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A COMPOSITE INDICATOR OF SOVEREIGN BOND MARKET LIQUIDITY IN THE EURO AREA

by Riccardo Poli* and Marco Taboga[+]

Abstract

We propose a methodology to build and validate a composite indicator of the market liquidity of euro-area sovereign bonds. The indicator aggregates several metrics from different trading venues, with the aim of providing a comprehensive measurement of prevailing bond-market liquidity conditions in the four largest euro-area economies (Germany, France, Italy and Spain). The composite indicator, which starts in 2010, allows us to put into historical context the sharp liquidity deterioration experienced at the height of the COVID-19 crisis. The deterioration was comparable to, although slightly less severe than, that experienced during the European sovereign debt crisis. However, while at the time the impairment in liquidity conditions had lasted for more than two years, this time it was quickly re-absorbed. We provide some evidence that the promptness and boldness of the ECB's interventions in 2020 could help to explain this difference: according to our indicator, the announcements of the Pandemic Emergency Purchase Programme and other policy measures having an explicit market stabilization function were immediately followed by significant improvements in the liquidity of sovereign bonds.

JEL Classification: G12.
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Contents

* Market operations Directorate, DG Markets and payment systems, Bank of Italy.
[+] Economic outlook and monetary policy Directorate, DG Economics, statistics and research, Bank of Italy.

1. Introduction[1]

According to several observers (e.g., Lane 2020a and 2020b, Fleming and Ruela 2020, Fontaine et al. 2020), the strong market tensions experienced at the peak of the Covid-19 crisis were characterized by a sharp deterioration in the trading liquidity of sovereign bond markets.

Since liquidity in fixed income markets is necessary for the smooth transmission of monetary policy and for preserving financial stability, the major central banks quickly adopted policy measures that had an explicit market stabilization function (e.g., Lane 2020a and 2020b) and were aimed at restoring normal liquidity conditions. A notable example is the Pandemic Emergency Purchase Programme (PEPP) announced by the European Central Bank (ECB) in March 2020.

These developments highlighted the need for robust and readily available measures of market liquidity, to be used for the real-time monitoring of trading conditions and for informing the decisions on how to use the flexibility of purchase programmes. Such a need poses several research challenges that have been only partly addressed by the existing literature: how can we best summarize the information provided by the multitude of liquidity measures proposed in the literature? How can we form a comprehensive picture of liquidity conditions taking into account the fact that sovereign bonds are traded on a multiplicity of venues (wholesale, retail, over the counter), including on future markets that are tightly integrated with cash markets? Is there any economic criterion to choose and validate the measures that summarize the information provided by different liquidity indices?

We attempt to answer these questions by focusing on the sovereign bond markets of the four largest euro-area economies (Germany, France, Italy and Spain). The time span covered by our analysis includes the European sovereign debt crisis, which provides a useful yardstick to assess the severity of the liquidity deterioration experienced during the Covid-19 stress episode.

We gather data from several different sources and markets (both cash and futures), and construct a broad range of liquidity metrics proposed in the literature, including bid-ask spreads, volatility[2], trading volumes and open interest, measures of market breadth (Hui and Heubel

[1] All the views expressed in this paper are the authors' and do not necessarily represent those of the Bank of Italy. We thank Gioia Cellai, Paolo Del Giovane, Alberto Locarno, Stefano Neri, Marcello Pericoli, Luca Filidi and Giampiero Guerra for helpful comments and suggestions.
[2] Which is considered a measure of market depth (e.g., Engle and Lange 2001).

1984, Amihud 2002), tightness (Roll 1984, Corwin and Schultz 2012, Abdi and Ranaldo 2017) and resiliency (Hasbrouck and Schwartz 1988, Hu, Pan and Wang 2013).

We use different methods to summarize the information coming from this multitude of liquidity measures, including simple and weighted averaging schemes, principal component analysis (PCA), weighted PCA and 2-stage PCA. The results are relatively robust, although different composite indicators sometimes disagree on the severity of some illiquidity spikes. This simple observation motivates some of the central research questions in this paper: which composite indicator should we monitor more closely? Which one provides more reliable indications about liquidity conditions? How can we choose which one to use for policy purposes? We propose a method to answer these questions, which is also one of the main novelties of this paper. We use an economic criterion to choose a preferred composite indicator, by exploiting the intuition that the illiquidity of an instrument should be highly and positively correlated with the liquidity risk premium required on that instrument (e.g., Acharya and Pedersen 2005, Jang et al. 2007, Favero et al. 2010). We build a proxy for the liquidity risk premium embedded in 10-year sovereign bond yields and then choose the composite liquidity indicator that has the maximum correlation with the proxy.

According to the preferred liquidity indicator, the deterioration in market liquidity experienced at the peak of the Covid-19 crisis was comparable to, although slightly less severe than, that experienced during the euro area sovereign debt crisis. In particular, the estimated level of illiquidity in March 2020 was the highest recorded since ECB's President Mario Draghi pronounced the famous "Whatever it takes" speech (e.g., Acharya et al. 2019) and the ECB launched the Outright Monetary Transactions, which started a progressive normalization of liquidity conditions in euro-area sovereign bond markets. However, we find a remarkable difference between the liquidity dry-up observed during the sovereign debt crisis and that of 2020: while the former lasted for more than two years, the latter was quickly re-absorbed. We provide some evidence that the promptness and boldness of ECB's interventions in 2020 could be an explanatory factor, although we recognize that euro-area bond markets experienced several structural changes in the last decade (see the reports by the Bank for International Settlements 2106a and 2016b). The dynamics of the composite liquidity indicator recorded sharp improvements immediately after the announcement of some of the ECB's most important measures: the Pandemic Emergency Purchase Programme (PEPP), the removal of some self-imposed limits on asset purchases, an easing of collateral rules that could benefit sovereigns under stress, the increases in the overall size of purchases.

The remainder of the paper is organized as follows. Section 2 reviews the concept of market liquidity and the literature that is most relevant to this paper. Section 3 illustrates the liquidity measures used to construct our composite indicator. Sections 4-6 present the data and the methodology used to build the indicator. Section 7 presents some descriptive evidence about the dynamics of the index during the Covid-19 crisis. Section 8 concludes.

2. The concept of market liquidity

Market liquidity is a multi-faceted concept. It can be defined as the ability to trade an asset without facing large transaction costs (such as bid-ask spreads, broker fees, delays and search costs; e.g., Constantinides 1986, Amihud and Mendelson 1986) and to execute large orders without significantly affecting prices (e.g., Kyle 1985, Engle and Lange 2001, Foucault et. al 2013).

The following features are often deemed essential characteristics of a liquid market (e.g., Kyle 1985, Lybec and Sarr 2002, Borio 2000):

1. *Breadth and depth*: the constant presence of many outstanding trading proposals (e.g., limit orders on a trading book) of non-negligible size.
2. *Immediacy*: the ability to quickly execute orders.
3. *Resiliency*: the capability of the order flow to adjust quickly to temporary imbalances in supply and demand; or, in other words, the ability of the quantity of outstanding trading proposals to swiftly revert to normal levels after sudden decreases caused by large trades.
4. *Tightness*: the closeness between the buy and the sell price of an asset, which is often approximated by the bid-ask spread.

Among the factors that determine the degree of liquidity of an asset class, a prominent role is played by market microstructure. A feature that distinguishes the sovereign bond markets analyzed in this paper from other markets such as equity markets is that the vast majority of trades is usually performed over the counter, that is, in a decentralized manner. The order flows are not aggregated into a unique exchange, but transactions are fragmented across multiple venues. In this context, dealers perform a crucial role of liquidity providers. Their ability and willingness to quote prices and to effectively perform a market making function are important determinants of market liquidity. In turn, these determinants are significantly affected by balance sheet capacity and market volatility, so much so that volatility spikes may hamper the smooth functioning of markets[3] (e.g., Fender and Lewrick 2015).

A comprehensive taxonomy of microstructure-related factors affecting market liquidity is provided by Amihud et al. (2006), who identify four main categories:

1. *Demand pressure and inventory risk*. Since not all agents are present in the market at all times, market makers offset temporary mismatches in the demand and supply of securities. Therefore, they are exposed to the risk that prices may change unexpectedly while they hold securities in their inventory. The cost of these risks is charged on trading fees and bid and ask prices offered to clients.
2. *Exogenous transaction costs.* Liquidity is influenced by all the costs faced to execute a trade, such as brokerage fees, order-processing costs charged by exchanges and trading platforms, and taxes.
3. *Private information*. Liquidity is influenced by informational asymmetries (e.g., Glosten et. al 1985, Kyle 1985). Buy (sell) prices are quoted at a discount (premium) with respect to the fair value to compensate the risk that the seller (buyer) is more informed than the liquidity provider.
4. *Search frictions*. The search for a counterparty may be costly, especially in over-the-counter markets, where no centralized marketplace is available. A lengthy search process may involve financing and opportunity costs while the trade is delayed, or induce agents to trade off speed of execution with large illiquidity discounts/premia.

The degree of liquidity of an asset can be reflected in its price: investors tend to attach a specific premium to liquidity, and less liquid securities tend to offer higher returns as a reward for the expected costs of buying and selling them. In other words, a security has greater value for an investor if it can be easily sold or bought without incurring large costs. The literature provides evidence of the existence of significant liquidity risk premia across several asset classes (Amihud 2006, Ang et al. 2014).

As far as government bonds are concerned, Amihud and Mendelson (1991) find evidence of a premium attributable to liquidity by comparing the yields on US Treasury notes

[3] When a dealer executes a client's buy or sell order, either it holds the resulting risk position on its balance sheet, or it hedges the risk. When volatility spikes, it becomes difficult both to hold risks and to hedge them. On the one hand, balance sheet capacity decreases because of the increased market risk of the assets already held. On the other hand, the costs of hedging increase because of the possible abrupt changes in prices and in the correlations between assets. These factors, along with potential increases in risk aversion, determine a decrease in the dealer's ability to provide liquidity.

and bills with the same maturity; similar results are reported in Kamara (1994). Longstaff (2002) compares the yields on US Treasury notes with those on the notes issued by Refcorp, a U.S. Government agency whose liabilities are guaranteed by the Treasury; he finds a positive and statistically significant yield premium on Refcorp bonds, attributable to their lower liquidity. Vayanos (2004) shows that liquidity premia increase when volatility is high. Beber et al. (2009) analyze euro-area government bond markets and find that liquidity is a significant determinant of yield spreads, particularly during times of heightened market uncertainty. The latter result is confirmed by Schwarz (2019).

Liquidity conditions affect the conduct of monetary policy and vice versa. Spikes in illiquidity that are accompanied by significant increases in liquidity risk premia are found to decrease the effectiveness of monetary policy in steering interest rates (Abbassi and Linzert 2012). Goyenko and Ukhov (2009) find that bond illiquidity acts as a channel through which monetary policy shocks are transmitted to the stock market. Moreover, they show that expansionary monetary shocks tend to have positive effects on market liquidity. Chatterjee (2015) provides evidence that bond liquidity plays a key role in the transmission of monetary policy through the credit channel and has a significant effect on the dynamics of bank's balance sheets.

Finally, government bond liquidity is important also for financial stability. Elliott (2015) lists a number of adverse effects of illiquidity on financial stability, including the fact that illiquidity creates greater potential for financial crises. Brunnermeier and Pedersen (2008) discuss mechanism through which the lack of market liquidity and that of funding liquidity reinforce each other, creating liquidity spirals that can undermine financial stability. Gadanecz and Jayaram (2008) propose to include measures of market liquidity in a dashboard of financial stability indicators.

3. Liquidity measures

The literature generally agrees on the fact that there is no single optimal measure of market liquidity, also because of the complexity of its definition (e.g., Lybec and Sarr 2002, Cao et al. 2013). Therefore, the best practice is to gauge liquidity conditions by analyzing several different measures among those proposed in the literature. In what follows, we briefly describe the measures that we use in our empirical exercises.

Bid-ask spread. Securities dealers quote purchase prices, called bid prices, which are lower than sell prices, called ask prices. The difference between the two is the bid-ask spread, a measure of the cost of trading, which in turn reflects inventory, processing and adverse selection costs borne by the dealers. Following a convention often adopted in fixed-income markets, we compute the bid-ask spread as

$$S = bid_{yield} - ask_{yield}$$

where bid_{yield} and ask_{yield} are the yields to maturity calculated from the bid and ask prices of a security, respectively.

Roll's estimator. As discussed in the previous section, sovereign debt markets are fragmented and mostly quote-driven[4], and outstanding trading proposals are not collected in a single book. Therefore, discovering the best bid and ask quotes and obtaining a reliable estimate of the effective bid-ask spread is a complex task. While financial information providers such as Bloomberg and Refinitiv do perform such a task by gathering prices from many different sources, the resulting estimates of the bid-ask spread may not fully reflect actual trading opportunities. For this reason, researchers often use indirect measures of the bid-ask spread that rely on information about transactions, closing prices and intraday highs and lows. A popular indirect measure was proposed by Roll (1984). Observing that the bounce of transaction prices between bid and ask quotes induces a negative auto-covariance in price changes, Roll proposes the following measure of illiquidity[5]:

$$S = 2\sqrt{-Cov(\Delta P_t, \Delta P_{t-1})}$$

where ΔP_t is the change in transaction prices observed between two consecutive time periods t and $t-1$. In our empirical exercises, we use closing yields instead of closing prices for cash markets, and returns instead of price differences for futures markets. We sample changes at a daily frequency, we use 5-day rolling windows[6] to estimate auto-covariances, and we drop the

[4] Although some cash markets, such as the retail MOT, are order-driven. Also the EUREX, which is the main European futures market, is order-driven.

[5] The measure can be derived by assuming that the true value of an asset follows a random walk, that a buy transaction is followed by a sell transaction with probability equal to 50%, and that the true value always coincides with the arithmetic mean of the bid and ask prices.

[6] The choice of a short time window makes the estimator less precise, but more timely and less biased. Precision is not the main concern because individual estimators are averaged to produce a composite indicator of liquidity, which allows to smooth out the noise embedded in individual estimators. The choice of the time windows used to build the individual measures of liquidity also reflects some quality cross-checks (on the correlations of each indicator with the other indicators) described in the Section 5.

observations that have positive covariance[7] (see Section 5 for an accurate discussion of missing values).

Corwin and Schultz's estimator. Corwin and Schultz (2012) proposed another popular estimator of the bid-ask spread, based on daily high and low prices. Their estimator builds on the intuition that the amplitude of high-low ranges is determined both by the volatility of the true value of an asset and by bid-ask spreads; however, the volatility component increases with the time interval over which high-low ranges are computed, while the bid-ask component does not. The estimator is

$$S = \frac{2(e^{\alpha} - 1)}{1 + e^{\alpha}}$$

where

$$\alpha = \frac{\sqrt{2\beta} - \sqrt{\beta}}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}$$

$$\beta = \sum_{j=0}^{1} \left[ln\left(\frac{H_{t+j}}{L_{t+j}}\right)\right]^2$$

$$\gamma = \left[\ln(\frac{H_{t,t+1}}{L_{t,t+1}})\right]^2$$

and H_{t+j} and L_{t+j} are daily high and low prices, while $H_{t,t+1}$ and $L_{t,t+1}$ are the high and low prices observed over two consecutive trading days. Intuitively, the sum of two daily price ranges contains two contributions from the daily true-price volatility and two from the bid-ask spread, whereas the price range over a two-day period contains two contributions from the daily true-price volatility and only one from the bid-ask spread. In order to avoid spurious effects due to low-frequency shifts in the average price, we assume that the last mid-price is always at par and, for cash markets, we use a first-order Taylor approximation based on duration to reconstruct high and low prices from observed yields.

Abdi and Ranaldo's estimator. Abdi and Ranaldo (2017) bridged the two estimation methodologies by Roll (1984) and Corwin and Schultz (2012) and proposed a new measure of the bid-ask spread that uses a larger information set:

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[7] In which case the square root would be a complex number. An alternative strategy is to set the covariance to zero. See Abdi and Ranaldo (2017) for a discussion of different strategies for dealing with positive estimated covariances.

$$S = 2\sqrt{\mathrm{E}[(c_t - \eta_t)(c_t - \eta_{t+1})]}$$

where c_t is the closing price, η_t is the arithmetic average of the daily high and low prices, and E denotes the expected value operator. In this paper, we replace expected values with rolling averages over 20-day windows.

Market efficiency coefficient. First introduced by Hasbrouck and Schwartz (1988) and also known as variance ratio (e.g., Campbell, Lo and MacKinlay 2012), the market efficiency coefficient (MEC) captures several aspects of market liquidity. Under the hypothesis of market efficiency (often operationalized by assuming that prices follow a random walk), the coefficient is equal to 1. On the contrary, market imperfections affecting liquidity, such as the bounce between bid and ask quotes and persistent order imbalances (lack of resiliency), tend to bring the value of the coefficient below 1. The coefficient is defined as:

$$MEC = \frac{\mathrm{Var}(\sum_{j=0}^{T-1} r_{t+j})}{T\mathrm{Var}(r_t)}$$

where Var denotes the variance operator, r_t is the return (or yield change) recorded over a trading interval, and T is the number of consecutive trading intervals used to compute the long-run variance. In our empirical exercises, we try various choices of T and of the time-windows used to estimate the variances, but this metric does not survive the quality checks performed to decide on the inclusion in the composite index.

Trading volumes and open interest. Various studies provide evidence that markets characterized by high levels of trading activity are also more liquid (e.g., Glassman 1987, Glosten and Harris 1988, Bessembinder and Seguin 1993, Brennan and Subrahmanyam 1996, Nemes et al. 2012). Therefore, proxies for the level of market activity are often used as measures of liquidity. In this paper we use trading volumes and open interest on the future market as proxies for the liquidity of that market, while we do not have reliable statistics about activity in the cash market due to the fragmentation of trading across multiple venues.

Amihud's measure. A more sophisticated measure of illiquidity based on trading volumes was proposed by Amihud (2002)

$$Illiquidity = \mathrm{E}\left[\frac{|r_t|}{volume_t}\right]$$

where r_t is the return recorded over a trading interval and $volume_t$ is the volume of transactions recorded over the same interval. Amihud's is a measure of price impact: the larger the price movement triggered by a given volume of trading is, the more illiquid a security is. In our exercises, we use daily returns on futures contracts and the number of contracts traded on each day. The expected value is approximated by rolling averages over 20-day windows.

Hui and Heubel's measure. A measure of price impact similar to Amihud's was proposed by Hui and Heubel (1984):

$$Illiquidity = \frac{\frac{H_t - L_t}{L_t}}{T_t}$$

Where H_t and L_t are high and low prices and T_t is a measure of turnover. Due to data availability reasons, when we implement the formula, we replace the turnover with the trading volume. Moreover, we compute volume, high and low prices over overlapping 5-day trading intervals.

Noise as information for illiquidity. Hu et al. (2013) proposed an illiquidity measure that links illiquidity to a proxy for the amount of arbitrage capital available in financial markets: the average deviation of observed bond yields from a smooth yield curve. Deviations from the curve are normally eliminated by arbitrage forces, but during crises arbitrage capital becomes scarce and/or the willingness to deploy it declines; the result is a reduction in the overall level of liquidity. More specifically, the noise measure is calculated as the root mean squared difference between observed yields and model-implied yields:

$$Noise = \sqrt{\frac{1}{N_t}\sum_{i=1}^{N_t}(y_t^i - \hat{y}_t^i)]^2}$$

where y_t^i is the observed yield at time t on bond i, $\hat{y}_t^i$ is the theoretical yield obtained by fitting a spline curve to yields, and N_t denotes the number of bonds with maturity between 1 and 10 years at time t. The measure is tightly related to off/on-the-run yield differentials, that are commonly explained as the result of differences in liquidity (Pasquariello and Vega 2009), and could hence be used as a proxy for market illiquidity.

Volatility. The volatility of yields (or returns) is also commonly used to measure illiquidity. Volatility affects liquidity by influencing market-making costs (e.g., Benston and Hagerman 1974, Ho and Stoll 1983, Amihud and Mendelson 1989, Brunnermeier and Pedersen 2009, Adrian et al. 2017). For example, higher volatility increases the cost of holding inventories and that of hedging risk exposures and tends to determine a decrease in market liquidity (see also Section 2 above). In the empirical part of the paper, we use historical volatilities, computed as 20-day rolling standard deviations of daily yield changes and returns.

4. Data and individual measures

As discussed in previous sections, not only there is no unique measure of the market liquidity of a financial instrument, but the same security can be traded on many different markets and trading platforms. In the euro area, government bonds are typically traded on wholesale markets (e.g., MTS), dealer-to-client platforms (e.g., Bondvision, Tradeweb), exchanges accessible by retail investors (e.g., MOT), classical over-the-counter markets (phone, chat). These markets are characterized by different microstructures and degrees of transparency, which complicates the task of obtaining thorough data about proposed and executed transactions, prices and traded volumes.

Moreover, there are active derivatives markets, which are tightly linked to spot markets by no-arbitrage relations. Among the most active, we mention electronic futures markets (e.g., EUREX) and over-the-counter markets for credit default swaps and total return swaps.

We gather data about some of the above markets from different sources (Table 1) and we use each data source to compute as many of the measures of liquidity introduced in Section 3 as the source allows. By doing so, we obtain 17 different liquidity indices, denoted from now on by x_{it}, where i identifies an index (for $i = 1, \dots, L$; $L = 17$) and t is time. Table 2 contains a list of all the indices (plotted in Figures 1-4) and provides some information about the time spans they cover. The list of 17 indices in Table 2 does not include some indices that were computed but excluded from the analysis because of insufficient quality (see below for more details).

In Table 2 we also classify the indices into "buckets", based on the aspect of liquidity prevalently captured by each index (Lybek and Sarr 2002). This classification will be subsequently used to down-weight indices whose buckets are over-represented.

We confine our attention to 10-year benchmark government bonds, which are typically the most actively traded in the market, and to the four largest countries in the euro area (Germany, France, Italy and Spain).

Our set of metrics includes measures of liquidity of the futures market. This is particularly important because futures and cash markets are tightly integrated, the former often lead the latter in terms of price discovery, and the majority of benchmark bond trading is performed through futures in some countries and time periods (e.g., Pagano and von Thadden 2004, Brandt et al. 2007, Pelizzon et al. 2014, Panzarino et al. 2016).

Table 3 reports a cross-country comparison of the indices; we divide the sample average of each index by the mean of the French index, so as to facilitate comparisons. According to the great majority of indices, during the analyzed period, the liquidity of French and German bonds is found to be higher than that of Italian and Spanish bonds.

5. Composite indicators

We conceptually frame the problem of summarizing the wealth of information provided by the indices x_{it} as a signal extraction problem. We posit that each index carries some information (signal) about a unique "true" liquidity measure y_t, although the information is buried in noise:

$$x_{it} = \alpha_i + \beta_i y_t + \varepsilon_{it} \tag{1}$$

where α_i and β_i are index-specific coefficients and ε_{it} are zero-mean noise terms. In econometric terms, the above equation can be seen as a factor model (e.g., Barigozzi 2018) in which all the observed variables are driven by the factor y_t.

A key element of our signal extraction strategy is the data imputation methodology. Not only there is variability in the time spans covered by the different liquidity indices, but there are missing values due to data quality issues and to the fact that some indices are not well-defined for certain values of the underlying variables (e.g., Roll's liquidity measure is not well-defined when the sample serial correlation of price changes is positive). Dropping all the dates on which some data is missing or dropping the time series that have many missing values would impoverish the analysis.

We use multivariate normal imputation (e.g., Rubin 1987). Let x_t be the $L \times 1$ vector of liquidity indices, assumed to be multivariate normal, m its sample mean and V its sample covariance matrix (both computed on the restricted sample that has no missing values). Consider the partitions

$$x_t = \begin{bmatrix} x_{Ut} \\ x_{Ot} \end{bmatrix} \quad m = \begin{bmatrix} m_U \\ m_O \end{bmatrix} \quad V = \begin{bmatrix} V_{UU} & V_{UO} \\ V_{OU} & V_{OO} \end{bmatrix}$$

where U and O denote the blocks of unobserved missing values and observed values respectively (without loss of generality we can assume that the missing values come first). Then, the missing values are replaced by their conditional expectation

$$x_{Ut} \coloneqq \mathrm{E}[x_{Ut}|x_{Ot}] = m_U + V_{UO}V_{OO}^{-1}(x_{Ot} - m_O)$$

Note that, although not explicitly indicated for notational simplicity, the variables included in the U and O blocks change over time.

As a preliminary data transformation step, we switch, if needed, the sign of liquidity indices, so that each index is increasing in the degree of illiquidity of the underlying instrument. For example, the sign of bid-ask spreads is left unchanged (the higher the spread is, the more illiquid the instrument), but we switch the sign of the Market Efficiency Coefficient (which is higher when the market is more efficient and more liquid). Furthermore, we standardize each index (we subtract the sample mean and divide by the sample standard deviation).

We also compute the sample correlations of each index with all the other indices (Figures 5-8) and drop from the analysis the indices that have average negative correlation with the others. We interpret the negative correlation as inability of an index to carry any meaningful information about the signal. Using this criterion, we drop from the analysis estimates of the market efficiency coefficient for the cash and futures market and depth measures based on traded volumes and open interest on the futures market.

Denote by $\hat{y}_t$ an estimate of the common liquidity signal y_t (henceforth called "composite indicator"). We analyze five different estimators of the signal:

1. **Arithmetic mean**:

$$\hat{y}_t = \frac{1}{L}\sum_{i=1}^{L} x_{it}$$

2. **Weighted mean**:

$$\hat{y}_t = \sum_{i=1}^{L} w_i x_{it}$$

where weights w_i sum to 1 and each weight w_i is inversely proportional to the number of indices in the bucket to which x_{it} belongs (see Table 2). In other words, we assign equal weight to each bucket.

3. **First principal component**:

$$\hat{y}_t = PC_{1t}$$

where PC_{1t} is the first principal component computed from the singular value decomposition of the $T \times L$ matrix of liquidity indices.

4. **First weighted principal component**:

$$\hat{y}_t = PC_{1t}^{w}$$

where PC_{1t}^{w} is the first principal component computed from the singular value decomposition of the $T \times L$ matrix of weighted liquidity indices (each liquidity index x_{it} is multiplied by the square root of the weight w_i computed in point 2 above).

5. **First principal component from two-stage PC**: for each bucket $b = 1, \ldots, B$, we compute the first principal component of the indices included in that bucket, denoted by PC_t^b, and then we set

$$\hat{y}_t = PC_{1t}^{2S-PC}$$

where PC_{1t}^{2S-PC} is the first principal component extracted from the singular value decomposition of the the $T \times B$ matrix of first-stage principal components PC_t^b.

Note that principal component analysis (PCA) is a simple and computationally efficient method to estimate factor models such as that in equation (1) (e.g., Barigozzi 2018). PCA has already been used in the literature on the construction of liquidity indices by Dick-Nielsen et al. (2012), who also proposed indices that load evenly on the different liquidity measures, as in estimator 1 above. From an intuitive standpoint, both averaging and PCA give rise to weighted sums of the noise terms ε_{it} in equation (1), whose variance decreases as the cross-sectional dimension L increases (by the law of large numbers).

Weighted principal component analysis (e.g., Meredith and Milsap 1985, Yue and Tomoyasu 2004, Delchambre 2015) allows to decrease the biases in signal reconstruction that may arise when specific aspects of liquidity are over-represented in the cross-section. In other words, when we include in the sample several highly correlated indices that capture a single (partial) aspect of liquidity, we incur the risk of biasing the first principal component towards a mere reproduction of that aspect; weighted PCA allows to reduce this type of risk by down-weighting over-represented aspects. Two-stage principal component analysis (e.g., Nagar and Basu 2002, Cámara and Tuesta 2014) is a different technique aimed at achieving the same goal; by applying PCA in two rounds, it helps to mitigate possible biases in weights (loadings) towards highly correlated input variables.

As illustrated in Figures 9-12, the five composite indicators are often highly correlated with each other. However, noticeable differences emerge in periods of low liquidity. In particular, the severity of illiquidity spikes tends to be more accentuated according to some indicators.

Being linear combinations of re-scaled liquidity indices, the composite indicators $\hat{y}_t$ do not allow to conduct cross-country comparisons. In order to circumvent this shortcoming, for each country, we re-project each un-standardized liquidity index[8] x_{it} on $\hat{y}_t$:

$$x_{it} = \gamma_{0i} + \gamma_{1i}\hat{y}_t + e_{it}$$

and compute a new composite indicator

$$\tilde{y}_t = \sum_{i=1}^{L} w_i(\hat{\gamma}_{0i} + \hat{\gamma}_{1i}\hat{y}_t)$$

where $\hat{\gamma}_{ji}$ is the OLS estimator of γ_{ji} for $j = 1{,}2$ and w_i are the weights defined previously (inversely proportonial to the numerosity of buckets).

The re-scaled indicator $\tilde{y}_t$ is an affine function of $\hat{y}_t$ that can be used in cross-country comparisons because it reflects the average differences between the liquidity indices in one country and those in another country.

6. Choice of preferred composite indicator

We propose an economic criterion to choose a preferred composite indicator, which is one of the main novelties of this paper. Specifically, we exploit the intuition that the illiquidity of an instrument should be highly and positively correlated with the liquidity risk premium required on that instrument (e.g., Acharya and Pedersen 2005, Jang et al. 2007, Favero et al. 2010).

We use the following proxy for the liquidity premium:

$$premium_t = yield_t - CDS_t - (OIS_t - EONIA_t) - REPO_t$$

[8] In other words, in this projection the liquidity indices do not undergo the standardization used in the rest of the analysis (subtraction of mean and division by standard deviation). However, in a preliminary step we divide each liquidity index by the sample mean of that index in France (as we do in Table 3).

where $yield_t$ is the yield on the 10-year benchmark bond, CDS_t is the premium on the 10-year CDS, OIS_t is the 10-year overnight indexed swap rate, $EONIA_t$ is the overnight rate, and $REPO_t$ is the STOXX GC Pooling index of the cost of financing a position via the repo market in the euro area. Longstaff et al. (2005) were among the first to use CDS premia to disentangle the default and non-default components of credit spreads, and relate the non-default components with measures of illiquidity.

The variable $premium_t$ is the carry that can be earned by: 1) buying a 10-year government bond; 2) financing the purchase through a repo transaction in which the bond itself is used as collateral; 3) hedging the credit risk of the bond via a CDS; 4) hedging interest rate risk via a swap indexed to the overnight rate. Such a trading strategy is known as a "bond-CDS basis trade" (e.g., Blanco et al. 2005, Berman 2005, De Wit 2006, Devasabai 2015) and it is mainly exposed to liquidity risk, as credit and interest rate risks are almost entirely eliminated by the CDS hedge[9] and the interest rate swap; indeed, some empirical studies find that the CDS-bond basis is significantly correlated with proxies for liquidity (e.g., Bai and Collin-Dufresne 2013 for the corporate bond market). Numerous ways to measure the bond-CDS basis have been proposed in the literature (e.g., asset-swap spreads and z-spreads; see, e.g., Choudhry 2006); we tried also other measures in our empirical exercises and results were relatively robust.

Following Beber et al. (2009), we express the liquidity premium of each country in relative terms, by subtracting from it the average premium in the other countries.

Table 4 reports, for each country, the sample correlations between $premium_t$ and the different composite indicators $\tilde{y}_t$.[10] All the liquidity indicators are positively correlated with $premium_t$, although the weighted mean and the first 2-stage principal component (estimators 2 and 5 above) have the highest average correlation (61 per cent averaged across countries in both cases). Because of the small difference in the performance of the two best indicators, in the remainder of the analysis we use their arithmetic average

$$\hat{y}_t^* = 0.5 \cdot PC_{1t}^{2S-PC} + 0.5 \cdot \sum_{i=1}^{L} w_i x_{it}$$

In the tables and figures, we refer to $\hat{y}_t^*$ as "average of the 2 best measures".

[9] There may be small imperfections in the ability of the CDS to hedge credit risk (see Hull et al. 2004).
[10] Also $\tilde{y}_t$ is expressed for each country in relative terms, by subtracting the mean of the other countries.

Table 5 reports the correlations between $\hat{y}_t^*$ and the individual liquidity indices x_{it}, which are found to be positive for all indices and countries, and highest (around 90 per cent on average) for the historical volatility on the cash markets and the Amihud index on the futures market. The finding that liquidity is tightly related to volatility is in line with the predictions from theoretical models of market making and market microstructure (see, e.g., Ho and Stoll 1983 for one of the earliest theoretical contributions, and Calamia 1999 and Będowska-Sójka and Kliber 2019 for reviews of the relevant literature).

Figure 13 displays the time series of $\tilde{y}_t^*$ (the re-scaled version of $\hat{y}_t^*$ that allows to conduct cross-country comparisons) for the four countries being analyzed, while Figure 14 displays its average across countries (weighted by notional bonds outstanding in 2020 Q2).

7. Dynamics during the Covid-19 crisis

According to the composite indicator displayed in Figure 14, the euro-area sovereign bond market experienced a severe liquidity deterioration during the most acute phase of the Covid-19 crisis, peaking around the third week of March 2020. The deterioration was comparable to, although slightly less severe than, that experienced during the so-called sovereign debt crisis (e.g., Lane 2012). In particular, the estimated level of illiquidity in March 2020 was the highest recorded since ECB's President Mario Draghi pronounced the famous "Whatever it takes" speech (e.g., Acharya et al. 2019) and shortly afterwards the ECB launched the Outright Monetary Transactions (OMT; e.g., Cœuré 2013), starting a progressive normalization of liquidity conditions in euro-area sovereign bond markets.

A remarkable difference between the liquidity dry-up of 2020 and that observed during the sovereign debt crisis is that the former was quickly re-absorbed while the latter lasted for more than two years. While structural changes observed in euro-area bond market since the sovereign debt crisis might have played a role, we also find that the promptness and boldness of ECB's interventions in 2020 were likely important factors. The lower panel of Figure 14 highlights the changes in the euro-area liquidity indicator after some of the ECB's most important measures: the announcement of the Pandemic Emergency Purchase Programme (PEPP), the removal of self-imposed limits on asset purchases, an easing of collateral rules that could benefit sovereigns under stress[11], and increases in the size of purchases. According to our indicator, all of these announcements were followed by significant improvements in the liquidity of sovereign bonds. Moreover, the PEPP was designed from the outset to be flexible across time, asset classes and jurisdictions because of its explicit market stabilization function (Lane 2020a and 2020b), which also could explain the quick recovery experienced by sovereign bond liquidity. Our findings are consistent with those of Bernardini and De Nicola (2020), who provide evidence that the flow effects of the purchases of Italian sovereign bonds conducted under the PEPP had a positive impact on the liquidity of the Italian sovereign bond market.

To conduct a more rigorous comparison of the PEPP announcement with other significant interventions announced by the ECB in the past, we construct block-bootstrap confidence intervals for the evolution of the euro-area liquidity indicator under the null hypothesis of absence of abnormal changes in liquidity.

We compare the announcement of the PEPP with those of:

- the Securities Market Programme (SMP, 10 May 2010), part of a package of measures, including interventions in the euro area public debt securities markets, with the aim to "*address the severe tensions in certain market segments which are hampering the monetary policy transmission mechanism*" (ECB 2010);
- the 3-year Long-Term Refinancing Operations (LTRO, 8 December 2011), part of a package of "*credit support measures to support bank lending and liquidity in the euro area money market*" (ECB 2011);
- the Outright Monetary Transactions (OMT, 2 August 2012), conditional purchases of sovereign bonds aimed at "*safeguarding an appropriate monetary policy transmission and the singleness of the monetary policy*" (ECB 2012).

To build the block-bootstrap confidence intervals, we exclude from our sample the time-windows starting 10 trading days before and ending 50 trading days after the four announcement dates of the SMP, 3-year LTROs, OMT and PEPP. From the remaining dates, we uniformly sample without replacement 1000 blocks of 50 consecutive days over which we compute cumulative changes in the liquidity index. The 1st and 99th percentiles of the empirical

[11] Eligibility criteria applied to collateral usable in Eurosystem refinancing operations (and to securities eligible for purchase programmes) were relaxed by allowing securities downgraded to high yield during the pandemic to remain eligible (they would have been excluded from the eligible collateral pool according previous criteria).

distribution thus obtained are the bounds of the confidence bands for the null hypothesis of no abnormal changes in liquidity.

In Figures 15 and 16, the cumulative changes in euro-area liquidity over the 50 days following the four announcements are plotted together with the confidence bands. We note that most of the proxies for liquidity used to construct the composite indicator (e.g., Roll's measure, Abdi and Ranaldo's, volatility) are computed as averages over rolling windows of several days. Therefore, even if the effect of an announcement on market liquidity were immediate, its effect on the composite indicator would be observed only over the course of several days.

We find that the cumulative improvement in liquidity after the PEPP announcement is highly statistically significant, in the sense that, for most days in the analyzed 50-day time-window, it lies outside of the confidence bands computed under the null hypothesis of absence of abnormal changes. At the end of the time-window, the effects of the PEPP are comparable to those of the 3-year LTRO, which are however found to be non-significant or marginally significant during the first 20 days following the announcement. The changes in liquidity after the other two announcements (OMT and SMP), while constituting improvements, are not found to be significant according to the proposed criterion.

Overall, the results from these exercises provide further evidence that the PEPP had significantly positive effects on market liquidity, on average more pronounced than those of other measures adopted in the past by the ECB with the aim of ensuring the correct functioning of financial markets and of the monetary-policy transmission mechanism.

8. Conclusions

We have built a composite indicator of the market liquidity of sovereign bonds in the four largest euro-area economies (Germany, France, Italy and Spain). For each country, the indicator is obtained by combining 17 liquidity indices that provide information about different aspects of liquidity, such as market breadth, depth, tightness and resiliency, on several trading venues, including the derivatives market.

We have proposed a novel methodology to choose the best strategy for index aggregation, based on the economic intuition that bond illiquidity should be tightly related to liquidity risk premia. In all countries, our preferred composite indicator is highly correlated with a proxy for the liquidity risk premium embedded in sovereign bond yields. The indicator could be used for the real-time monitoring of market liquidity conditions and for informing the decisions on how to use the flexibility of purchase programmes. According to the evidence provided by Bernardini and De Nicola (2020) for the Italian bond market, not only asset purchases improve market liquidity, but their (intended) effects on bond prices are more pronounced when the bond market is less liquid. Therefore, a liquidity indicator for the euro-area, such as the one we propose, could help to identify opportunities to optimally calibrate the pace of asset purchases at the Eurosystem level.

The time span covered by our composite indicator starts in 2010 and includes the European sovereign debt crisis, which provides a useful yardstick to assess the severity of the liquidity deterioration experienced during the market turbulences at the beginning of the Covid-19 crisis. The latter episode of liquidity deterioration was signaled by several central banks (e.g., Lane 2020a and 2020b, Fleming and Ruela 2020, Fontaine et al. 2020) and was promptly followed by interventions aimed at restoring the normal functioning of sovereign bond markets.

We find that the recent liquidity dry-up was comparable to, although slightly less severe than, that experienced during the European sovereign debt crisis. However, while the latter impairment in liquidity conditions lasted for more than two years, the former was quickly re-absorbed. The promptness and boldness of ECB's interventions in 2020 likely played an important role. Some of the ECB's most relevant measures, such as the Pandemic Emergency Purchase Programme (PEPP), the removal of self-imposed limits on asset purchases, an easing of collateral rules that could benefit sovereigns under stress, and increases in the size of purchases led to a significant improvement in the composite liquidity indicator.

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Tables and figures

Table 1 – Data sources

Source	Market	Data types	Sample
Bloomberg	Cash	Yield (closing bid) Yield (closing ask) Yield (closing price) Yield (daily minimum) Yield (daily maximum)	Jan-10 / Feb-21
Tradeweb	Cash	Yield (closing bid) Yield (closing ask) Yield (closing price) Yield (daily minimum) Yield (daily maximum)	Jan-10 / Feb-21
Eurex	Future	Price (settlement) Price (daily mimimum) Price (daily maximum) Traded volume Open interest	Btw. 2010 and 2015 depending on country and series / Feb-21

Table 2 – Liquidity measures

Liquidity dimension	Liquidity measure
Depth	Rolling volatility (TW cash)
	Rolling volatility (BBG cash)
	Rolling volatility (Eurex future)
Resiliency	Noise as illiquidity
Tightness	Bid-ask spread (TW cash)
	Bid-ask spread (BBG cash)
Tightness (indirect)	Roll (TW cash)
	Roll (BBG cash)
	Roll (Eurex future)
	Abdi-Ranaldo (TW cash)
	Abdi-Ranaldo (BBG cash)
	Abdi-Ranaldo (Eurex future)
	Corwin-Schultz (TW cash)
	Corwin-Schultz (BBG cash)
	Corwin-Schultz (Eurex future)
Breadth	Amihud (Eurex future)
	Hui-Heubel (Eurex future)

Note: this table subdivides the liquidity measures described in Sections 3-5 into buckets, based on the aspect of liquidity that they prevalently capture (depth, resiliency, tightness and breadth). The acronyms BBG and TW are used to indicate measures constructed with Bloomberg and Tradeweb data respectively. Both BBG and TW data refers to transactions on the cash market, while EUREX data refers to transactions on the futures market.

Table 3 – Cross-country comparison

(sample means; each measure is divided by the sample mean of that measure for France)

Cross-country comparisons
(sample averages; each measure divided by mean[France])

	France	Germany	Italy	Spain
Realized Vol TradeWeb Cash	1	1.013	1.697	1.588
Realized Vol BBG Cash	1	1.023	1.736	1.599
Realized Vol BBG Future	1	1.034	1.581	1.048
Noise as illiquidity	1	1.299	3.179	2.175
Bid-Ask spread TradeWeb Cash	1	0.357	2.086	3.018
Bid-Ask spread BBG Cash	1	0.4821	1.742	2.707
Roll TradeWeb Cash	1	1.032	1.561	1.387
Roll BBG Cash	1	1.065	1.588	1.395
Roll Future BBG	1	1.099	1.49	1.072
Abdi-Ranaldo BBG Cash	1	1.083	1.474	1.307
Abdi-Ranaldo Tradeweb Cash	1	0.6961	1.971	2.968
Abdi-Ranaldo EUREX Future	1	1.197	1.484	1.108
Corwin-Schultz BBG Cash	1	1.03	1.641	1.462
Corwin-Schultz Tradeweb Cash	1	0.9428	1.828	1.819
Corwin-Schultz EUREX	1	1.196	1.615	0.9521

Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: each row corresponds to one of the liquidity measures described in Sections 3-5. Each column corresponds to a country. The acronyms BBG and TW are used to indicate measures constructed with Bloomberg and Tradeweb data respectively. Both BBG and TW data refers to transactions on the cash market, while EUREX data refers to transactions on the futures market. RVol is the 20-day rolling standard deviation of rate changes (for the cash markets) and returns (for the future market). The numbers in the cells are the sample averages of the liquidity measures. In order to ease cross-country comparisons, each measure is divided by the sample mean for France.

Table 4 – Correlation between CDS-bond basis and composite liquidity measures

	France	Germany	Italy	Spain
Arithmetic mean	0.5932	0.6531	0.4633	0.6185
Weighted mean	0.6079	0.7021	0.526	0.6094
PC	0.596	0.6388	0.4623	0.6051
Weighted PC	0.607	0.6948	0.5254	0.5968
2-stage PC	0.6103	0.6884	0.5203	0.608
Avg. of 2 best	0.608	0.6989	0.5259	0.6034

Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: each row corresponds to one of the composite liquidity indicators obtained with the methodologies described in Sections 5 and 6. Each column corresponds to a country. The numbers in the cells are the coefficients of linear correlation between the composite indicators and the proxy for the liquidity risk premium introduced in Section 6.

Table 5 – Correlations of individual liquidity measures with the preferred composite measure

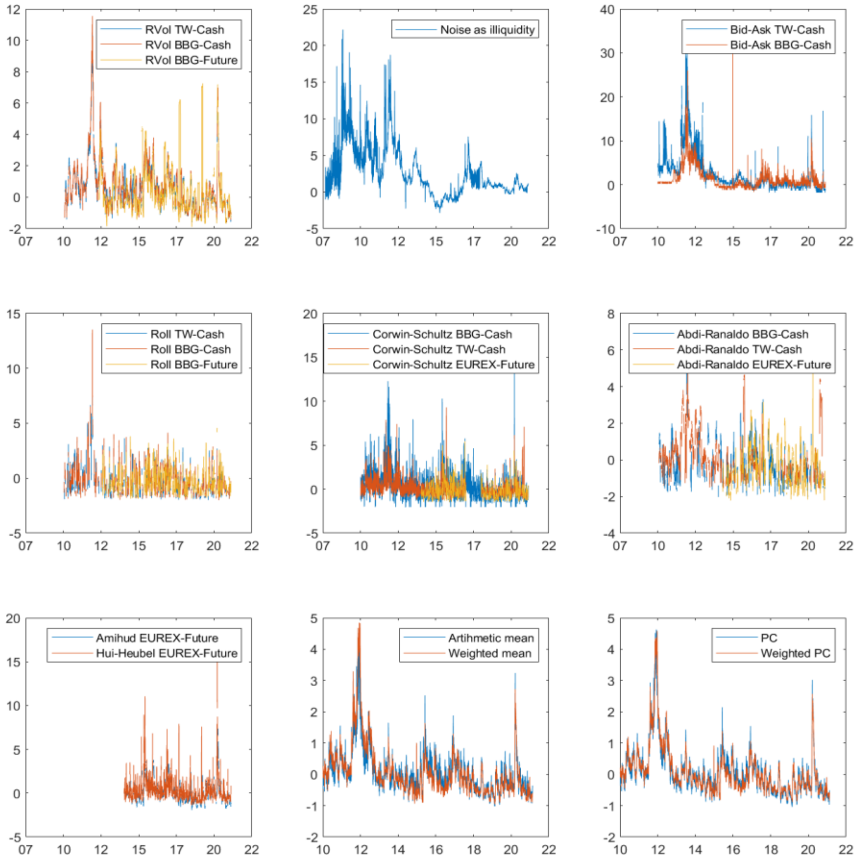
Correlations of individual liquidity measures with summary measures

	France	Germany	Italy	Spain
Realized Vol TradeWeb Cash	0.8595	0.8695	0.9194	0.9156
Realized Vol BBG Cash	0.8427	0.8745	0.9059	0.9187
Realized Vol BBG Future	0.5684	0.724	0.8795	0.7776
Noise as illiquidity	0.8001	0.5769	0.832	0.7832
Bid-Ask spread TradeWeb Cash	0.9	0.6718	0.7186	0.8806
Bid-Ask spread BBG Cash	0.7024	0.4651	0.6762	0.7426
Roll TradeWeb Cash	0.5135	0.5054	0.5766	0.5775
Roll BBG Cash	0.5203	0.541	0.5665	0.6133
Roll Future BBG	0.3122	0.4442	0.5717	0.3658
Abdi-Ranaldo BBG Cash	0.5049	0.5754	0.4485	0.5535
Abdi-Ranaldo Tradeweb Cash	0.659	0.529	0.4604	0.5576
Abdi-Ranaldo EUREX Future	0.3158	0.5678	0.5026	0.3433
Corwin-Schultz BBG Cash	0.6106	0.5363	0.5931	0.5553
Corwin-Schultz Tradeweb Cash	0.5827	0.551	0.5644	0.536
Corwin-Schultz EUREX	0.3349	0.4247	0.4414	0.3599
Amihud EUREX Future	0.5914	0.6953	0.7254	0.5291
Hui-Heubel EUREX Future	0.6311	0.6464	0.7603	0.6087

Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: each row corresponds to one of the liquidity measures described in Sections 3-5. Each column corresponds to a country. The acronyms BBG and TW are used to indicate measures constructed with Bloomberg and Tradeweb data respectively. Both BBG and TW data refers to transactions on the cash market, while EUREX data refers to transactions on the futures market. RVol is the 20-day rolling standard deviation of rate changes (for the cash markets) and returns (for the future market). The numbers in the cells are the coefficients of linear correlation of the individual liquidity measures with the “preferred” composite liquidity indicator described in Section 6.

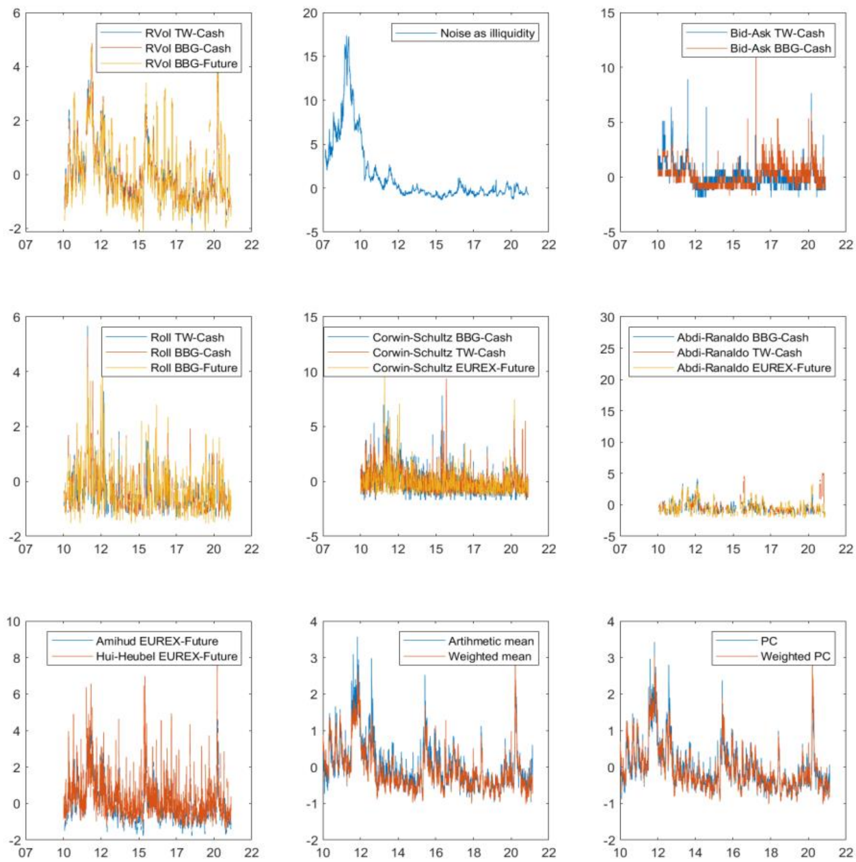
Figure 1 – Liquidity measures – France



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the liquidity measures described in Sections 3-5, and calculated for the French 10-year benchmark bond. The acronyms BBG and TW are used to indicate measures constructed with Bloomberg and Tradeweb data respectively. Both BBG and TW data refers to transactions on the cash market, while EUREX data refers to transactions on the futures market. RVol is the 20-day rolling standard deviation of rate changes (for the cash markets) and returns (for the future market). All the measures are standardized so as to have zero mean and unit variance. The center- and right-bottom panels display four of the composite indicators analyzed in the paper (Section 5). PC stands for principal components.

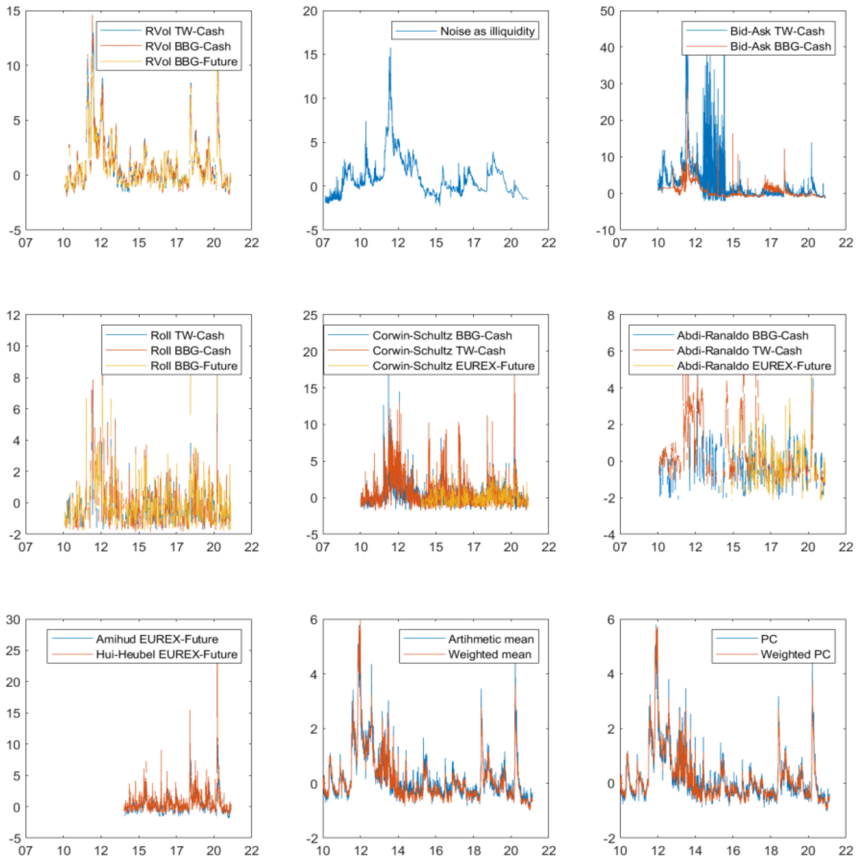
Figure 2 – Liquidity measures – Germany



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the liquidity measures described in Sections 3-5, and calculated for the German 10-year benchmark bond. The acronyms BBG and TW are used to indicate measures constructed with Bloomberg and Tradeweb data respectively. Both BBG and TW data refers to transactions on the cash market, while EUREX data refers to transactions on the futures market. RVol is the 20-day rolling standard deviation of rate changes (for the cash markets) and returns (for the future market). All the measures are standardized so as to have zero mean and unit variance. The center- and right-bottom panels display four of the composite indicators analyzed in the paper (Section 5). PC stands for principal components.

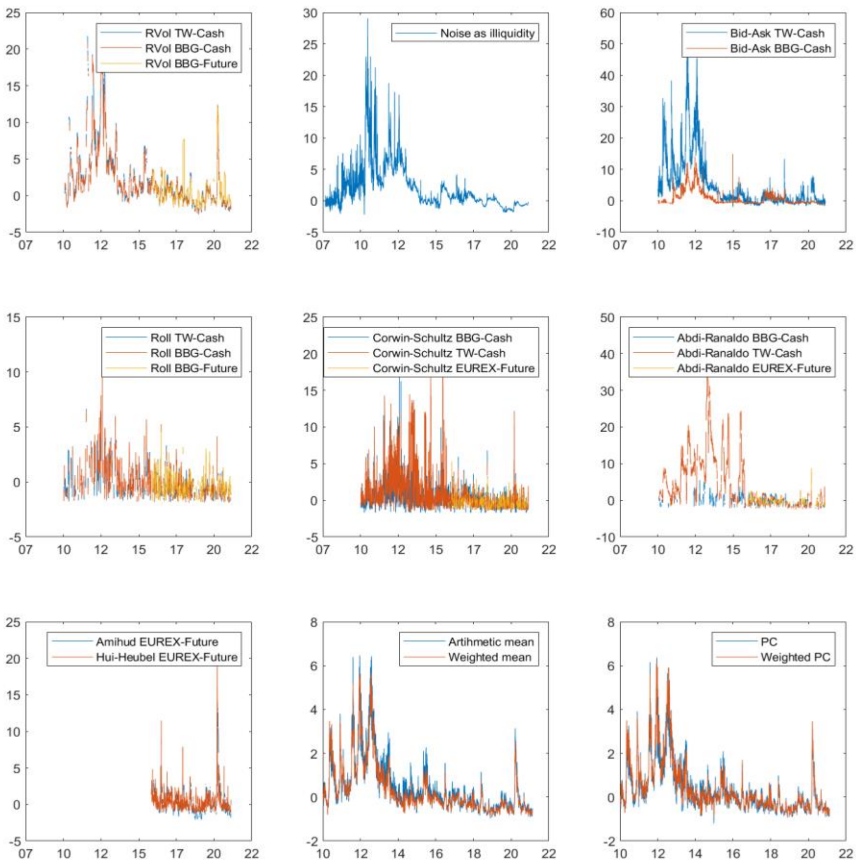
Figure 3 – Liquidity measures – Italy



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the liquidity measures described in Sections 3-5, and calculated for the Italian 10-year benchmark bond. The acronyms BBG and TW are used to indicate measures constructed with Bloomberg and Tradeweb data respectively. Both BBG and TW data refers to transactions on the cash market, while EUREX data refers to transactions on the futures market. RVol is the 20-day rolling standard deviation of rate changes (for the cash markets) and returns (for the future market). All the measures are standardized so as to have zero mean and unit variance. The center- and right-bottom panels display four of the composite indicators analyzed in the paper (Section 5). PC stands for principal components.

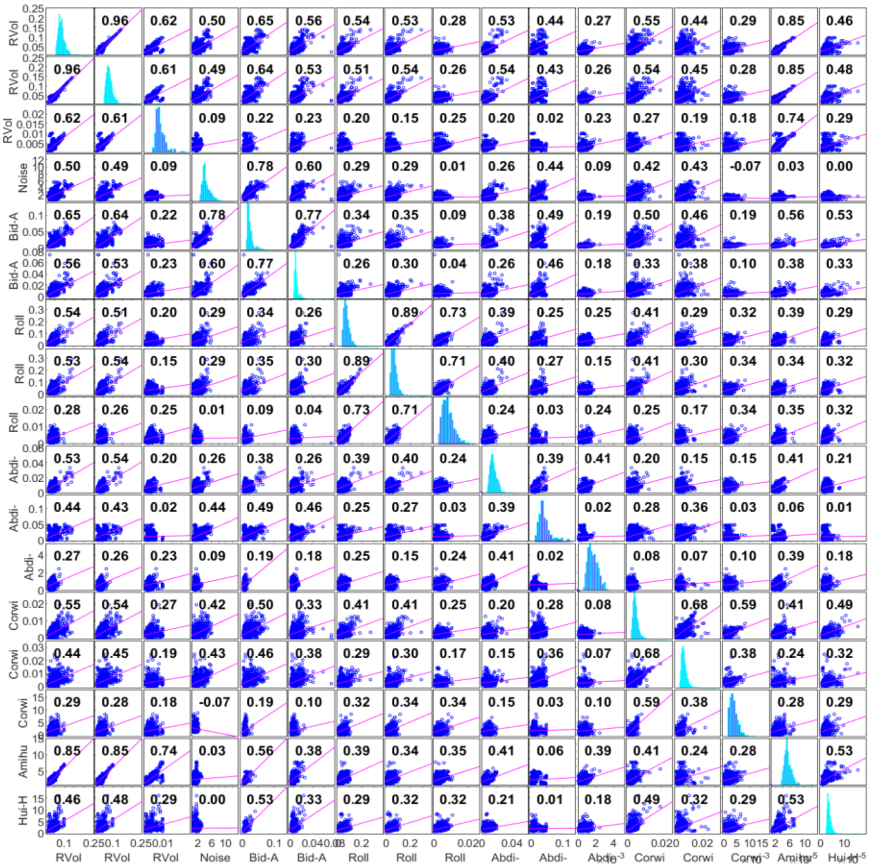
Figure 4 – Liquidity measures – Spain



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the liquidity measures described in Sections 3-5, and calculated for the Spanish 10-year benchmark bond. The acronyms BBG and TW are used to indicate measures constructed with Bloomberg and Tradeweb data respectively. Both BBG and TW data refers to transactions on the cash market, while EUREX data refers to transactions on the futures market. RVol is the 20-day rolling standard deviation of rate changes (for the cash markets) and returns (for the future market). All the measures are standardized so as to have zero mean and unit variance. The center- and right-bottom panels display four of the composite indicators analyzed in the paper (Section 5). PC stands for principal components.

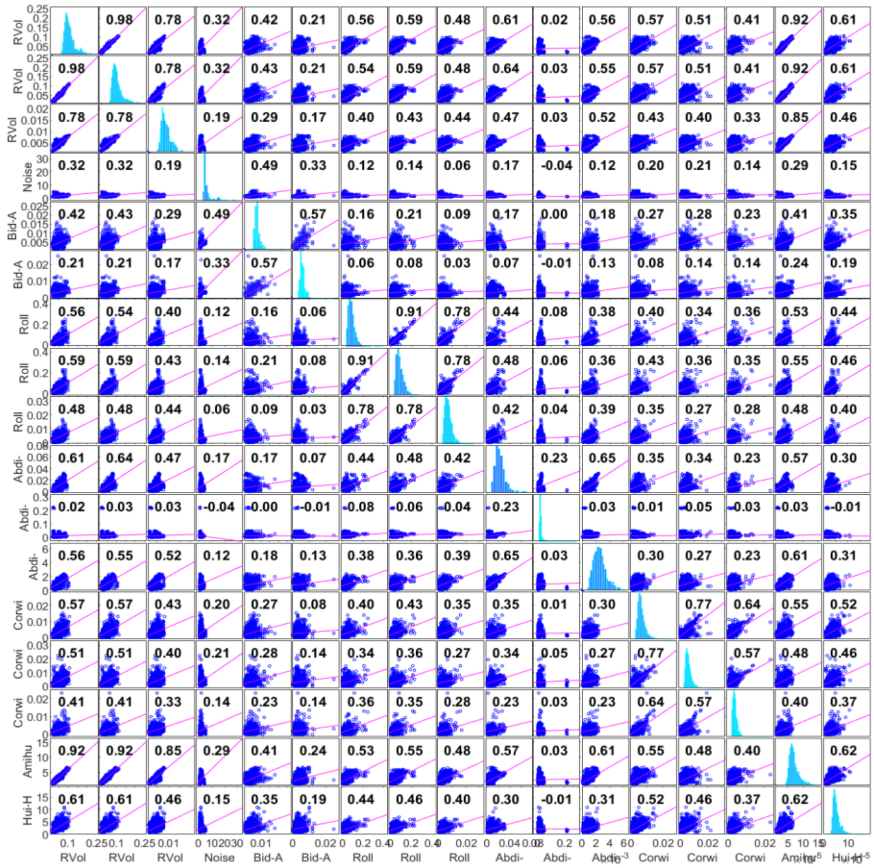
Figure 5 – Correlations between liquidity measures – France



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: this matrix displays the scatterplots (and corresponding interpolating lines obtained through linear regressions) of all the possible pairs of liquidity measures used to construct the composite indicators. The liquidity measures refer to the French 10-year benchmark bond. The measures appear in the same order (from top to bottom and from left to right) in which they appear in Figure 1. Each entry of the above matrix also reports the coefficient of linear correlation. The sample distribution of each liquidity measure is represented by a histogram on the main diagonal of the matrix.

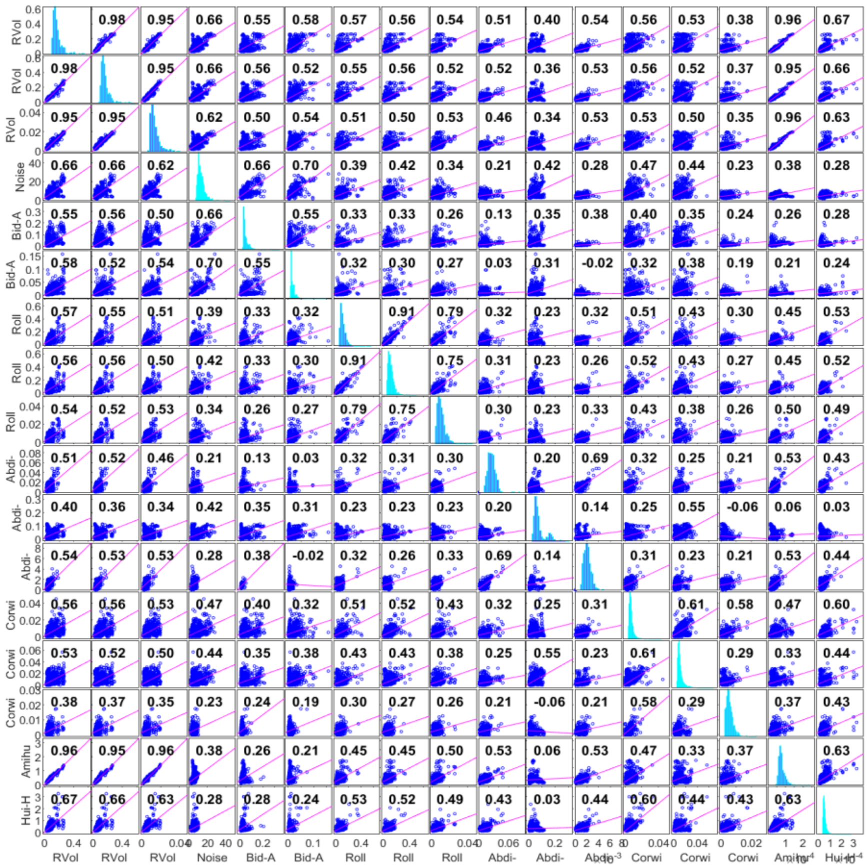
Figure 6 – Correlations between liquidity measures – Germany



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: this matrix displays the scatterplots (and corresponding interpolating lines obtained through linear regressions) of all the possible pairs of liquidity measures used to construct the composite indicators. The liquidity measures refer to the German 10-year benchmark bond. The measures appear in the same order (from top to bottom and from left to right) in which they appear in Figure 2. Each entry of the above matrix also reports the coefficient of linear correlation. The sample distribution of each liquidity measure is represented by a histogram on the main diagonal of the matrix.

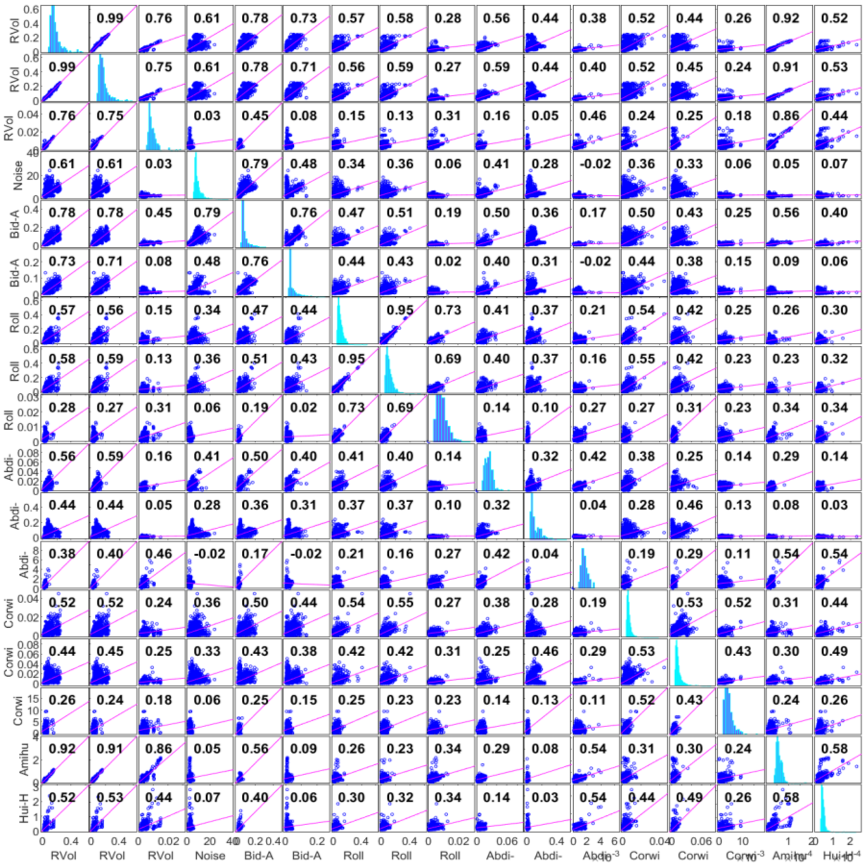
Figure 7 – Correlations between liquidity measures – Italy



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: this matrix displays the scatterplots (and corresponding interpolating lines obtained through linear regressions) of all the possible pairs of liquidity measures used to construct the composite indicators. The liquidity measures refer to the Italian 10-year benchmark bond. The measures appear in the same order (from top to bottom and from left to right) in which they appear in Figure 3. Each entry of the above matrix also reports the coefficient of linear correlation. The sample distribution of each liquidity measure is represented by a histogram on the main diagonal of the matrix.

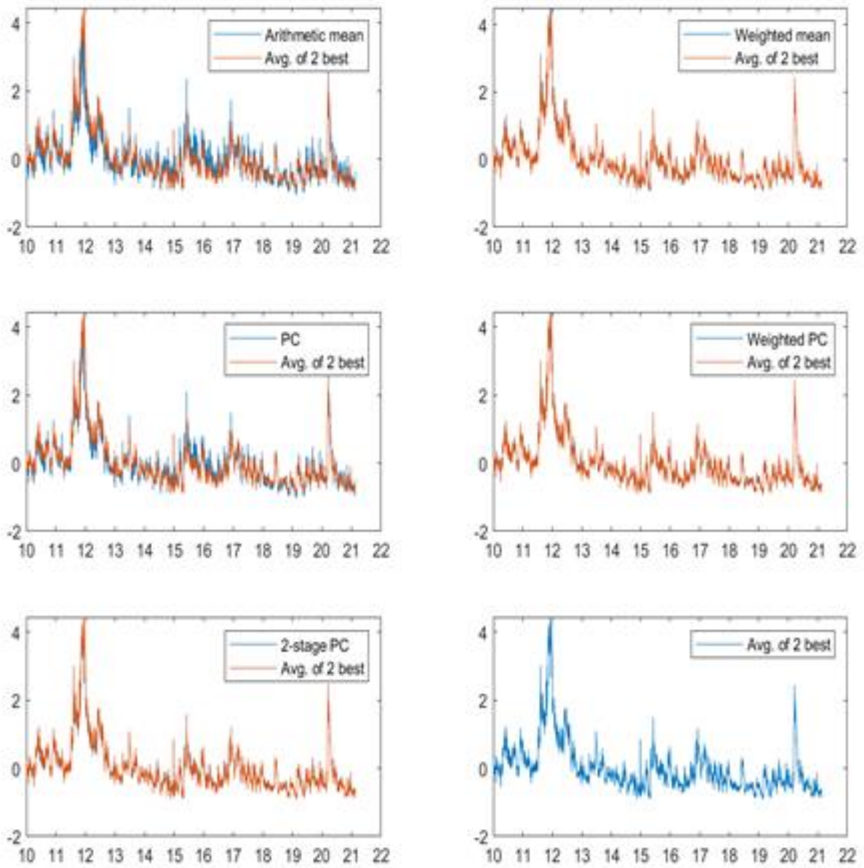
Figure 8 – Correlations between liquidity measures – Spain



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: this matrix displays the scatterplots (and corresponding interpolating lines obtained through linear regressions) of all the possible pairs of liquidity measures used to construct the composite indicators. The liquidity measures refer to the Spanish 10-year benchmark bond. The measures appear in the same order (from top to bottom and from left to right) in which they appear in Figure 4. Each entry of the above matrix also reports the coefficient of linear correlation. The sample distribution of each liquidity measure is represented by a histogram on the main diagonal of the matrix.

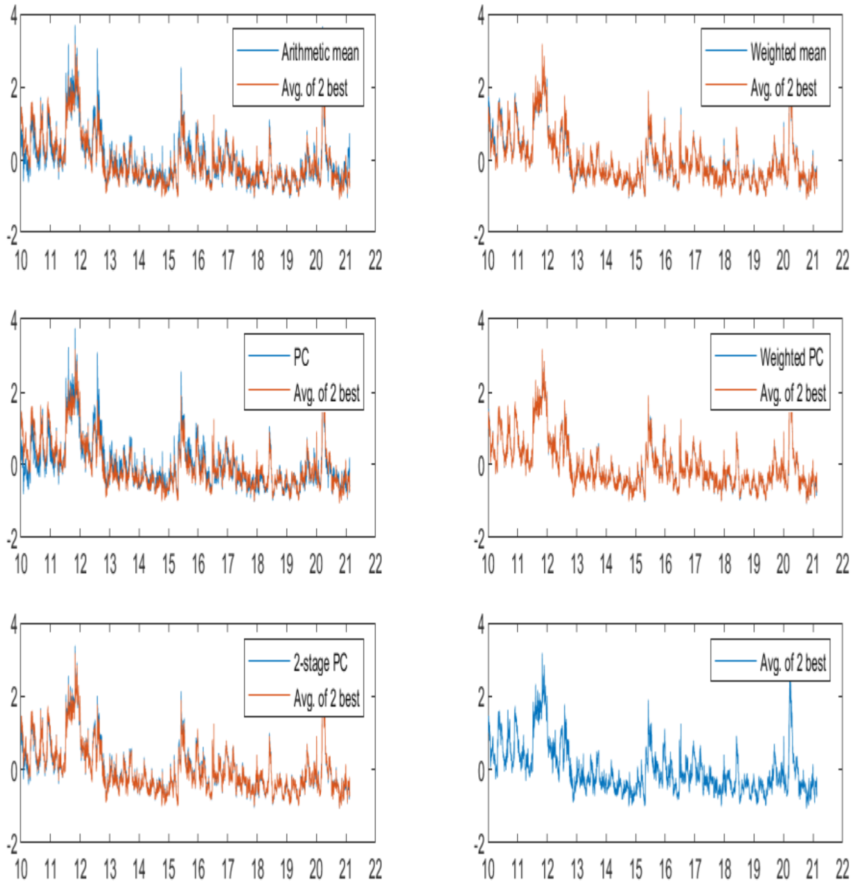
Figure 9 – Comparison of composite liquidity measures – France



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the composite liquidity indicators obtained with the methodologies described in Sections 5 and 6. Avg. of two best is the "preferred" indicator, computed as the arithmetic average of the two composite indicators that have the highest correlation with a proxy for the liquidity risk premium. All the indicators refer to the French 10-year benchmark bond.

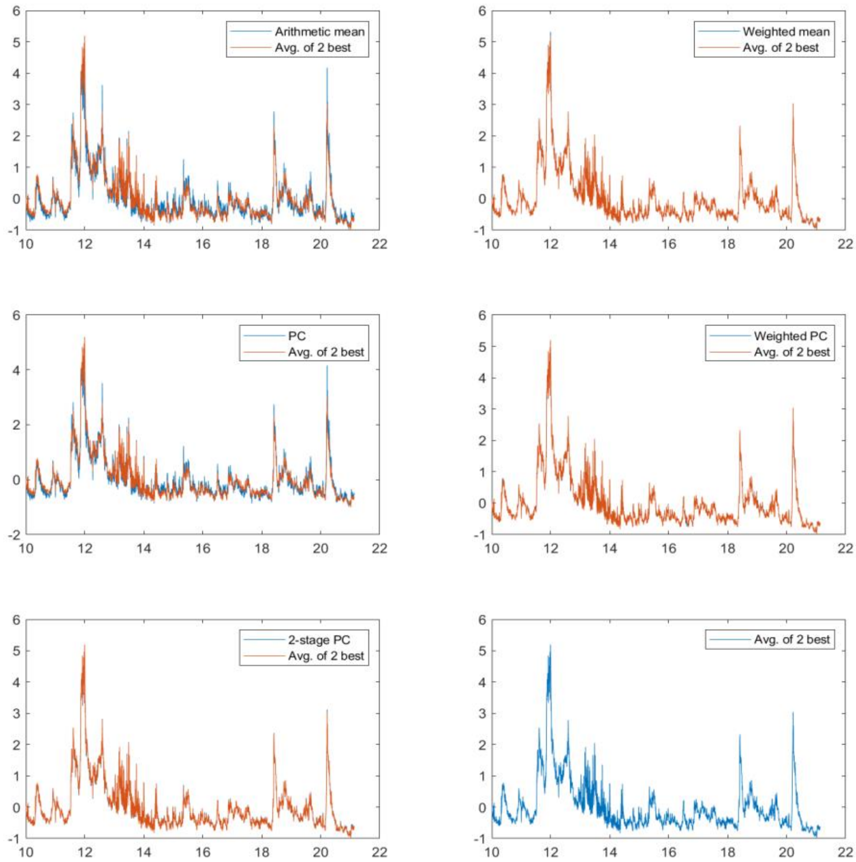
Figure 10 – Comparison of composite liquidity measures – Germany



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the composite liquidity indicators obtained with the methodologies described in Sections 5 and 6. Avg. of two best is the "preferred" indicator, computed as the arithmetic average of the two composite indicators that have the highest correlation with a proxy for the liquidity risk premium. All the indicators refer to the German 10-year benchmark bond.

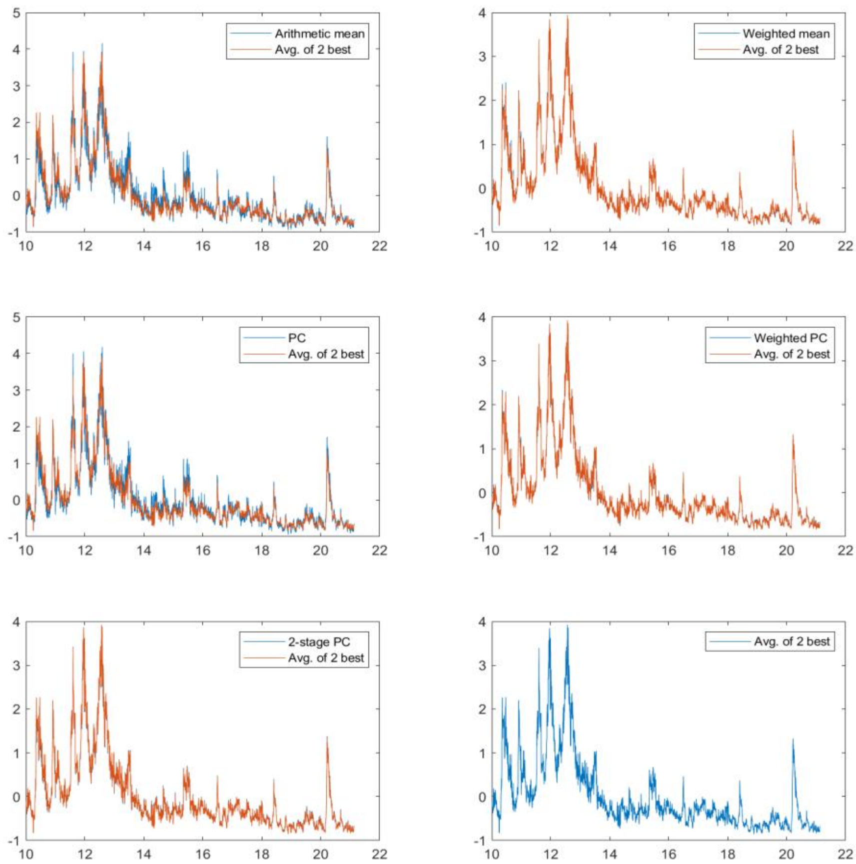
Figure 11 – Comparison of composite liquidity measures – Italy



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the composite liquidity indicators obtained with the methodologies described in Sections 5 and 6. Avg. of two best is the “preferred” indicator, computed as the arithmetic average of the two composite indicators that have the highest correlation with a proxy for the liquidity risk premium. All the indicators refer to the Italian 10-year benchmark bond.

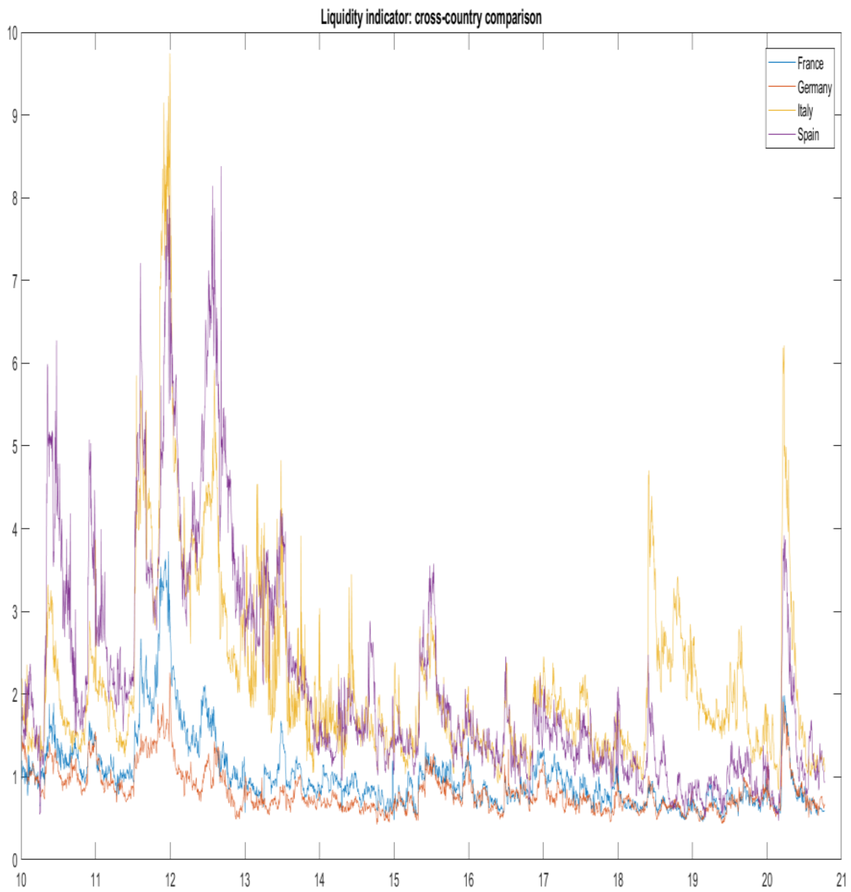
Figure 12 – Comparison of composite liquidity measures – Spain



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the composite liquidity indicators obtained with the methodologies described in Sections 5 and 6. Avg. of two best is the “preferred” indicator, computed as the arithmetic average of the two composite indicators that have the highest correlation with a proxy for the liquidity risk premium. All the indicators refer to the Spanish 10-year benchmark bond.

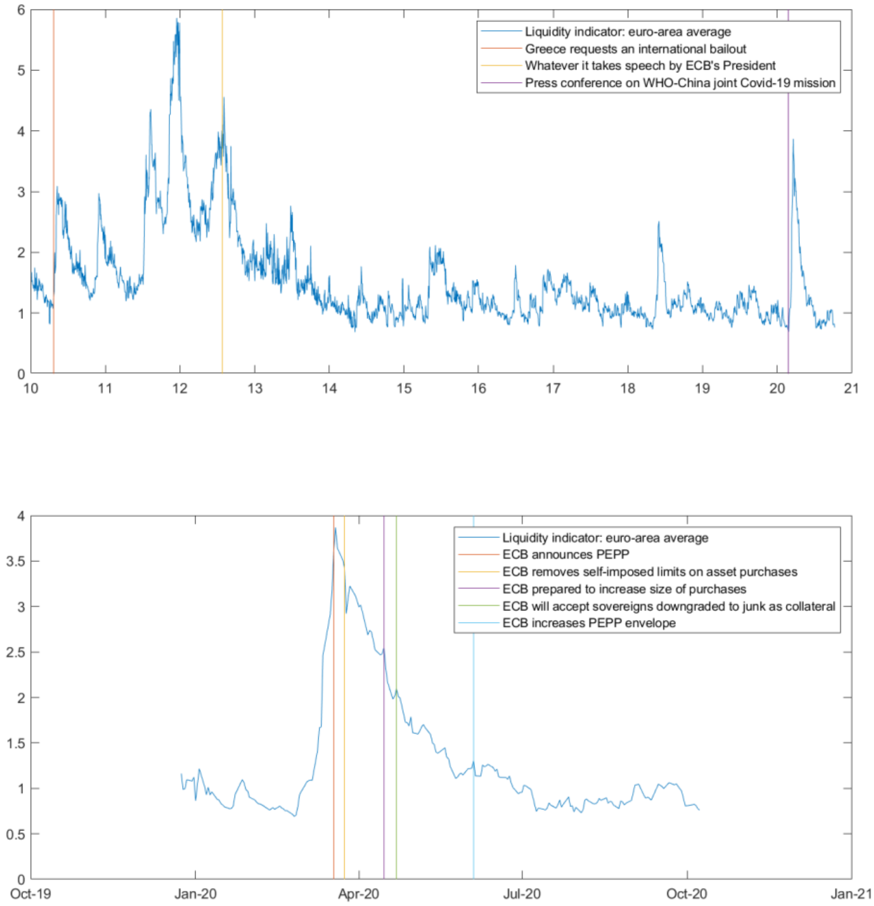
Figure 13 – Preferred composite liquidity measure – Cross-country comparison



Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: this figure displays the "preferred" composite liquidity indicators obtained with the methodologies described in Sections 5 and 6, and re-scaled so as to allow cross-country comparisons. All the indicators refer to 10-year benchmark bonds.

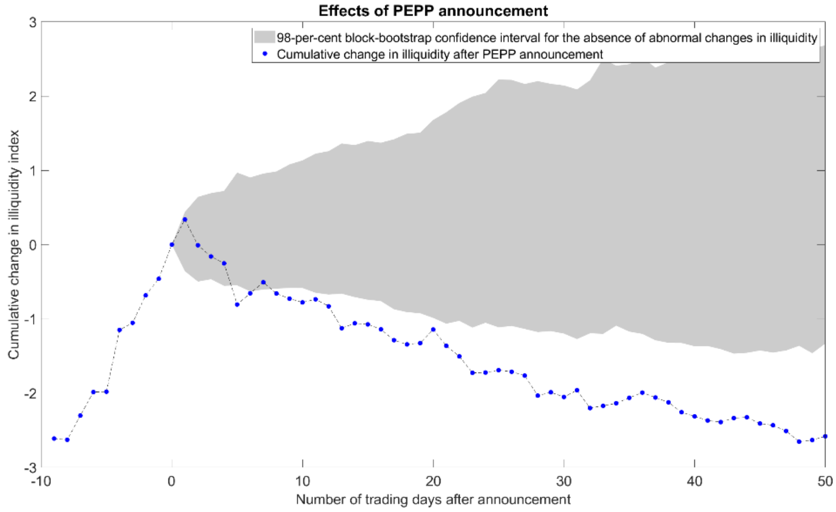
Figure 14 – Preferred composite liquidity measure – Euro-area average

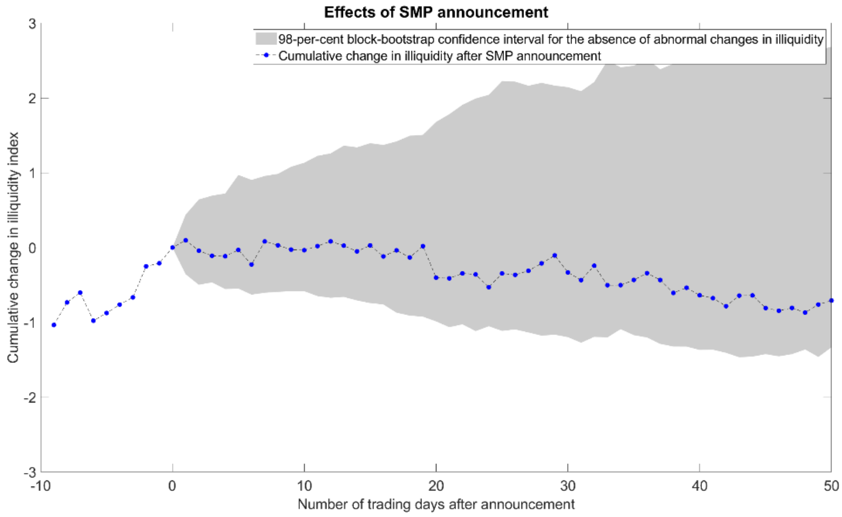


Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the weighted average of the “preferred” composite liquidity indicators across the four countries being analyzed (France, Germany, Italy and Spain). Notional bonds outstanding in 2020 Q2 are used as weights. The “preferred” composite liquidity indicators used in the weighted average are obtained with the methodologies described in Sections 5 and 6, and re-scaled so as to allow cross-country comparisons. All the indicators refer to 10-year benchmark bonds. Vertical lines indicate market-sensitive announcements described in the legends. The liquidity indicator is the same in both panels, and the bottom panel zooms on the end of the sample.

Figure 15 – Effects of ECB's announcements on euro-area liquidity

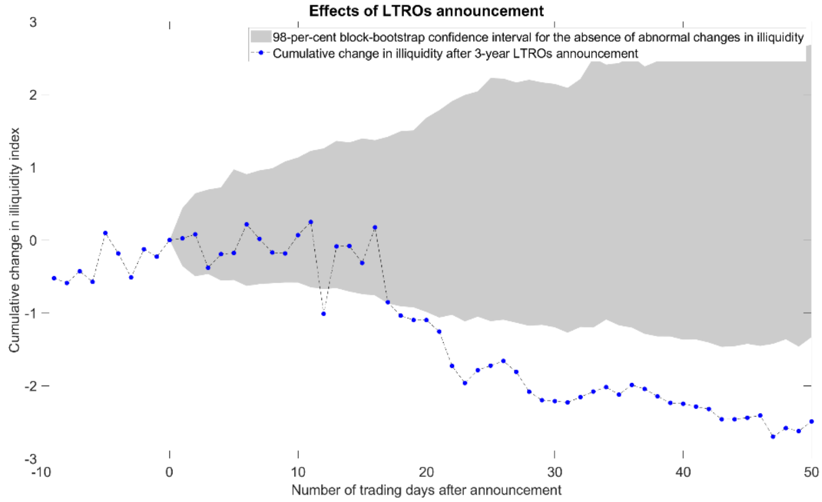


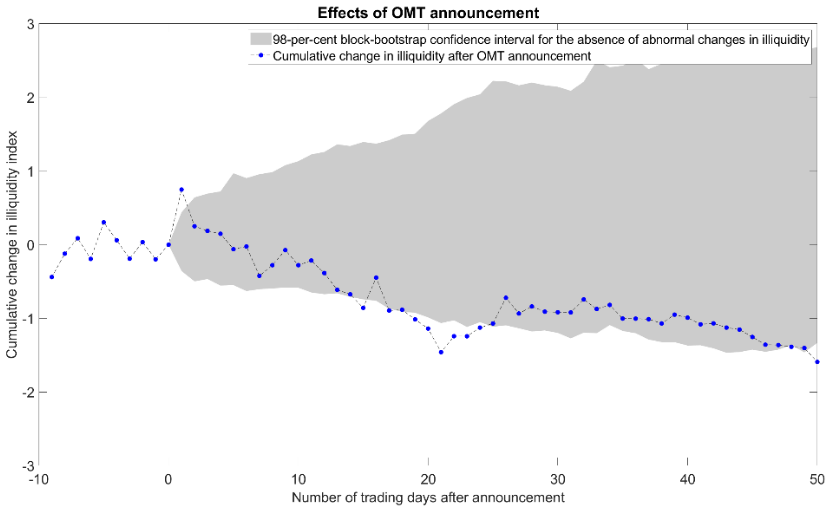


Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the cumulative changes in euro-area composite liquidity indicator together with block-bootstrap confidence bands for the null hypothesis of absence of abnormal changes in liquidity.

Figure 16 – Effects of ECB's announcements on euro-area liquidity





Sources: Bloomberg, Tradeweb, Refinitiv, own calculations.

Note: these figures display the cumulative changes in euro-area composite liquidity indicator together with block-bootstrap confidence bands for the null hypothesis of absence of abnormal changes in liquidity.