Full | Index | Full | Index |
| PCA 1 (%) | 29.84 | 87.57 | 32.10 | 91.64 | 16.40 | 47.73 | 12.82 | 43.90 |
| PCA 1+2 (%) | 53.65 | 95.84 | 52.18 | 94.98 | 25.29 | 68.07 | 23.76 | 65.21 |
| PCA 1+2+3 (%) | 70.51 | 98.14 | 71.59 | 97.91 | 32.91 | 85.11 | 32.91 | 84.74 |
| **Panel B: Quoted depth resiliency** | | | | | | | | |
| | LASSO | | | | OLS | | | |
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | Full | Index | Full | Index | Full | Index | Full | Index |
| PCA 1 (%) | 17.40 | 53.70 | 19.80 | 56.61 | 12.81 | 36.06 | 18.37 | 49.89 |
| PCA 1+2 (%) | 28.78 | 71.59 | 32.68 | 78.35 | 21.87 | 60.65 | 26.54 | 68.03 |
| PCA 1+2+3 (%) | 37.93 | 87.41 | 43.15 | 89.62 | 29.60 | 82.44 | 34.19 | 85.21 |

*Notes:* The table presents Principal Component Analysis (PCA) results for periphery euro area bond markets (Italy and Spain). Panel A presents results for relative spread resiliency, whilst Panel B reports the corresponding results for quoted depth resiliency. OLS-based resiliency is estimated according to Eq. (2) while LASSO-based resiliency is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The full set of data employs spread-based resiliency and depth-based resiliency for each country across four maturity segments. The index data equally weights each individual spread or depth-based resiliency measure available at a given maturity. The pre-crisis period spans the dates from January 2008 to October 2009, while the crisis period extends from November 2009 to December 2013.

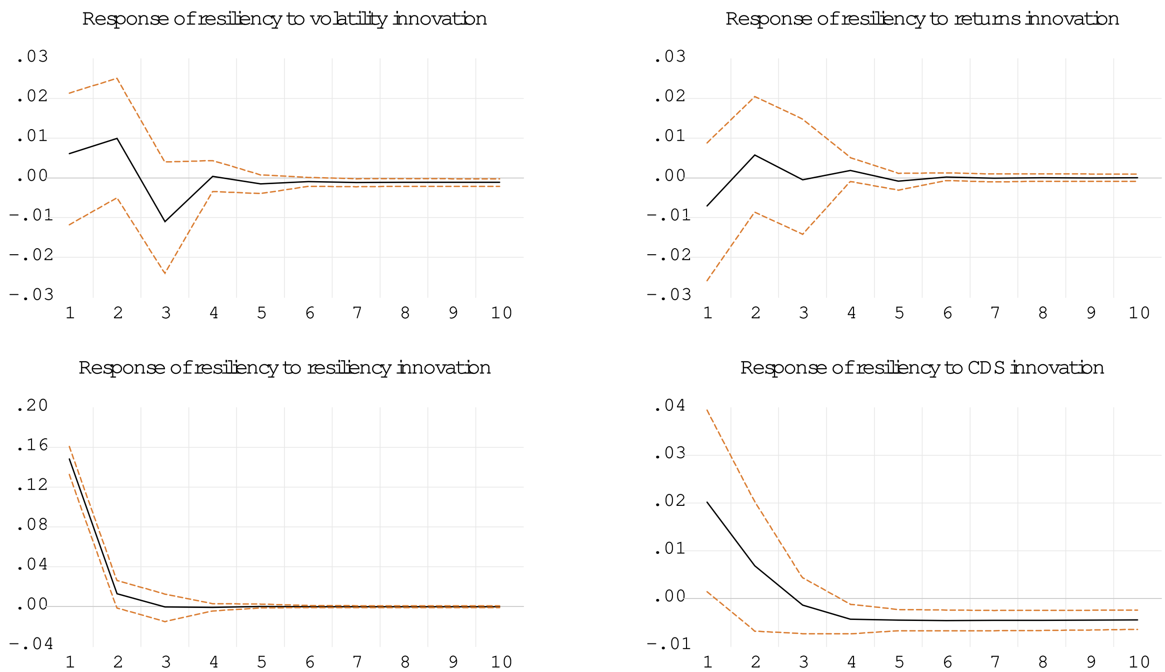


**Fig. 4(a).** Response of LASSO-based relative spread resiliency to the endogenous variables in Germany for the 10-year benchmark. The Impulse Response Functions run during the crisis period in the euro area (November 2009 to December 2013).

for quoted depth resiliency in Figs. 9(a) and 9(b). Overall, for Spanish 10-year bonds, we find that resiliency is most closely linked to CDS spreads with shocks to CDS spreads significantly decreasing resiliency.

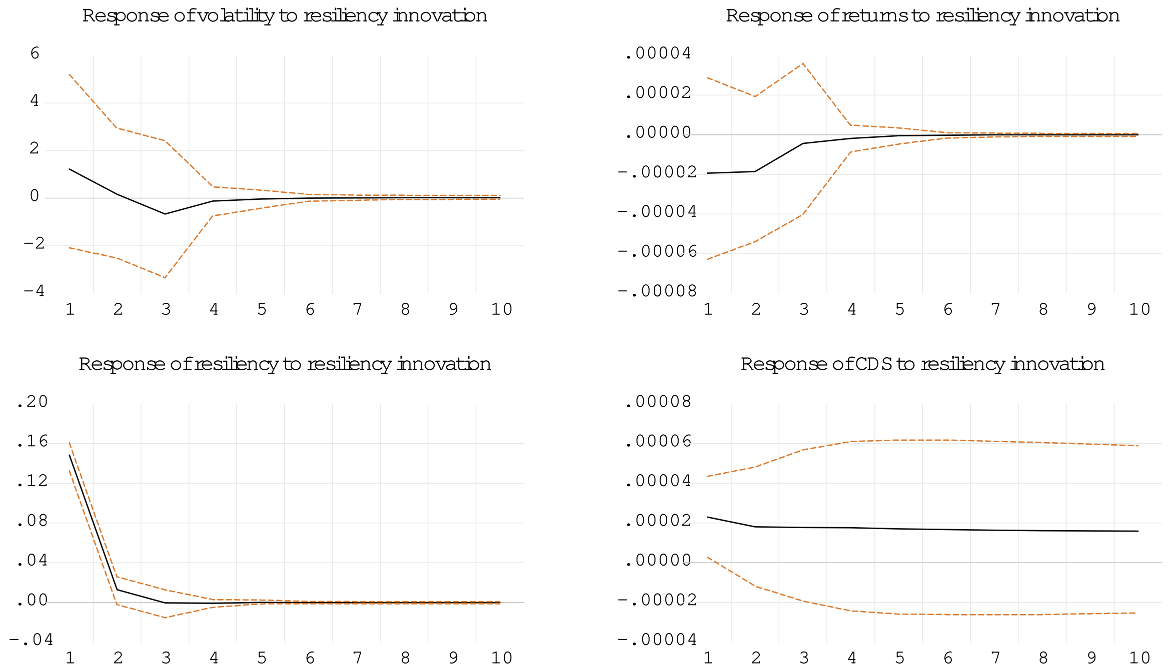


**Fig. 4(b).** Response of the endogenous variables to LASSO-based relative spread resiliency in Germany for the 10-year benchmark. The Impulse Response Functions run during the crisis period in the euro area (November 2009 to December 2013).

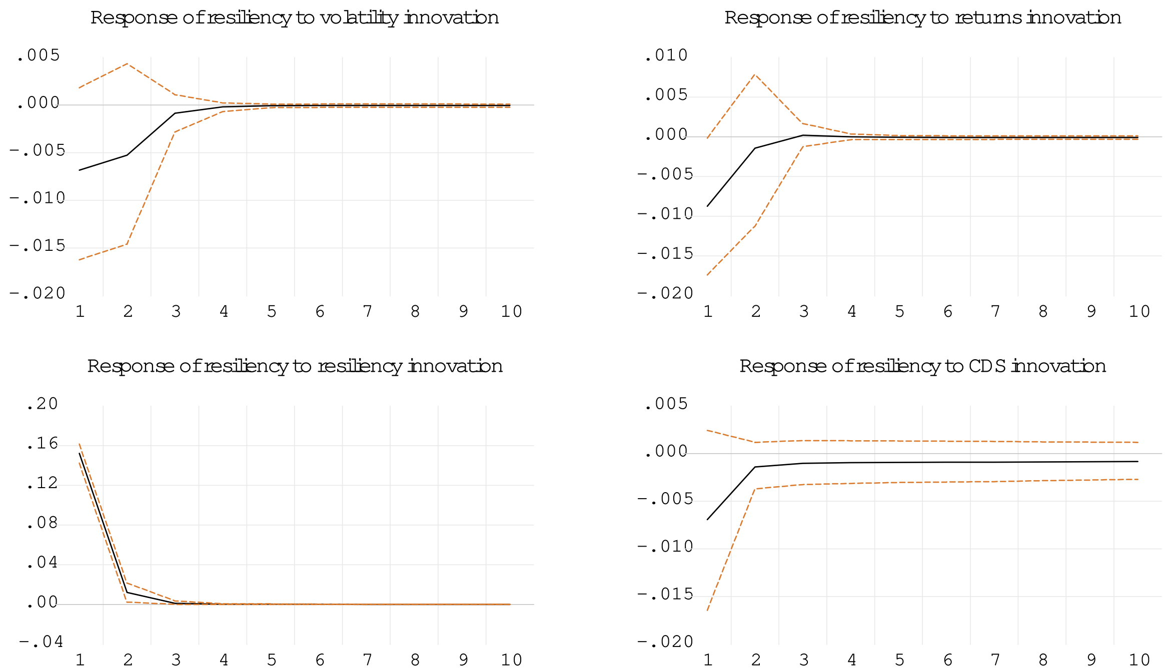


**Fig. 5(a).** Response of LASSO-based quoted depth resiliency to the endogenous variables in Germany for the 10-year benchmark. The Impulse Response Functions run during the crisis period in the euro area (November 2009 to December 2013).

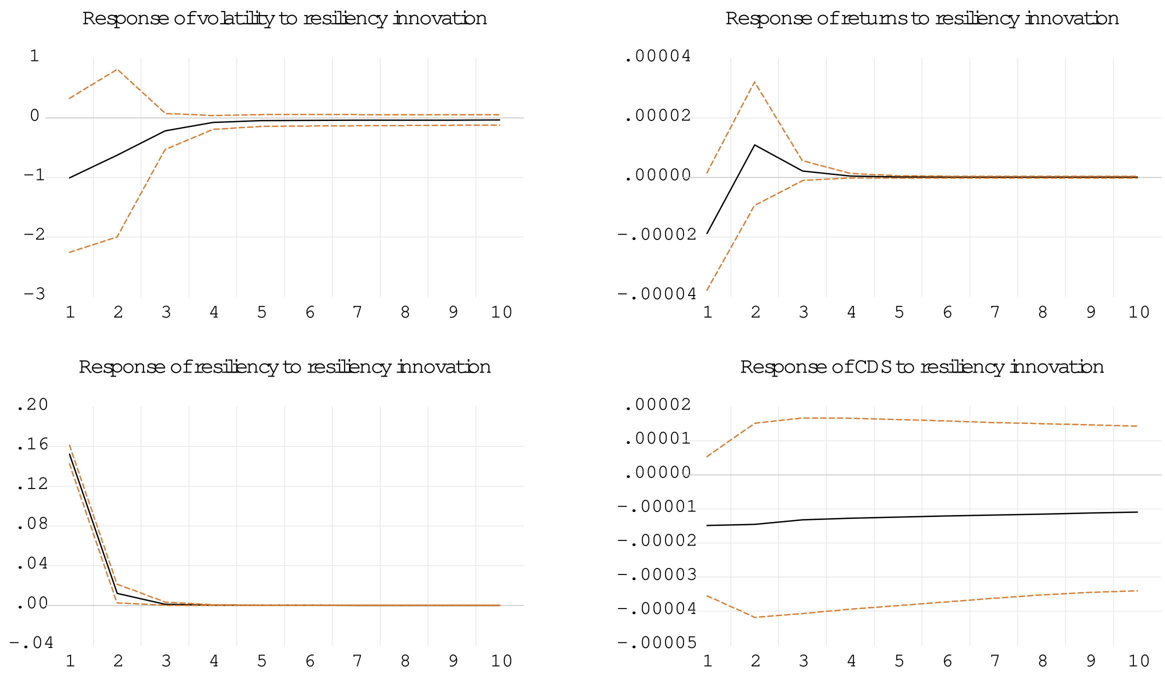


**Fig. 5(b).** Response of the endogenous variables to LASSO-based quoted depth resiliency in Germany for the 10-year benchmark. The Impulse Response Functions run during the crisis period in the euro area (November 2009 to December 2013).

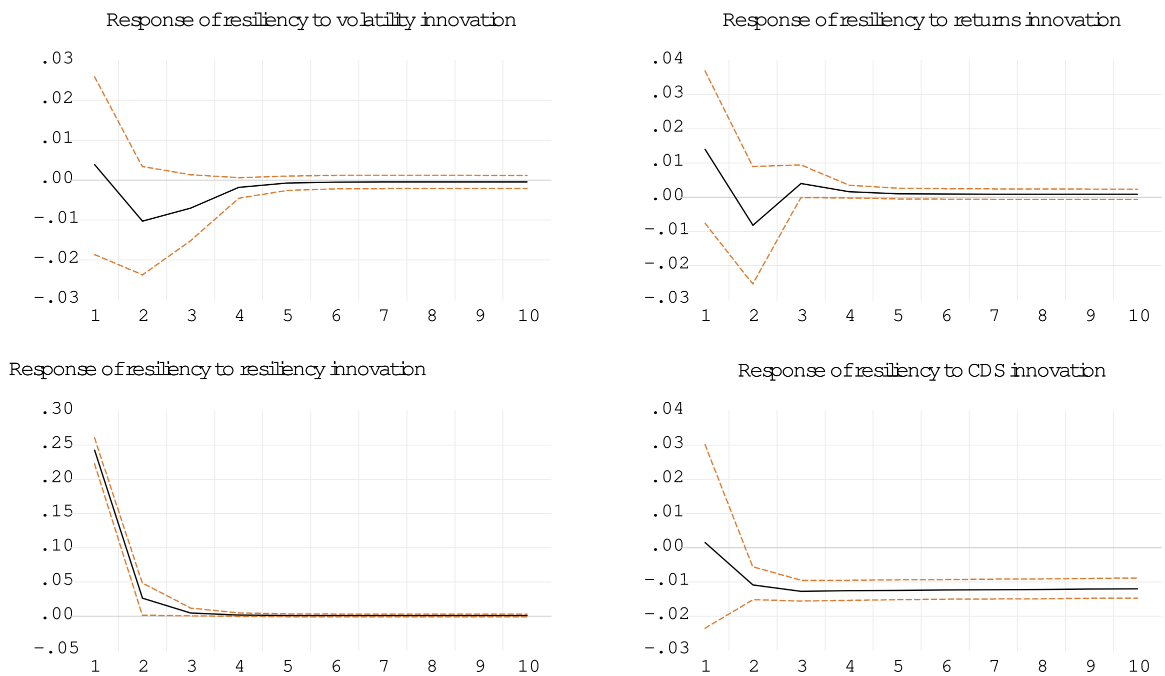


**Fig. 6(a).** Response of LASSO-based relative spread resiliency to the endogenous variables in Spain for the 10-year benchmark. The Impulse Response Functions run during the pre-crisis period in the euro area (January 2008 to October 2009).

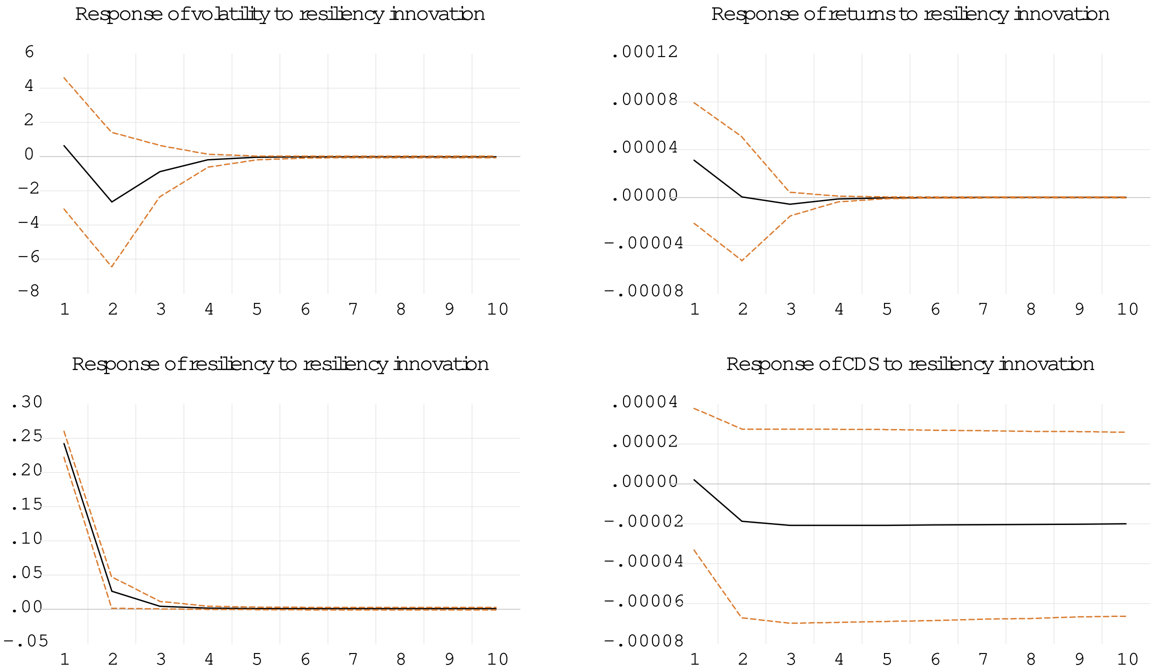


**Fig. 6(b).** Response of the endogenous variables to LASSO-based relative spread resiliency in Spain for the 10-year benchmark. The Impulse Response Functions run during the pre-crisis period in the euro area (January 2008 to October 2009).

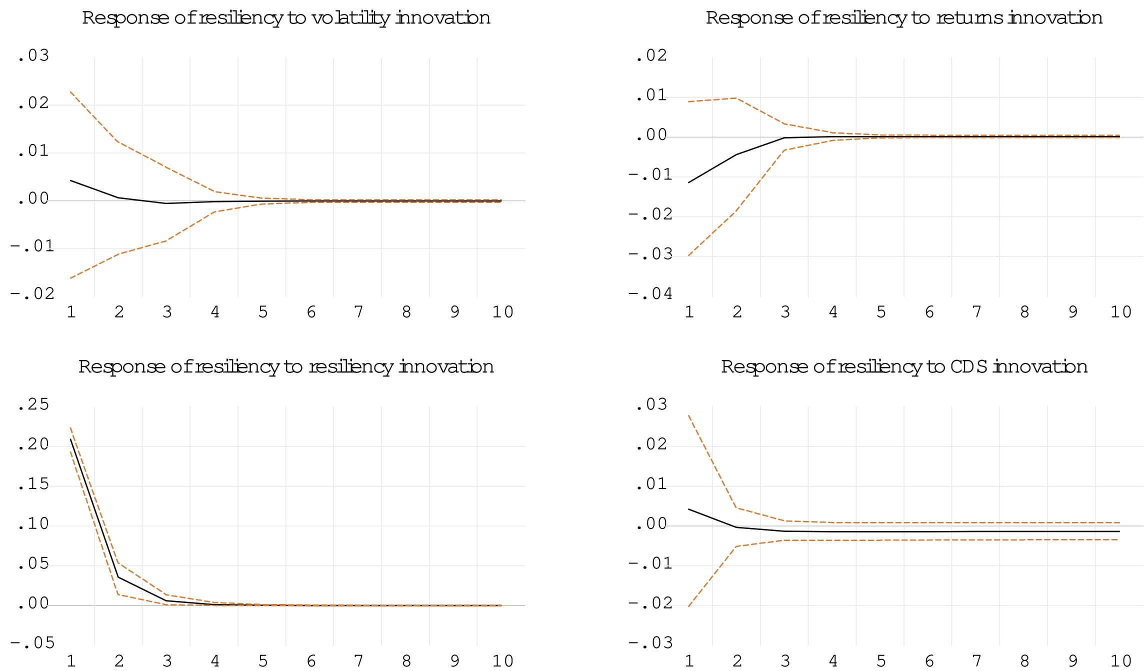


**Fig. 7(a).** Response of LASSO-based quoted depth resiliency to the endogenous variables in Spain for the 10-year benchmark. The Impulse Response Functions run during the pre-crisis period in the euro area (January 2008 to October 2009).

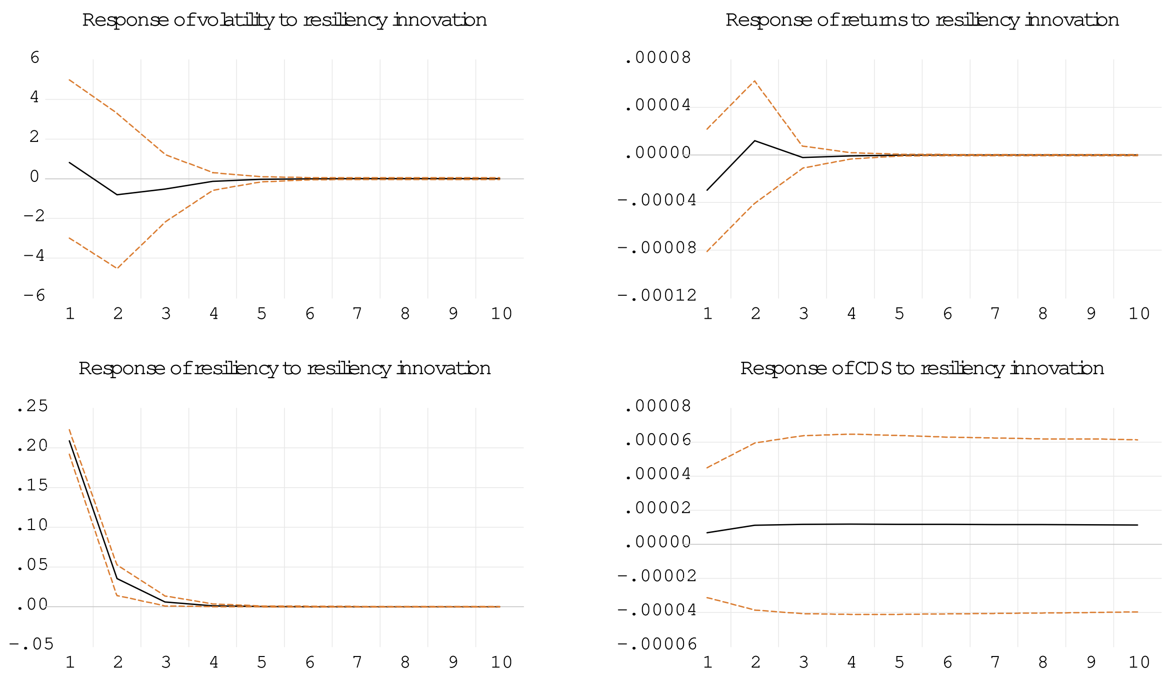


**Fig. 7(b).** Response of the endogenous variables to LASSO-based quoted depth resiliency in Spain for the 10-year benchmark. The Impulse Response Functions run during the pre-crisis period in the euro area (January 2008 to October 2009).

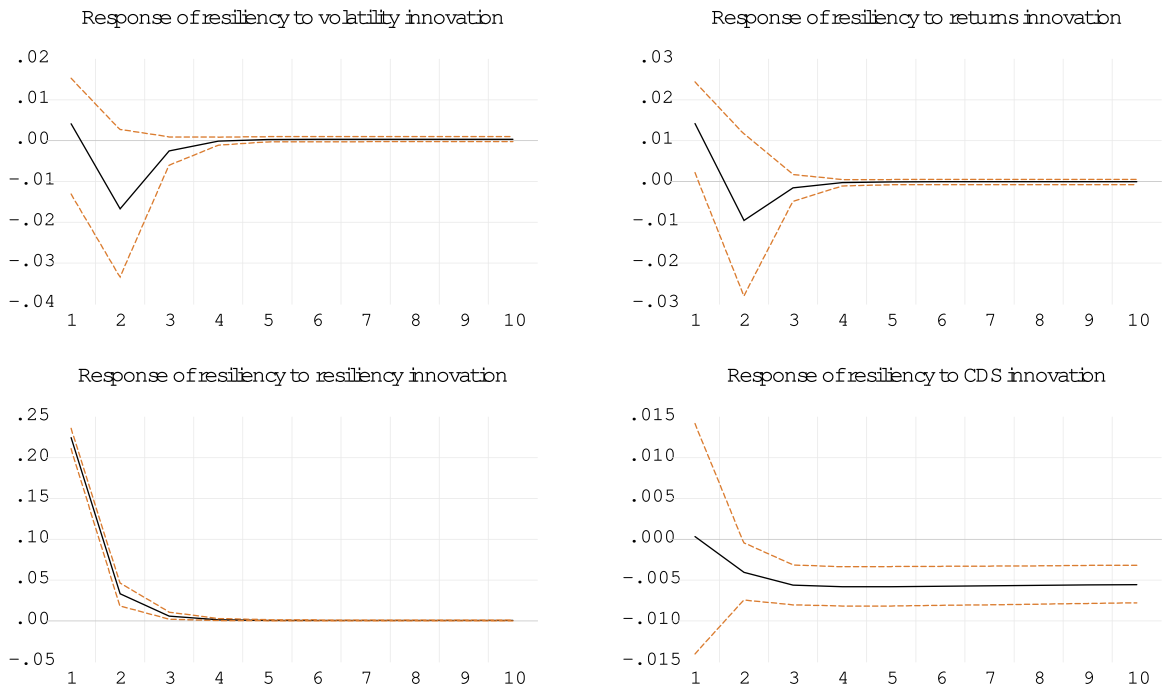


**Fig. 8(a).** Response of LASSO-based relative spread resiliency to the endogenous variables in Spain for the 10-year benchmark. The Impulse Response Functions run during the crisis period in the euro area (November 2009 to December 2013).

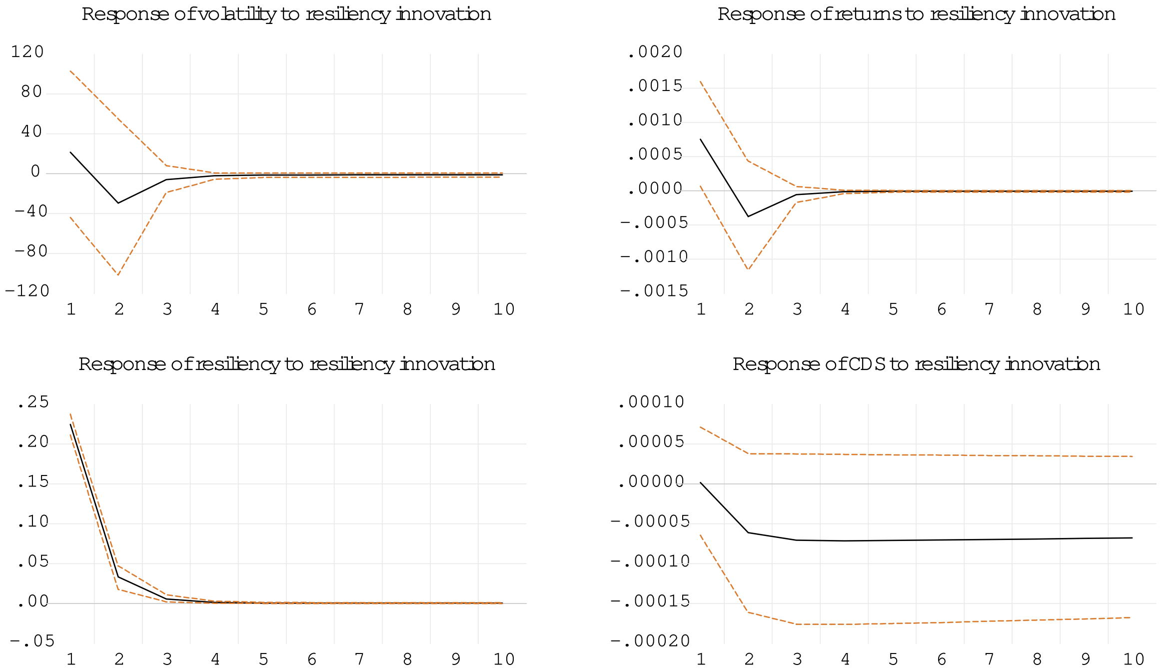


**Fig. 8(b).** Response of the endogenous variables to LASSO-based relative spread resiliency in Spain for the 10-year benchmark. The Impulse Response Functions run during the crisis period in the euro area (November 2009 to December 2013).

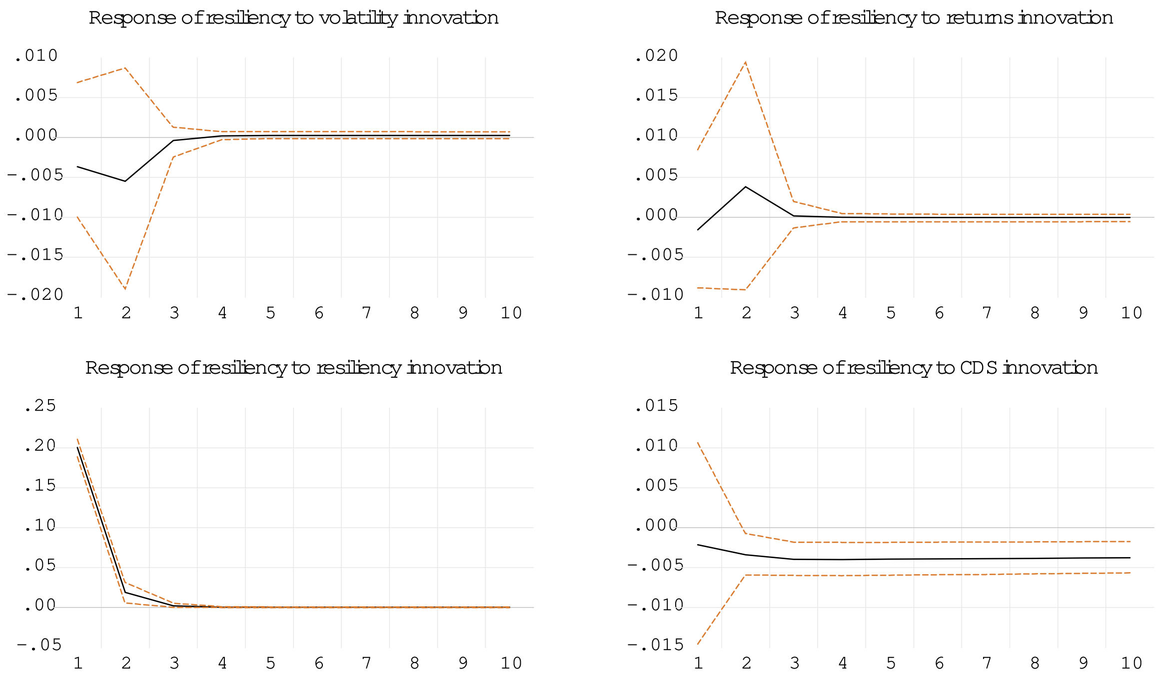


**Fig. 9(a).** Response of LASSO-based quoted depth resiliency to the endogenous variables in Spain for the 10-year benchmark. The Impulse Response Functions run during the crisis period in the euro area (November 2009 to December 2013).

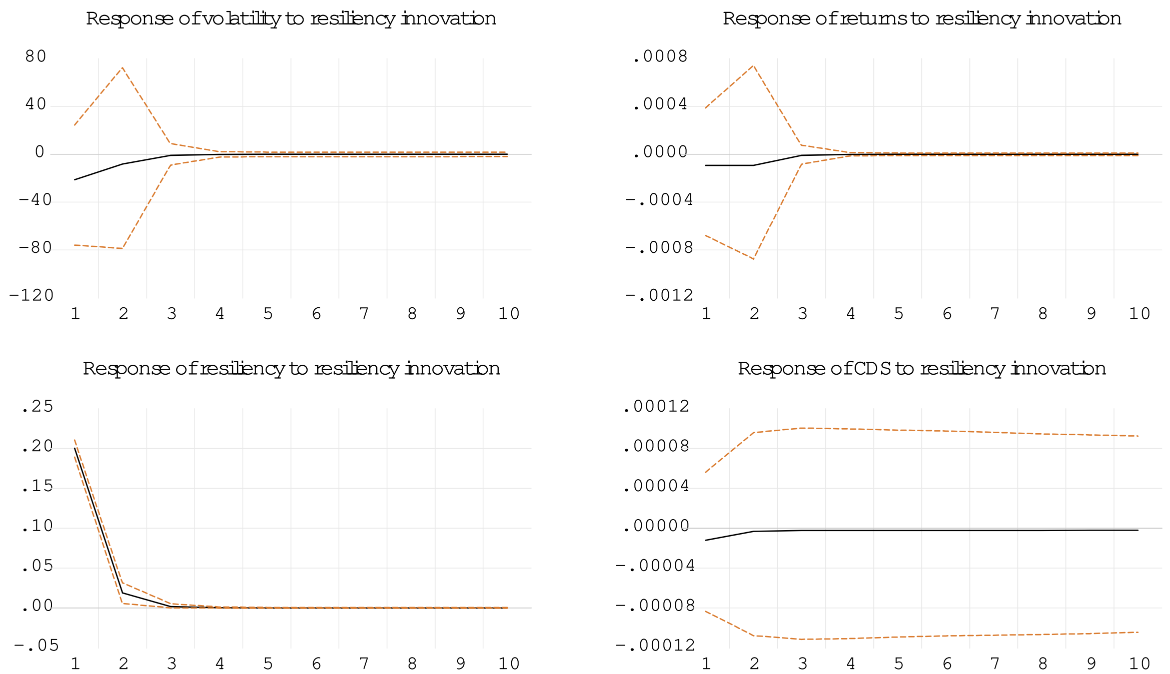


**Fig. 9(b).** Response of the endogenous variables to LASSO-based quoted depth resiliency in Spain for the 10-year benchmark. The Impulse Response Functions run during the crisis period in the euro area (November 2009 to December 2013).

### *5.3. Commonality in resiliency*

The seminal papers on commonality in liquidity are those of Chordia et al. (2000), Hasbrouck and Seppi (2001), Huberman and Halka (2001). All these studies find evidence of commonality in liquidity for U.S. listed stocks. O'Sullivan and Papavassiliou (2020) were the first to analyse commonality in liquidity in the context of bond markets, and in particular, the European sovereign bond market. Their results indicate that commonality is weaker during the European debt crisis period for both core and periphery countries, whilst it appears stronger for periphery than for core countries and is more pronounced for spread-based than it is for depth-based liquidity proxies. In a later study Panagiotou et al. (2022) also find strong commonality in liquidity for European sovereign bond markets. Therefore, we investigate whether the presence of common factors in spread and depth liquidity proxies carries over to resiliency liquidity proxies.

We use principal components analysis (PCA) to study commonality in our LASSO and OLS-based resiliency measures. Prior to applying PCA we standardize our series in order to remove deterministic time-of-day effects and to prevent the first principal component from being dominated by the most volatile variable. As our input variables are level stationary no transformation into first differences is needed before PCA is applied. Similar to Hasbrouck and Seppi (2001) we prefer to decompose the sample covariance matrix instead of the correlation matrix, that is, we transform the variances of the principal components into a covariance matrix of the original system using the factor weights.

Following O'Sullivan and Papavassiliou (2020) we use two sets of data. First, we use a "full set" of data from the following 11 core and periphery countries: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, and Spain. In the full set of data we employ spread-based resiliency and depth-based resiliency for each country across four maturity segments. We also use an "index set" of data in which we equally weight each individual spread or depth-based resiliency measure available at a given maturity, enabling us to average away individual country effects.

The PCA results are presented in Tables 10 and 11 where the proportion of total variation that is explained by the first three principal components is used as a metric to measure commonality in liquidity resiliency. Panel A in Table 10 presents the results for relative spread resiliency while Panel B presents the corresponding results for quoted depth resiliency. It is apparent that there exists strong commonality in resiliency in both pre-crisis and crisis periods for the periphery euro area countries (Greece, Ireland, Italy, Portugal, and Spain) regardless of how resiliency is measured. That is, we document strong commonalities in both our spread and depth resiliency proxies, especially for the index set of data. Kempf et al. (2015) also document strong commonality in resiliency for FTSE-100 stocks. In the pre-crisis period the first principal component of the LASSO-based spread resiliency explains nearly 30 percent of the variation in the full cross-section of spread resiliency considered, while the first principal component from the index data explains nearly 88 percent of total variation. The proportion of variation explained by the first three principal components amounts to 70.51 percent for the full set and 98.14 for the index set, respectively. The proportion of variation explained by the first three principal components in the crisis period is 71.59 percent for the full set and 97.91 percent for the index, showing that

**Table 11**
PCA core countries.

| Panel A: Relative spread resiliency | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | LASSO | | | | OLS | | | |
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | Full | Index | Full | Index | Full | Index | Full | Index |
| PCA 1 (%) | 22.16 | 86.34 | 20.10 | 88.42 | 12.69 | 45.79 | 12.71 | 46.49 |
| PCA 1+2 (%) | 38.39 | 91.52 | 35.44 | 93.34 | 19.57 | 65.81 | 18.09 | 68.47 |
| PCA 1+2+3 (%) | 50.98 | 96.15 | 50.44 | 96.99 | 25.66 | 84.10 | 23.45 | 86.18 |
| **Panel B: Quoted depth resiliency** | | | | | | | | |
| | LASSO | | | | OLS | | | |
| | Pre-crisis | | Crisis | | Pre-crisis | | Crisis | |
| | Full | Index | Full | Index | Full | Index | Full | Index |
| PCA 1 (%) | 11.53 | 49.56 | 9.57 | 47.48 | 10.00 | 41.77 | 8.73 | 37.90 |
| PCA 1+2 (%) | 19.91 | 68.86 | 18.29 | 69.21 | 17.81 | 65.28 | 14.83 | 61.36 |
| PCA 1+2+3 (%) | 27.56 | 85.06 | 26.12 | 85.76 | 23.54 | 84.59 | 20.19 | 82.32 |

*Notes:* The table presents Principal Component Analysis (PCA) results for core euro area bond markets (Germany and Netherlands). Panel A presents results for relative spread resiliency, whilst Panel B reports the corresponding results for quoted depth resiliency. OLS-based resiliency is estimated according to Eq. (2) while LASSO-based resiliency is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The full set of data employs spread-based resiliency and depth-based resiliency for each country across four maturity segments. The index data equally weights each individual spread or depth-based resiliency measure available at a given maturity. The pre-crisis period spans the dates from January 2008 to October 2009, while the crisis period extends from November 2009 to December 2013.

**Table A.1**
Descriptive statistics.

| Panel A: OLS-based resiliency - Relative Spread | | | | | |
|---|---|---|---|---|---|
| Maturity | Period | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.247 | 0.233 | 0.276 | 0.244 |
| | Crisis | 0.240 | 0.272 | 0.217 | 0.230 |
| 5-Year | Pre-crisis | 0.282 | 0.278 | 0.244 | 0.258 |
| | Crisis | 0.254 | 0.309 | 0.289 | 0.257 |
| 10-Year | Pre-crisis | 0.310 | 0.288 | 0.284 | 0.279 |
| | Crisis | 0.274 | 0.357 | 0.342 | 0.289 |
| 30-Year | Pre-crisis | 0.278 | 0.281 | 0.320 | 0.304 |
| | Crisis | 0.269 | 0.341 | 0.304 | 0.289 |
| **Panel B: LASSO-based resiliency - Relative Spread** | | | | | |
| Maturity | Period | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.504 | 0.244 | 0.279 | 0.251 |
| | Crisis | 0.212 | 0.276 | 0.219 | 0.233 |
| 5-Year | Pre-crisis | 0.240 | 0.293 | 0.244 | 0.259 |
| | Crisis | 0.200 | 0.313 | 0.289 | 0.260 |
| 10-Year | Pre-crisis | 0.280 | 0.294 | 0.284 | 0.286 |
| | Crisis | 0.230 | 0.361 | 0.344 | 0.293 |
| 30-Year | Pre-crisis | 0.277 | 0.287 | 0.321 | 0.300 |
| | Crisis | 0.230 | 0.346 | 0.307 | 0.295 |

*Notes:* Panel A shows the mean OLS-based relative spread resiliency for Germany (DE), Netherlands (NL), Italy (IT), and Spain (ES). Relative spread is defined as the best bid–ask spread divided by the midpoint of the bid and ask quotes. The OLS-based relative spread resiliency is estimated according to Eq. (2). The pre-crisis period spans the dates from January 2008 to October 2009 whilst the crisis period extends from November 2009 to December 2013. We use benchmark securities across four maturity segments, i.e. 2-, 5-, 10-, and 30-year maturity. Panel B shows the corresponding statistics for the LASSO-based relative spread resiliency which is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The liquidity measures have been winsorized by 99% in order to avoid extreme values in the resiliency estimates.

**Table A.2**
Descriptive statistics.

| Panel A: OLS-based resiliency - Quoted Depth | | | | | |
|---|---|---|---|---|---|
| Maturity | Period | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.392 | 0.445 | 0.484 | 0.428 |
| | Crisis | 0.393 | 0.454 | 0.416 | 0.393 |
| 5-Year | Pre-crisis | 0.471 | 0.504 | 0.518 | 0.532 |
| | Crisis | 0.425 | 0.562 | 0.535 | 0.522 |
| 10-Year | Pre-crisis | 0.422 | 0.489 | 0.532 | 0.527 |
| | Crisis | 0.389 | 0.573 | 0.545 | 0.449 |
| 30-Year | Pre-crisis | 0.450 | 0.643 | 0.521 | 0.566 |
| | Crisis | 0.458 | 0.681 | 0.520 | 0.503 |
| Panel B: LASSO-based resiliency - Quoted Depth | | | | | |
| Maturity | Period | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.345 | 0.459 | 0.488 | 0.438 |
| | Crisis | 0.358 | 0.458 | 0.420 | 0.402 |
| 5-Year | Pre-crisis | 0.373 | 0.519 | 0.519 | 0.487 |
| | Crisis | 0.337 | 0.567 | 0.538 | 0.489 |
| 10-Year | Pre-crisis | 0.371 | 0.508 | 0.532 | 0.536 |
| | Crisis | 0.339 | 0.576 | 0.548 | 0.455 |
| 30-Year | Pre-crisis | 0.340 | 0.653 | 0.522 | 0.571 |
| | Crisis | 0.333 | 0.687 | 0.522 | 0.512 |

*Notes:* Panel A shows the mean OLS-based quoted depth resiliency for Germany (DE), Netherlands (NL), Italy (IT), and Spain (ES). Quoted depth is defined as best bid size plus best ask size, where size denotes the quantity of securities bid or offered for sale at the posted bid and ask prices. The OLS-based quoted depth resiliency is estimated according to Eq. (2). The pre-crisis period spans the dates from January 2008 to October 2009 whilst the crisis period extends from November 2009 to December 2013. We use benchmark securities across four maturity segments, i.e. 2-, 5-, 10-, and 30-year maturity. Panel B shows the corresponding statistics for the LASSO-based quoted depth resiliency which is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The liquidity measures have been winsorized by 99% in order to avoid extreme values in the resiliency estimates.

the magnitude of commonality has remained almost unchanged from its pre-crisis levels. Commonality in the OLS-based spread resiliency is also high in both periods, however, the proportion of variation explained by the first three principal components for the full set hardly exceeds 30 percent, thus it is much lower than that of the LASSO-based spread resiliency.

Panel B of Table 10 presents the corresponding PCA results for quoted depth resiliency. The proportion of variation explained by the first three principal components for the index set pre-crisis is 87.41 percent for the LASSO-based resiliency and 82.44 percent for the OLS-based resiliency indicating the presence of strong commonalities in quoted depth resiliency. These figures slightly increase in the crisis period showing that the liquidity of periphery countries although impaired (shown in Table 2), demonstrates high depth resiliency. This may be due to the high selling pressure on the periphery benchmarks as investors were looking for safety and were rebalancing their portfolios towards the less risky benchmark securities of core euro area countries. Commonality appears to be weaker, although still of good value, in the full set taking on values that do not exceed 40 percent pre-crisis and 45 percent during the crisis.

Panel A of Table 11 presents the PCA results for spread resiliency of core euro area countries (Austria, Belgium, Finland, France, Germany, Netherlands). Commonality of spread resiliency is lower than that documented in the periphery region confirming the findings of O'Sullivan and Papavassiliou (2020). These findings can also be related to the work of Karolyi et al. (2012) who find higher commonality when prices decline and lower commonality when prices increase for global equity markets. The results reveal strong commonalities for the index set using both the LASSO-based and OLS-based approaches that take on values between 84 and 97 percent. Notably, commonality increases slightly in the crisis period for core countries (from 96.15 to 96.99 percent for the LASSO-based spread resiliency and from 84.10 to 86.18 percent for the OLS-based resiliency) in contrast to the commonality of periphery countries which slightly declines in the crisis. The proportion of variation explained by the first three principal components for the full set LASSO-based resiliency is 50.98 percent pre-crisis and drops slightly to 50.44 percent during the crisis period. The variation explained for the OLS-based spread resiliency is much lower than that of the LASSO-based resiliency and slightly declines during the crisis from 25.66 to 23.45 percent.

The PCA results for quoted depth resiliency shown in Panel B of the table document small declines in commonality in the crisis in contrast to the corresponding figures for periphery countries. The proportion of variation explained by the first three principal

**Table A.3**
Descriptive statistics.

| Panel A: OLS-based resiliency - Relative Spread | | | | | |
|---|---|---|---|---|---|
| Maturity | Period | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.259 | 0.253 | 0.291 | 0.260 |
| | Crisis | 0.249 | 0.296 | 0.229 | 0.246 |
| 5-Year | Pre-crisis | 0.314 | 0.320 | 0.276 | 0.292 |
| | Crisis | 0.266 | 0.350 | 0.307 | 0.278 |
| 10-Year | Pre-crisis | 0.339 | 0.328 | 0.315 | 0.311 |
| | Crisis | 0.290 | 0.421 | 0.359 | 0.307 |
| 30-Year | Pre-crisis | 0.290 | 0.297 | 0.337 | 0.315 |
| | Crisis | 0.280 | 0.378 | 0.323 | 0.305 |
| Panel B: LASSO-based resiliency - Relative Spread | | | | | |
| Maturity | Period | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.531 | 0.265 | 0.294 | 0.268 |
| | Crisis | 0.240 | 0.298 | 0.231 | 0.249 |
| 5-Year | Pre-crisis | 0.268 | 0.334 | 0.276 | 0.294 |
| | Crisis | 0.225 | 0.354 | 0.306 | 0.280 |
| 10-Year | Pre-crisis | 0.308 | 0.335 | 0.315 | 0.320 |
| | Crisis | 0.258 | 0.425 | 0.361 | 0.311 |
| 30-Year | Pre-crisis | 0.309 | 0.302 | 0.339 | 0.312 |
| | Crisis | 0.255 | 0.381 | 0.326 | 0.311 |

*Notes:* Panel A shows the mean OLS-based relative spread resiliency for Germany (DE), Netherlands (NL), Italy (IT), and Spain (ES). Relative spread is defined as the best bid–ask spread divided by the midpoint of the bid and ask quotes. The OLS-based relative spread resiliency is estimated according to Eq. (2). The pre-crisis period spans the dates from January 2008 to October 2009 whilst the crisis period extends from November 2009 to December 2013. We use benchmark securities across four maturity segments, i.e. 2-, 5-, 10-, and 30-year maturity. Panel B shows the corresponding statistics for the LASSO-based relative spread resiliency which is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The liquidity measures are not winsorized.

components for the index set exceeds 80 percent both in the pre-crisis and crisis periods and across the LASSO and OLS-based resiliency estimates. The substantially lower commonality of the full set than that of the index is due to the fact that individual country effects are averaged away for the index set but not for the full set, thus elevating commonality to higher levels when each country's spread and depth resiliency measures available at a given maturity are equally weighted.

In summary, our findings reveal significant commonalities in spread and depth-based resiliency, however, commonality in spread resiliency is higher than depth resiliency in both core and periphery countries and during crisis and calm periods. Moreover, we provide evidence that commonality in resiliency is stronger for periphery countries in the crisis period during which the liquidity of those countries was significantly impaired and liquidity risk was of particular importance.

## 6. Conclusions

We offer new insights into liquidity resiliency using a high-frequency dataset from the MTS sovereign bond markets. We measure resiliency using an OLS approach and a combination of an OLS approach and the LASSO machine learning approach and show that these methods can be used interchangeably in the measurement of market resiliency regardless of whether resiliency is estimated in terms of spreads or depths. We find that the information contained in resiliency is unique and independent of other dimensions of liquidity. We find significant intertemporal relationships between resiliency and sovereign credit risk, volatility, and sovereign bond returns, as well as strong commonalities in resiliency which are greater for spread-based than depth-based resiliency proxies.

Liquidity resiliency is of paramount importance today given that the speed of the order book replenishment mechanism has increased. Resiliency enables market participants to rebalance their portfolios in light of illiquidity episodes that occur more frequently in today's financial markets, in order to minimize trading costs and slippage. Market resiliency is also essential to institutional investors who wish to manage effectively their order flow. Our findings on commonality in resiliency have an impact on market quality as they indicate that the liquidity replenishment process for sovereign bonds can have contagious, market-wide effects, especially during periods of increased market uncertainty.

There are several policy implications from this research. Resiliency is important to market participants and regulators. Traders and arbitrageurs in limit order book markets face execution risk and take seriously into consideration liquidity risk when they buy and sell securities. Stock exchanges and alternative trading venues (including OTC trading) have a genuine interest in understanding the mechanics of limit order books in order to attract liquidity. Likewise, regulators need to understand liquidity resiliency to

**Table A.4**
Descriptive statistics.

| Panel A: OLS-based resiliency - Quoted Depth | | | | | |
|---|---|---|---|---|---|
| Maturity | Period | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.399 | 0.451 | 0.489 | 0.435 |
| | Crisis | 0.401 | 0.461 | 0.425 | 0.401 |
| 5-Year | Pre-crisis | 0.475 | 0.510 | 0.525 | 0.539 |
| | Crisis | 0.429 | 0.570 | 0.541 | 0.532 |
| 10-Year | Pre-crisis | 0.426 | 0.493 | 0.537 | 0.533 |
| | Crisis | 0.394 | 0.580 | 0.551 | 0.459 |
| 30-Year | Pre-crisis | 0.456 | 0.648 | 0.529 | 0.574 |
| | Crisis | 0.466 | 0.687 | 0.527 | 0.511 |
| Panel B: LASSO-based resiliency - Quoted Depth | | | | | |
| Maturity | Period | DE | NL | IT | ES |
| 2-Year | Pre-crisis | 0.350 | 0.465 | 0.493 | 0.444 |
| | Crisis | 0.373 | 0.465 | 0.429 | 0.410 |
| 5-Year | Pre-crisis | 0.377 | 0.524 | 0.526 | 0.494 |
| | Crisis | 0.342 | 0.575 | 0.544 | 0.498 |
| 10-Year | Pre-crisis | 0.376 | 0.513 | 0.538 | 0.542 |
| | Crisis | 0.343 | 0.583 | 0.554 | 0.464 |
| 30-Year | Pre-crisis | 0.347 | 0.659 | 0.531 | 0.579 |
| | Crisis | 0.337 | 0.693 | 0.530 | 0.521 |

*Notes:* Panel A shows the mean OLS-based quoted depth resiliency for Germany (DE), Netherlands (NL), Italy (IT), and Spain (ES). Quoted depth is defined as best bid size plus best ask size, where size denotes the quantity of securities bid or offered for sale at the posted bid and ask prices. The OLS-based quoted depth resiliency is estimated according to Eq. (2). The pre-crisis period spans the dates from January 2008 to October 2009 whilst the crisis period extends from November 2009 to December 2013. We use benchmark securities across four maturity segments, i.e. 2-, 5-, 10-, and 30-year maturity. Panel B shows the corresponding statistics for the LASSO-based quoted depth resiliency which is estimated according to Eqs. (2) and (3) following a two-stage regression approach. The liquidity measures are not winsorized.

monitor market quality and stability and to design and implement new regulations. It is hoped that the current analysis can be useful for portfolio managers and policymakers who design and implement portfolio diversification strategies and new financial market regulations.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Data availability

Research data used in this study is proprietary.

## References

Ali Nasir, M., 2022. Off the Target: The Stagnating Political Economy of Europe and Post-Pandemic Recovery. Palgrave Macmillan Cham.
Ali Nasir, M., Ngoc Lan Le, T., Ghabri, Y., Duc Toan Huynh, L., 2023. Sovereign bonds and flight to safety: Implications of the COVID-19 crisis for sovereign debt markets in the G-7 and E-7 economies. Int. Rev. Financ. Anal. 86, 102548.
Amihud, Y., Mendelson, H., 1986. Asset pricing and the bid–ask spread. J. Financ. Econ. 17, 223–249.
Amihud, Y., Mendelson, H., Pedersen, L.H., 2005. Liquidity and asset prices. Found. Trends Finance 1, 269–364.
Andersen, T.G., Bollerslev, T., 1998. Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. Internat. Econom. Rev. 39, 885–905.
Andersen, T.G., Bollerslev, T., Diebold, F.X., Ebens, H., 2001. The distribution of realized stock return volatility. J. Financ. Econ. 61, 43–76.
Augustin, P., 2018. The term structure of CDS spreads and sovereign credit risk. J. Monetary Econ. 96, 53–76.
Bai, J., Bali, T.G., Wen, Q., 2016. Do the Distributional Characteristics of Corporate Bonds Predict Their Future Returns? Unpublished Working Paper, McDonough School of Business, Georgetown University.
Bandi, F.M., Russell, J.R., 2006. Separating microstructure noise from volatility. J. Financ. Econ. 79, 665–692.
Batten, J.A., Kinateder, H., Wagner, N., 2022. Beating the average: Equity premium variations, uncertainty, and liquidity. Abacus 58, 567–588.
Beetsma, R., Giuliodori, M., de Jong, F., Widijanto, D., 2013. Spread the news: The impact of news on the European sovereign bond markets during the crisis. J. Int. Money Finance 34, 83–101.

Benston, G., Hagerman, R., 1974. Determinants of bid–asked spreads in the over-the-countermarket. J. Financ. Econ. 1, 353–364.
Bessembinder, H., Carrion, A., Tuttle, L., Venkataraman, K., 2016. Liquidity, resiliency and market quality around predictable trades: Theory and evidence. J. Financ. Econ. 121, 142–166.
Bessembinder, H., Kaufman, H.M., 1997. A comparison of trade execution costs for NYSE and Nasdaq-listed stocks. J. Financ. Quant. Anal. 32, 287–310.
Bewley, T.F., 2002. Knightian decision theory. Part I. Decis. Econ. Finance 25, 79–110.
Bhattacharya, U., Spiegel, M., 1998. Anatomy of a market failure: NYSE trading suspensions (1974–1988). J. Bus. Econom. Statist. 16, 216–226.
Biais, B., Hillion, P., Spatt, C., 1995. An empirical analysis of the limit order book and the order flow in the Paris Bourse. J. Finance 50, 1655–1689.
Bickel, P.J., Ritov, Y., Tsybakov, A.B., 2009. Simultaneous analysis of lasso and dantzigselector. Ann. Statist. 37, 1705–1732.
Borio, C., 2000. Market liquidity and stress: selected issues and policy implications. BISQuarterly Review November, 38–48.
Broto, C., Lamas, M., 2020. Is market liquidity less resilient after the financial crisis? Evidence for US Treasuries. Econ. Model. 93, 217–229.
Brunnermeier, M.K., Pedersen, L.H., 2009. Market liquidity and funding liquidity. Rev. Financ. Stud. 22, 2201–2238.
Calice, G., Chen, J., Williams, J., 2013. Liquidity spillovers in sovereign bond and CDS markets: An analysis of the Eurozone sovereign debt crisis. J. Econ. Behav. Organ. 85, 122–143.
Chinco, A., Clark-Joseph, A.D., Ye, M., 2019. Sparse signals in the cross-section ofreturns. J. Finance 74, 449–492.
Chordia, T., Roll, R., Subrahmanyam, A., 2000. Commonality in liquidity. J. Financ. Econ. 56, 3–28.
Chordia, T., Roll, R., Subrahmanyam, A., 2001. Market liquidity and trading activity. J. Finance 56, 501–530.
Chordia, T., Roll, R., Subrahmanyam, A., 2002. Order imbalance, liquidity and market returns. J. Financ. Econ. 65, 111–130.
Chordia, T., Sarkar, A., Subrahmanyam, A., 2005. An empirical analysis of stock and bond market liquidity. Rev. Financ. Stud. 18, 85–129.
Chung, K.H., Chuwonganant, C., 2014. Uncertainty, market structure, and liquidity. J. Financ. Econ. 113, 476–499.
Claeys, P., Vašíček, B., 2014. Measuring bilateral spillover and testing contagion on sovereign bond markets in Europe. J. Bank. Financ. 46, 151–165.
Clapham, B., Haferkorn, M., Zimmermann, K., 2020. Does speed matter? The role of high-frequency trading for order book resiliency. J. Financ. Res. 43, 933–964.
Coppejans, M., Domowitz, I., Madhavan, A., 2004. Resiliency in an Automated Auction. Working Paper, Barclays Global Investors.
Czech, R., 2021. Credit default swaps and corporate bond trading. J. Financ. Intermediation 48, 100932.
Danielson, J., Panayi, E., Peters, G.W., Zigrand, J.-P., 2018. Market Resilience. Working Paper, London School of Economics and Systemic Risk Centre.
Das, S., Kalimipalli, M., Nayak, S., 2014. Did CDS trading improve the marketfor corporate bonds? J. Financ. Econ. 111, 495–525.
De Santis, R.A., 2014. The euro area sovereign debt crisis: identifying flight-to-liquidity and the spillover mechanisms. J. Empir. Financ. 26, 150–170.
Degryse, H., De Jong, F., Van Ravenswaaij, M., Wuyts, G., 2005. Aggressive orders and the resiliency of a limit order market. Rev. Finance 9, 201–242.
Dellas, H., Tavlas, G.S., 2013. The gold standard, the euro, and the origins of the Greek sovereign debt crisis. Cato J. 33, 491–520.
Diaz, A., Escribano, A., 2020. Measuring the multi-faceted dimension of liquidity in financial markets: A literature review. Res. Int. Bus. Finance 51, 101079.
Dick-Nielsen, J., Feldhütter, P., Lando, D., 2012. Corporate bond liquidity before and after the onset of the subprime crisis. J. Financ. Econ. 103, 471–492.
Dong, J., Kempf, A., Yadav, P.K., 2007. Resiliency, the Neglected Dimension of Market Liquidity: Empirical Evidence from the New York Stock Exchange. Working Paper, University of Cologne.
Duffie, D., Gârleanu, N., Pedersen, L.H., 2007. Valuation in over-the-counter markets. Rev. Financ. Stud. 20, 1865–1900.
Dufour, A., Nguyen, M., 2013. Time-Varying Price Discovery in the European Treasury Markets. Working Paper, University of Reading.
Easley, D., López de Prado, M., O'Hara, M., Zhang, Z., 2021. Microstructure in the machine age. Rev. Financ. Stud. 34, 3316–3363.
Easley, D., O'Hara, M., 2010. Liquidity and valuation in an uncertain world. J. Financ. Econ. 97, 1–11.
Fan, J., Peng, H., 2004. Nonconcave penalized likelihood with a diverging number of parameters. Ann. Statist. 32, 928–961.
Félez-Vinas, E., 2019. Effects of Market Fragmentation on Resiliency. Working Paper, Stockholm Business School.
Feng, G., Giglio, S., Xiu, D., 2020. Taming the factor zoo: A test of new factors. J. Finance 75, 1327–1370.
Fishe, R.P.H., Haynes, R., Onur, E., 2022. Resiliency in the E-mini futures market. J. Futures Mark. 42, 5–23.
Foucault, T., Kadan, O., Kandel, E., 2005. Limit order book as a market for liquidity. Rev. Financ. Stud. 18, 1171–1217.
Freyberger, J., Neuhierl, A., Weber, M., 2020. Dissecting characteristics nonparametrically. Rev. Financ. Stud. 33, 2326–2377.
Garbade, K.D., 1982. Securities Markets. McGraw-Hill.
Gargano, A., Pettenuzzo, D., Timmermann, A., 2019. Bond return predictability: Economic value and links to the macroeconomy. Manage. Sci. 65, 508–540.
Gomber, P., Schweickert, U., Theissen, E., 2015. Liquidity dynamics in an electronicopen limit order book: An event study approach. Eur. Financial Manag. 21, 52–78.
Goyenko, R., Subrahmanyam, A., Ukhov, A., 2011. The term structure of bond market liquidity and its implications for expected bond returns. J. Financ. Quant. Anal. 46, 111–139.
Griffith, T.G., Roseman, B.S., 2019. Making cents of tick sizes: The effect of the 2016 U.S. SEC tick size pilot on limit order book liquidity. J. Bank. Financ. 101, 104–121.
Harris, L., 1994. Minimum price variations, discrete bid–ask spreads, and quotation sizes. Rev. Financ. Stud. 7, 149–178.
Harris, L., 2002. Trading and Exchanges: Market Microstructure for Practitioners. Oxford University Press.
Hasbrouck, J., Seppi, D.J., 2001. Common factors in prices, order flows and liquidity. J. Financ. Econ. 59, 383–411.
Hua, J., Peng, L., Schwartz, R.A., Alan, N.S., 2020. Resiliency and stock returns. Rev. Financ. Stud. 33, 747–782.
Huberman, G., Halka, D., 2001. Systematic liquidity. J. Financ. Res. 24, 161–178.
Huck, N., 2019. Large data sets and machine learning: Applications to statistical arbitrage. European J. Oper. Res. 278, 330–342.
Ibikunle, G., Li, Y., Mare, D., Sun, Y., 2021. Dark matters: The effects of dark trading restrictions on liquidity and informational efficiency. J. Int. Financ. Mark. Inst. Money 75, 101435.
Karolyi, G.A., VanLee, K.H., Dijk, M.A., 2012. Understanding commonality in liquidity around the world. J. Financ. Econ. 105, 82–112.
Kempf, A., Mayston, D., Gehde-Trapp, M., Yadav, P.K., 2015. Resiliency: A Dynamic View of Liquidity. Working Paper, University of Cologne.
Kim, J., Kim, Y., 2019. Transitory prices, resiliency, and the cross-section of stock returns. Int. Rev. Financ. Anal. 63, 243–256.
Kinateder, H., Papavassiliou, V.G., 2019. Sovereign bond return prediction with realized higher moments. J. Int. Financ. Mark. Inst. Money 62, 53–73.
Kyle, A.S., 1985. Continuous auctions and insider trading. Econometrica 53, 1315–1335.
Large, J., 2007. Measuring the resiliency of an electronic limit order book. J. Financial Mark. 10, 1–25.
Moorthy, S., 2003. Liquidity in the equity market: A portfolio trader's perspective. In: Persaud, A. (Ed.), Liquidity Black Holes: Understanding, Quantifying and Managing Financial Liquidity Risk. Haymarket House, Risk Books, London, pp. 21–40.
Obizhaeva, A.A., Wang, J., 2013. Optimal trading strategy and supply/demand dynamics. J. Financial Mark. 16, 1–32.
O'Sullivan, C., Papavassiliou, V.G., 2019. Measuring and analyzing liquidity and volatility dynamics in the euro-area government bond market. In: Boubaker, S., Nguyen, D.K. (Eds.), Handbook of Global Financial Markets: Transformations, Dependence, and Risk Spillovers. World Scientific Publishing, pp. 361–400, (Ch. 15).
O'Sullivan, C., Papavassiliou, V.G., 2020. On the term structure of liquidity in the European sovereign bond market. J. Bank. Financ. 114, 105777.
O'Sullivan, C., Papavassiliou, V.G., 2021. A high-frequency analysis of return andvolatility spillovers in the European sovereign bond market. Eur. J. Finance published online: 06 Apr 2021.
Ozsoylev, H., Werner, J., 2011. Liquidity and asset prices in rational expectations equilibrium with ambiguous information. Econom. Theory 48, 469–491.

Panagiotou, P., Jiang, X., Gavilan, A., 2022. The determinants of liquidity commonality in the euro-area sovereign bond market. Eur. J. Finance published online: 19 July 2022.

Papavassiliou, V.G., Kinateder, H., 2021. Information shares and market quality before and during the European sovereign debt crisis. J. Int. Financ. Mark. Inst. Money 72, 101334.

Pástor, L., Stambaugh, R.F., 2003. Liquidity risk and expected stock returns. J. Polit. Econ. 111, 642–685.

Pelizzon, L., Subrahmanyam, M.G., Tomio, D., Uno, J., 2016. Sovereign credit risk, liquidity, and European Central Bank intervention: Deus ex machina? J. Financ. Econ. 122, 86–115.

Rehse, D., Riordan, R., Rottke, N., Zietz, J., 2019. The effects of uncertainty on market liquidity: Evidence from Hurricane Sandy. J. Financ. Econ. 134, 318–332.

Roşu, I., 2020. Liquidity and information in limit order markets. J. Financ. Quant. Anal. 55, 1792–1839.

Routledge, B.R., Zin, S.E., 2009. Model uncertainty and liquidity. Rev. Econ. Dyn. 12, 543–566.

Schneider, M., Lillo, F., Pelizzon, L., 2016. How Has Sovereign Bond Market Liquidity Changed? An Illiquidity Spillover Analysis. SAFE Working Paper No. 151, Goethe University.

Shojaie, A., Fox, E.B., 2022. Granger causality: A review and recent advances. Annu. Rev. Stat. Appl. 9, 289–319.

Tang, C., Liu, X., Zhou, D., 2022. Financial market resilience and financial development: A global perspective. J. Int. Financ. Mark. Inst. Money 80, 101650.

Tian, S., Yu, Y., Guo, H., 2015. Variable selection and corporate bankruptcy forecasts. J. Bank. Financ. 52, 89–100.

Tibshirani, R., 1996. Regression shrinkage and selection via the lasso. J. R. Stat. Soc. Ser. B Stat. Methodol. 58, 267–288.

Vayanos, D., 2004. Flight to Quality, Flight to Liquidity, and the Pricing of Risk. National Bureau of Economic Research Working Paper 10327.