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Asset class liquidity risk indicators. Timing the risk in the European and US equity and bond markets*

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September 30, 2024

Abstract

In this paper, we propose asset class liquidity risk indicators constructed by aggregating financial, monetary and credit variables. We measure the presence of liquidity in six highly representative markets such as the Equity Europe, Long Term Italian Government Bond, Short Term European Government Bond, Equity US, Bond Corporate Investment Grade USD, Short Term US Government Bond markets over the period January 2007-January 2023. Our approach allows for a time-varying measure of the relative contribution of the raw drivers to the asset class indicators. The use of the endogenous Markov-switching model allows to identify episodes of financial distress which have characterised the behaviour of assets over the last two decades. Finally, we map the Markov-switching regimes with the bubble episodes we identify using recursive testing procedures.

Keywords: Asset Class Liquidity Risk Indicators, Aggregation, Endogenous Markov-Switching Models, Bubble Episodes.

J.E.L. Classification Numbers: C13, C22, G12, G14, G15.

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Abstract

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1 INTRODUCTION

In this paper, we propose novel asset class liquidity risk indicators, constructed by aggregating financial, monetary and credit variables, able to incorporate the behaviour of both the universe of individual and institutional investors.

The liquidity risk indicators we develop are associated with market liquidity, volatility, and funding liquidity (see Brunnermeier and Pedersen, 2009; and Nagel, 2012). Liquidity risk has specific connotations in the literature (see Pastor and Stambaugh, 2003; and Acharya and Pedersen, 2005; among others). A financial market can be considered liquid when trades can be executed at very low costs, in a timely manner and with large trades having only limited impact on market prices, as defined in Foucault, Pagano, and Röell (2013). Liquidity is not directly observed or uniquely defined and in financial markets it is generally measured across five dimensions such as *tightness* (the possibility of executing transactions at a low cost), *immediacy* (the speed at which orders can be executed), *depth* (the existence of enough orders at prices above or below market price and can be proxied with volume of trades), *breadth* (ability to transact large volumes with minimum impacts on prices), and *resilience* (the availability of liquidity under stressful conditions in markets). Investors may not be rational and thus their investment decisions and funds allocation may be driven by biases, worries, uncertainty and emotional risk aversions, with a significant impact on financial markets, and thus on price volatility and asset liquidity. Policy makers recognise the importance to measure liquidity risk, indeed considered an important risk source for financial markets. The International Monetary Fund (2014) indicates that liquidity risks have increased significantly due to an upward pattern in risk appetite of investors aiming at yields in less liquid assets. Recent periods of high uncertainty, G20 reforms and policy responses to the Covid-19 pandemic, Russian invasion of Ukraine, high inflation and the strong increase of interest rates are key to measure the effects on financial system, in particular regarding both the potential for sudden sharp movements in asset prices and liquidity demands that may lead to spillovers across the financial system (Financial Stability Board, 2021).

There is huge body of literature suggesting several variables able to proxy the multiple dimension of liquidity of securities in equity, fixed income and commodity markets. We consider the most commonly used liquidity metrics, as recently summarised in Poli and Taboga (2021)[1]: the bid ask spread, that refers to the tightness of liquidity; the Amihud index, suggested in Amihud (2002), that proxies depth and breadth giving the idea of the impact on daily prices of a unit of trade[2]; the turnover value, that

[1] See also Sarr and Lybek (2002), Gabrielsen, Marzo and Zagaglia (2011), Vajanos and Wang (2013) , Jain and Singla (2018), Tripathi, Dixit and Vipul (2020), Diaz and Escribano (2020), Naik and Reddy (2021), Verma and Kundlia (2021).

[2] Recent contributions are Lou and Shu (2017), Amihud and Noh (2020), and Barardehi, Bernhardt, Ruchti, and Weidenmier (2021).

is the sum of trade values exchanged within a time period; the turnover ratio defined as the ratio between turnover value and market capitalization; volumes; futures volatility, as a proxy of breadth and resilience; the volatility of Repo rates; the listed implied volatility indices (VIX Index, V2X index); the listed liquidity indices calculated by Bloomberg provider for government bond markets (GVLQUSD Index, GVLQGBP Index, GVLQJPY Index, GVLQIT Index); and the yield to maturity of government and corporate bonds[3].

The main contribution of this paper is threefold. The first important novelty of this paper is that in addition to financial liquidity measures, as discussed above, we also consider monetary and credit variables as proxies of global liquidity conditions such growth rate of money aggregates (base money, broad money) proposed in D'Agostino and Surico (2009); domestic credit index recently introduced in Bruno and Shin (2015) and Domanski, Fender, and McGuire (2011); the cost of borrowing for households and corporate, the growth rate in commercial paper outstanding, the indicator of the interbank funding conditions (Ted Spread for US market, Libor OIS Spread) as in Bechtel et al (2023), and the money market interest rates all discussed in Eickmeier, Gambacorta, and Hofmann (2014). A second important contribution is that our approach allows to identify relevant periods of stress and provides a time-varying measure of the relative contribution of the liquidity drivers to the liquidity indicators. Finally, we identify stress events in the liquidity risk indicators using the dynamic threshold Markov-switching approach, which we complement by measuring the presence of bubbles then mapped to the (low-, medium-, and high-risk) regimes identified via the endogenous Markov-switching model.

Our empirical methodology is developed by measuring liquidity in six highly representative markets such the Equity Europe, Long Term Italian Government Bond, Equity US and Bond Corporate Investment Grade USD, Short Term European Government Bond and Short Term US Government Bond markets, over the period running from January 2007 to January 2023. These are the most important and meaningful asset classes for the US and Europe, the biggest and most developed economies and financial markets, where financial transactions are very liquid and reliable. The central banks (Federal Reserve and ECB), the private and institutional wealth, the financial industry, public investments and budgets are the most relevant. Moreover, according to the IMF macroeconomic and financial data[4], US Dollar and Euro make up respectively 58.9% and 20.0% of world currency reserves, in this respect USD and EUR money markets are at the cornerstone of global liquidity. With their status of "safe assets", US and Germany treasury bills underpin the modern developed financial markets. The ECB's

[3]Brunnermeier and Pedersen (2009), Goyenko, Holden, and Trzcinka (2009), Drehmann and Nikolaou (2013), Kahraman and Tookes (2017), Moshirian, Qian, and Wee (2017), Pástor and Stambaugh (2019), Chaieb, Errunza, and Langlois (2020), Nguyen, Engle, Fleming, and Ghysels (2020), Li, Li, and Tee (2020).

[4]`https://data.imf.org/?sk=e6a5f467-c14b-4aa8-9f6d-5a09ec4e62a4`

Euro money market study[5] shows the importance of secured transactions in the Euro money market, highlighting that the shortage of German government bonds might undermine transmission mechanism of monetary policy. Therefore, studying money market liquidity is of paramount importance for both financial markets and policy makers. In addition to the money market, we focused on the government and credit markets by considering the longer part of the government bond curve of Italy and the US corporate investment grade bonds. On the one hand, Italy has the fifth largest national debt with an outstanding amount of about 2.8 trillion euros of which almost 2.4 trillions are financed by treasuries bonds (BTP) with an average maturity higher than 7 years. Furthermore, the Italian BTPs have been the top three investments from the ECB in the QE programs (public sector purchase programme, PSPP, and pandemic emergency purchase programme, PEPP) with more than 700 billions. Historically, stress on Italy's government debt has been forerunner of volatility on the broad financial markets (e.g. sovereign debt crisis) which makes this a relevant asset class in the context of Euro denominated government debt[6]. On the other hand, the US corporate investment grade is not only the largest credit market, but also the one that has grown faster in the last ten years (average growth rate of 6% against the 4% of whole corporate credit market), which makes it a natural choice for our study. Finally, in the stock market realm, US and Europe add up to more than 90% of the developed equity markets and more than 80% of the global stock markets capitalization. Hence, to better understand the stock market liquidity dynamics, both asset classes (Equity Europe and Equity US) are the key to answer our research purpose.

The liquidity risk indicators we propose for the six asset classes are able to incorporate the relevant episodes of distress experienced over the last decades. As far as the contributions to risk on events for Equity Europe, the non-volatility financial group of variables showed the highest impact during the global financial crisis with respect to the mayor role played by the credit variables during the sovereign debt crisis and the monetary indicator during the Covid-19 period; for the Long Term Italian Government Bond, during the sovereign debt crisis the highest contribution comes from the credit market, which also plays a crucial role as main driver for Equity US over the global financial crisis though for this market the monetary variables dominate the event associate to the Covid-19 crisis. As far as the Bond Investment Corporate USD market is concerned, the main contribution comes from

[5] `https://www.ecb.europa.eu/pub/euromoneymarket/html/ecb.euromoneymarket202204.en.html#toc3`

[6] The important role played by the Italian debt can be appreciated by that it is the seventh issuer, with weight similar to France, UK and Germany, as far as the Global Aggregate Bond Index; it is the second issuer, after France, on the Euro Aggregate Bond Index with a weight of 12%; and, it is the second issuer, after France and before Germany, on the Euro Government Bond, with a weight of 22%. It has been demonstrated that to hedge the European government bond risk, the Italian government bond future is very effective and meaningful (Bessler and Wolff, 2014). Furthermore, the importance of this asset class is represented by its the relevance in the ECB asset purchase program. In the period 2015-2023, the ECB held a minimum of 16% of the public sector purchased programme in Italian government Treasuries with an outstanding exceeding 440 billion Euros (ECB official data).

credit market over the crisis period we consider; for the Short Term Euro Government Bond, there is a strong evidence of the crucial role played by the credit indicators from the last quarter of 2021, while the Short Term US Government Bond are mainly affected by financial indicators, the only exception being the second quarter of 2022 when again the credit indicators show a dominant spike. In general, bubble episodes are found in correspondence of a high-risk regime charactering the Eurozone debt crisis of 2011 and 2012, the Chinese stock market crash in 2015/6, the covid-19 pandemic and the invasion of Ukraine in 2022.

The reminder of the paper is as follows. Section 2 reports a description of the financial, monetary and credit liquidity variables used to construct the liquidity indicators for the six equity and bond markets. In Section 3, we introduce the aggregation technique we propose to construct asset classes liquidity risk indicators and we describe the main features of the six liquidity indicators. In Section 4, we present the way in which our framework allows to measure the time-varying contribution of financial, credit and monetary drivers aggregated in four main groups on the indicators. In Section 5, we identify stress events via the combined use of the endogenous Markov-switching model and bubble episodes using recursive procedures. Section 6 concludes.

2 DATA COLLECTION

We construct our measure of liquidity risk index using various sources. Financial data are obtained from Bloomberg, while monetary and credit variables are extracted from Central Banks' datasets (ECB for Europe and Italy, and FRED for US). The dataset covers the period from January 2007 to January 2023. The dataset covers a large number of liquidity measures and in particular a set of financial variables that summarize the different dimensions of market liquidity (i.e. bid ask spread, Amihud, turnover, turnover ratio, volumes). We also include money market rates, interbank rates and long-term government bond yields as important indicators of funding liquidity conditions faced by the bank sector. Furthermore, implied stock market volatility and asset volatility (i.e. futures volatility) are included in our analysis as a proxy of risk appetite and as information of investors' willingness to provide funding. We further include *monetary variables*, such as base money and broader monetary aggregates, in particular M1 and M3. Our analysis comprises also *credit variables*, such as domestic credit, commercial paper outstanding and cost of borrowing for corporate and households, since slowdown in credit conditions implies the worsening of liquidity framework. For government bond markets, we include also listed indices of Bloomberg that measure the prevailing liquidity conditions through the average yield errors. When liquidity worsen, difference between the curve fitter and bond's fair value can be persistent so that average yield error can be large.

The six equity and bond markets considered are deeply affected by liquidity stress events over the years. Worsening liquidity conditions can often be linked with financial crisis events (Garabedian & Inghelbrecht, 2015, 2020). The financial crisis in the early phase manifested itself as a deep liquidity shortage among financial institutions (Szekely & van den Noord, 2009). Fears of insolvency caused a reduction in interbank lending and consequent temporary disruptions in the pricing system of short-term debt markets. The pool of assets eligible as collateral sharply decreased resulting in a liquidity shortage. Via the banking system, the liquidity stress soon infected the European financial system, causing a crisis in the banking system and in many peripheral Euro area countries (Moro, 2013). The sovereign debt crisis began with Greece and suddenly it spread over some other countries like Portugal, Ireland, Italy and Spain (Moro, 2013). The rising sovereign risk led to an increase in the repo haircuts on government bonds issued by peripheral countries, reducing their capacity to serve as collateral in the secured interbank market (Molteni, 2019). The coronavirus pandemic led to acute stress in the global economy and in many parts of the global financial system (Helwege and Wang (2021), O'Hara and Zhou (2021), Kargar et al. (2021), Chakrabarty and Pascual (2022), Ebsim et al. (2022)). In the US in early to mid-March 2020, many financial markets plummeted, and liquidity shortages began to surface, and between March 5 and March 23, the S&P 500 index fell more than 25% (Kargar et al., 2021). Over the same period, the US corporate bond market faced high selling pressure, causing a sharp increase in the the ICE Bank of America AAA U.S. Corporate Index Option-Adjusted spread of about 150 bps. The high-yield (HY) corporate debt spread increased by more than 500 bps (Kargar et al., 2021). In the pandemic stage of Covid-19 crisis European equity markets registered higher negative returns as compared to other equity markets, showing the highest sensitivity towards the pandemic (Ali et al., 2020).

For the $i-th$ asset class and the $t-th$ time, a set of p liquidity variables $X_t^i = \{x_{t,1}^i, ..., x_{t,z}^i, ..., x_{t,p}^i\}$ summarizes the dimensions of liquidity. $x_{t,z}^i$ represents the generic liquidity variable, defined in Equation (1) below. Some indicators are built at security level and then aggregated at market level. Other indicators are directly referred to a market. More in detail, bid ask spread, Amihud index, turnover value, turnover ratio, volume are available for each security of the market and then are aggregated after outlier removal procedure for time series, as specified below. Source of raw data is Bloomberg (See Appendix A for more details).

To proxy the six markets, we consider the following listed indices:

1. Equity Europe is proxied by constituents of MSCI World index (Bloomberg ticker: MSDUWI), that includes large and mid cap representation of 23 developed markets[7].

[7] Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Ireland, Israel, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, the UK, and the US.

2. Long Term Italian Government Bond is represented by bonds in the ICE BofAML 7-10Year Italy Government Index (Bloomberg ticker: G4I0). It is a subset of ICE BofA Italian Government Index including securities with a remaining time to maturity between 7 and 10 years.
3. Short Term Euro Government Bond is represented by short term bonds in the Eur German Sovereign Curve (Bloomberg ticker: YCGT0016).
4. Equity US is proxied by constituents of MSCI World index with US as country, on the basis of Morgan Stanley criteria.
5. Bond Corporate Investment Grade USD is proxied by constituents of ICE BofAML US Corporate & Yankees Index (Bloomberg ticker: CY00). The index gives a representation of US dollar denominated debt issued in the US market by US corporations and non-US corporations and quasi-governments. Constituents must have an investment grade rating, a time to maturity of at least 12 months, a fixed coupon and a minimum amount oustanding of $250 million.
6. Short Term US Government Bond is proxied by short term bonds in the US Treasury Actives Curve (Bloomberg ticker: YCGT0025).

The $z-th$ aggregate measure of liquidity referred to index i, time t, $x^i_{t,z}$, with $z = 1, ..., p$ is defined as follows:

$$x^i_{t,z} = \sum_{s=1}^{h} \tilde{x}^i_{t,z;s} w^i_{t;s} \tag{1}$$

where $w^i_{t;s}$ is the weight of the sth instrument in index i at time t, h is the number of members in the $i-th$ index and $\tilde{x}^i_{t,z;s}$ is the $z-th$ liquidity index referred to security s that is constituent of asset class i at time t after a winsorization to minimise the influence of outliers. We define q_α as the quantile of order α of the time series of liquidity indicators referred to the sth security of the ith index, $x^i_{t,z;s}$. Level α is set to 5% and the winsorizing procedure can be summarized as follows[8]:

- for volume, turnover and turnover ratio indicators:

$$\tilde{x}^i_{t,z;s} = x^i_{t,z;s} \mathbf{1}_{\{q_{\frac{\alpha}{2}} < x^i_{t,z;s} < q_{1-\frac{\alpha}{2}}\}} \tag{2}$$

- for bid ask spread:

$$\tilde{x}^i_{t,z;s} = x^i_{t,z;s} \mathbf{1}_{\{|x^i_{t,z;s}| < q_{1-\alpha}\}} \tag{3}$$

  where $q_{1-\alpha}$ is the quantile of order $1-\alpha$ of the absolute value of the time series of liquidity indicator.

[8]Note that volume, turnover, turnover ratio and Amihud indicators are used for the construction of the liquiditiy risk indicators for Equity Euro and Equity US only. We do not use these variables for the government and corporate bond indicators in the light that the segmentation of these markets does not allow us to construct a consistent time series for each bond and thus for the bond liquidity indicators.

- for Amihud indicator:

$$\tilde{x}^i_{t,z;s} = x^i_{t,z;s} \mathbf{1}_{\{x^i_{t,z;s} < q_{1-\alpha}\}} \tag{4}$$

Other liquidity measures are directly referred to the market and available on Bloomberg, such as futures volatility, listed implied volatility, listed liquidity indices, yield to maturity of bonds and indicators of the interbank funding conditions. In our analysis, we also deal with credit indicators and monetary aggregates that are referred to a market and that are available in the Central Banks' databases.

The full list of variables included in the database is reported in Appendix A, where we also provide details about the source of the data and how variables are transformed prior to the empirical analysis. Asset volatility and interest rates enter in levels, while credit and monetary variables are transformed in year on year growth rate . Furthermore, in order to have that when the index rises liquidity conditions get worse, we change the sign of some time series. For instance, since a positive growth rate of domestic credit implies better liquidity framework, we invert the sign. The same transformation is applied to commercial paper outstanding, base money, monetary aggregates, volume, turnover and turnover ratio. Given the monthly frequency of credit and monetary aggregates, daily variables are also converted into monthly by taking the average.

Table 1 reports the summary statistics of the series of the six markets. Among the liquidity proxies, domestic credit, commercial paper outstanding, base money, aggregate broad money and M1 are expressed as year on year growth rate. Equity Europe, Long Term Italian Govt Bond and Short Term European Government Bond share some variables (domestic credit, Libor OIS monetary base, broad money and M1) referred to the Euro area. Domestic credit grows on average by 3.50% and has a standard deviation of the growth rate of 3.43%. A similar volatility is shown by broad money and M1 growth rates, while base money has a mean of 16.35% with a volatility of 22.30%. Another volatile liquidity proxy is Libor OIS spread, with a standard deviation of 44.45% and a mean of 27.96%. Equity US, Bond Corporate Investment Grade US and Short Term US Government Bond share the TED spread, mortgage rate to Treasury yield, Libor OIS spread, growth rate in commercial paper outstanding, base money, broad money and M1. Among them the most volatile liquidity proxy is the Libor OIS, with a standard deviation of 32.33% and a mean of 29.20% over the period. As in the Euro area, growth rate in base money has an high variability with a volatility of 22.30%, if compared with standard deviation of the monetary aggregates broad money (3.48%). The highest volatile monetary aggregate is M1 (79.96%). Growth rate in commercial paper outstanding is negatively skewed, with mean and median respectively of -1.81% and -0.94%.

[INSERT SOMEWHERE HERE TABLE 1]

Liquidity indices are then standardized by converting them into order statistics through their Empirical Cumulative Distribution Function (ECDF), as described in Hollo, Kramer, and Lo Duca (2012), Iachini and Nobili (2014, 2016), and Garabedian and Inghelbrecht (2015, 2020). This process is critical for liquidity measures because of differences in the unit of measurement and in scale. The order statistic takes a value in $[0, 1]$, where a value of 0 (1) means minimum (maximum) degree of liquidity risk.

We transform the data with rolling window ECDF with a presample of five years which allows us to manage stationary liquidity time series and to obtain a responsive index, and it is consistent with the literature on short memory of investors (Garabedian & Inghelbrecht, 2015, 2020).

3 ASSET CLASS LIQUIDITY RISK INDICATORS

In this section, we describe the aggregation technique we propose to summarize the rich information contained in the raw liquidity measures, monetary and credit variables using time-varying correlations. The liquidity indicator we propose is able to signal risk in presence of stress with high level of correlations.

3.1 Empirical methodology

The aggregation technique we propose allows to summarize the information given by different financial indices into a unified composite index, that explores the time varying nature of correlations. The index gives a risk on signal in case of high correlated index that take simultaneously high levels. After standardization through ECDF technique, raw indices are aggregated into uniform groups in term of *liquidity* dimensions. The aggregation is done by taking the simple arithmetic mean of the individual measures within the same group.

Let us define the gth cluster, with $g = 1, ..., G_i$, and the set A_g of liquidity indices belonging to the gth group. Denote $l^i_{t,g}$ the liquidity indices related to asset class i with $i = 1, ..., n$ and cluster g at time t. The aggregation is taken as follows:

$$l^i_{t,g} = \frac{1}{|A_g|} \sum \mathbf{1}_{\{z: l^i_{t,z} \in A_g\}} l^i_{t,z} \tag{5}$$

where $|A_g|$ is the cardinality of the set A_g and $\mathbf{1}$ is the indicator function. For Equity Europe, as reported in Appendix B, G_i is equal to 9, the A_1 set contains the three liquidity indices of volume,

turnover and turnover ratio, while base money, broad money and M1 belong to the $9th$ group.

The liquidity risk indicator for the ith asset class at time t, LRI_t^i, is built though portfolio based approach as follows:

$$LRI_t^i = (\mathbf{w}_t^i \circ \mathbf{l}_t^i)\mathbf{C}_t^i(\mathbf{w}_t^i \circ \mathbf{l}_t^i)' \tag{6}$$

where:

- $\circ$ indicates the Hadamard product;
- $\mathbf{w}_t^i$ is the G_i dimension row vector of time varying weights for each group of liquidity indicators at time t;
- $\mathbf{l}_t^i$ is the G_i dimension row vector of liquidity indicators $l_{t,g}^i$ for each group g and for each time t;
- $\mathbf{C}_t^i$ is the time varying correlation matrix of dimension $G_i \times G_i$ that, as in Garabedian and Inghelbrecht (2015, 2020), is estimated through exponential weighted moving averages approach with decay factor of 0.94.

The time varying weights, function of the liquidity indices and of time-varying volatility, are defined as:

$$w_{t,g}^i = \frac{exp^{l_{t,g}^i} + (l_{t,g}^i * (\sigma_{t,g}^i)^2)}{\sum_{g=1}^{G_i}\left(exp^{l_{t,g}^i} + (l_{t,g}^i * (\sigma_{t,g}^i)^2)\right)} \tag{7}$$

where $\sigma_{t,g}^i$ is the time varying volatility estimated through exponential weighted moving averages approach.

In the next section, we report the LRIs for Equity Europe, Long Term Italian Government Bond, Equity US and Bond Corporate Investment Grade USD, Short Term European Government Bond, and Short Term US Government Bond.

3.2 Liquidity risk indicators

Figure 1 shows the LRIs for each of the six asset classes over the period January 2007 to January 2023. As already mentioned above, the LRI is scaled from 0 to 1 and the higher the value, the higher the risk of liquidity distress.

[INSERT SOMEWHERE HERE FIGURE 1]

3.2.1 Equity Europe

The biggest increases in the LRI for the Equity Europe occur during the financial crisis and the first signal of worsened liquidity conditions was in August 2007, when concerns about subrime mortgages were confirmed by that the rating agencies downgraded billions of dollars of structured securities and

BNP Paribas interrupts redemptions on three investment funds. The LRI sharply rises in March 2008 with the collapse of the global investment bank Bear Stearns. Liquidity distress is observed over some months until July 2008, when the LRI sharply increases following the failure of IndyMac Bank and the worsening of financial conditions of Fannie Mae and Freddie Mac. Since July 2008, the LRI confirmed its increasing trend in correspondence increase risk shadowed. September 2008 is interested by the first big liquidity stress event following the Lehman Brothers collapse with panic spreads across financial markets world widely. In the following days, the Federal Reserve (FED) intervenes with the bailout of the American International Group, and the Securities and Exchange Commission halts the short selling of financial stocks as a temporary emergency action to protect investors and markets. An even large increase in the LRI occurs in October 2008, despite bailout programs and synchronised rate cuts across major central banks. Between October and November, the index reaches the maximum level ever and remains in risk on area until July 2009.

The next large increase occurs in May 2010 when serious concerns about credit risk in the Euro area emerged. The LRI spikes also in April 2011 when Portugal requests financial assistance from the European Union following the deterioration of market conditions priced by Portuguese banks and sovereign debt. LRI signals the presence of risk over the period from July 2011 to February 2012, when the sovereign debt crisis spreads beyond the peripheral countries of the Eurozone. Following a short tranquil period, the LRI turns back up in July 2013 though at a lower level than in 2011. The uncertainty surrounding financial markets during this risk period is mainly caused by the lack of optimism over the bank bailout due to Spain's borrowing costs rise to the highest rate since the launch of the Euro in 1999 and by fears of contagion due to the scenario of a bailout for Ireland and Italy, in addition to the concrete possibility of a Grexit. The LRI shows a clear sign of risk for Equity Europe until February 2013. In July 2013, the LRI sharply rose because of a crunch of domestic credit and a decrease in volume, turnover and turnover ratio in European stock market.

The LRI gives another warning in August 2015, when a large drop in the Asian market triggered a drop in equity index futures in Europe and the U.S. generating a panic effect and seek to buy protection. The following shock was registered in January 2016, when the Chinese equity market experienced a sharp sell off that quickly sent stocks tumbling globally, hitting the European and the U.S. stock markets. The index retreats since then and shows new relevant peaks in 2018, when concerns about a possible slowdown of the expansionary monetary policy of the FED and other central banks caused a liquidity crunch. Moreover some developed and emerging countries are affected by other events, such as the political tensions in Italy and concerns about a trade war.

A period of liquidity distress lasts until March 2020 when Covid-19 triggered the deepest liquidity

squeeze since 2008 and 2011. The level of LRI is similar to that achieved during the sovereign debt crisis and is not at levels of 2008 because of the central banks responses to the pandemic emergency, that have been extraordinary in speed and on a huge scale.

The LRI sharply arises since September 2021 when energy crisis triggered shocks in the global financial markets, with acute effects in Europe. Return differentials between European and US firms significantly widened after the invasion of Ukraine in February 2022, when price of natural gas and, as a consequence electricity price, reached record highs. Oil prices registered their highest level since 2008. The liquidity stress continues and achieves its maximum level in 2023, year that can be characterized as the time of "inflation and rates crisis" with a mix of unusual macroeconomic conditions that proved to be extreme. Exceptionally high inflation and a historically strong reaction by monetary policies were the main market movers. The underlying causes must be sought in a succession of unprecedented shocks that hit the global economy in the last two years, starting with the reversal of the pandemic lockdown in 2021 and the consequent explosion of a huge amount of pent-up demand, that created a big unbalance in the goods market: owing to exceptional fiscal stimulus, demand grew much more than supply, backlog orders increased enormously, and prices spiralled out of control. The Ukrainian war, then, added to this fragile environment, spreading out uncertainty and pressing up energy prices towards record levels. In the Euro Area (nearer to the conflict and more exposed to the energy shock) prices went even higher from negative levels, driven above all by supply side (cost) factors: inflation was -0.2% in December 2020, 7.4% in 2021 and reached 10.4% in October 2022. Central banks, perhaps with some delay, reacted vigorously. The ECB started its tightening campaign a bit later than the FED, in July 2022, bringing the main rate from zero to 4.5%, highest level since 2008: two moves were of 75bps; this restrictive cycle has no comparison in the past. In addition, the central bank reduced its balance-sheet from €8.8 to €7.1 trillions, by gradually stopping the reinvestments of its asset purchase programs. One of the first signs of these more restrictive monetary conditions was the decline in global liquidity growth, measured by the OECD M3 indicator, which turns to -0.27% between January and March with a marked -0.18% between February and March. In the government bond markets, rates were pushed strongly up by the fastest pace of hiking in history, which triggered a yield curve inversion, both in US and Europe, with the exception of Italy where the high level of Debt/GDP ratio forces a positive shape of the interest rate curve. This unusual negative shape of the curve, with the short end above the long one, signals that investors anticipate that restrictive policies, normally, would result in a global recession. However, this has not been the case so far: the global economy is slowing but still growing, US economy is resilient and now embarked on a path of soft-landing (GDP was up 2% in the first quarter of 2023) and declining inflation but above 3%; more pain for Europe, with lower growth

(GDP stalled in Q1 2023) and stickier inflation (above 5% inflation due to cost is less responsive to monetary policy). From Table C6, it is worth stressing the highest impact of domestic credit from October 2022 to January 2023, while the Libor OIS dominates the period between March and May 2022.

3.2.2 Long term Italian government bond

As far as Long Term Italian Government Bond is concerned, the LRI already reacts to the subprime mortgage crisis in the second semester of 2007, with a first liquidity shock in June 2007, when in the timeline of events Bear Stearns liquidates the two hedge funds Bear Stearns High-Grade Structured Credit Fund and Bear Stearns High-Grade Structured Credit Enhanced Leveraged Fund, deeply invested in mortgage-backed securities. Next, there is evidence of a sharp increase in September 2007, due to an unexpected divergence of the Libor rate, from the FED funds rate signals the coming liquidity stress. The panic continued in October when the difficulty for investors to determine the real value of collateralized debt obligations and other derivatives emerges. Since April 2008 a sustained risk on area is signalled by the Long Term Italian Government Bond LRI. The first substantial decrease in the index is registered in November 2008 when the Governing Council of the European Central Bank (ECB) took some monetary policy decisions about lowering the minimum bid rate on the main refinancing operations of the Euro-system, about decreasing the interest rate on the marginal lending facility and the interest rate on the deposit facility by 50 basis points. The extraordinary monetary policy triggered the lowering of Italian government bonds yields since November 2008, with the Italian 10 year yield that returned back to levels observed in March 2008. A liquidity distress is registered in April 2009 after a new extraordinary intervention of ECB, that in March lowered again by 50 basis point the interest rate on the main refinancing operations of the Euro-system, the interest rate on the marginal lending facility and the rate on the deposit facility.

In 2009 and 2010, the Euro debt crisis takes place with the first concerns about all the heavily indebted countries in Europe and especially Portugal, Ireland, Greece and Spain. In May 2010, a first spike in LRI for the Long Term Italian Government Bond is recorded, when the Euro continues to fall and the EU member state debt start to come under scrutiny. Since the beginning of 2011, the LRI shows a series of sharp increases that triggered a risk on area since August 2011, with spread sailing straight over 400 basis points and with Italian public debt falling under increasing scrutiny from investors. The LRI achieves its pick in July 2012 and started its downward trend only after the Mario Draghi "whatever it takes" speech. Despite the decreasing trend, the LRI continues to indicate the presence of liquidity stress conditions in the second half of 2012 and in 2013, triggered by the credit

crunch cause by the strict sovereign-bank dependence. A liquidity distress starts in 2014 and lasts until 2016, when the index registers some peaks in the second half of 2016, when the UK referendum for Brexit took place and following the US election in November 2016. Despite these two important events, the LRI remains at low levels until May and June 2018, when the index sharply increases. In June 2018, the level of the index triples if compared to the LRI of April 2018, because of the turmoil over the failed Italian coalition after the political elections. The uncertainty hit investors, awed by the prospect of the Italian exit from the Euro. Italian bonds suffer their worst period since 1992, with significant spikes in yields and the Euro dropped against the dollar. The surge of the Covid-19 in February-March 2020 triggers a new global crisis and a liquidity stress phase that involved all markets.

The LRI gives another warning in June 2022, when Italian government bond spread widens against German bond, as a signal that markets are becoming increasingly worried about the ability of Italy to repay its debt. The LRI sharply arises with respect to the last quarter of 2021 with energy crisis with an even most dramatic increase since February 2022 with the war in Ukraine that, combined with COVID-related disruptions to global supply chains, triggered inflation, spikes in energy prices and shortage of key products. The consequence was a worsening outlook for Italian economy, yields, uncertainty about the future dynamics of public debt given that the increase in yields on government securities raises debt-servicing costs in nominal terms, fears about the possibility that persistence of inflation at high level would be a further risk for the purchasing power of households' incomes.

3.2.3 Short term Euro government bond

The LRI for the Short Term Euro Government Bond shows a first sharp increase in the second semester of 2007, as a reaction to the sub-prime mortgage crisis. The liquidity status persists since April 2009, when the indicator registers a downward trend after the extraordinary intervention of ECB, that in March lowered again by 50 basis point the interest rate on the main refinancing operations of the Euro-system, the interest rate on the marginal lending facility and the rate on the deposit facility.

Figure 2 compares the LRI for Short Term Euro Government Bond and Equity Europe during the subprime mortgage crisis and shows that the fixed income market' s reaction to contagion occurs faster the for equity markets, mainly driven by sharp increase registered by short term government bond's yield to maturity and bid ask spread.

[INSERT SOMEWHERE HERE FIGURE 2]

The liquidity distress persists until 2011, when LRI started its increasing trend during the Euro Debt crisis and reach its peak in December 2011. The downward trend starts in July 2012 after he Mario Draghi "whatever it takes" speech and the liquidity distress persisted until March 2020 when Covid-19

triggered a liquidity risk on area. Short Term Euro Government Bond LRI retreats since then and it firmly stands in a risk off area until the last quarter of 2021 with energy crisis that, combined with the war in Ukraine in February 2022, caused one of the deepest liquidity crunch since 2008 and 2011.

3.2.4 Equity US

The indicator for Equity US shows its first spikes in June 2007 and in August 2007, when it becomes apparent that the financial markets could not solve the sub-prime crisis and that its consequences would have an impact beyond United States. Uncertainty triggered liquidity stress conditions and hit first of all the interbank market. To restore liquidity and confidence in the market, the FED lowers the benchmark rate. The next upturns in LRI are in September and November 2007, despite the coordinated actions of central banks to provide loans to the global credit markets, that became stuck as asset prices fell. Liquidity conditions start to worsen and the index rose again from January to March 2008. Despite that in January 2008 the FED cuts its benchmark rate by three-quarters of a percentage point, liquidity stress sharply rises during the turmoil surrounding the collapse of the global investment bank Bear Stearns in March. It remains stable until July 2008, when IndyMac Bank becomes one of the largest banks ever to fail in the United States and Fannie Mae and Freddie Mac showing significant signs of trouble. The biggest increase in the index is registered in September 2008 with the collapse of Lehman Brother and with major U.S. financial indexes suffering some of the worst losses in the history. Another sharp increase, even if of smaller magnitude as compared to the September 2008, follows in October 2008 when the Wall Street bailout package is approved. The package stabilizes the U.S. stock markets that achieved the lowest point in March 2009. This is confirmed by our LRI that rises until March and then retreats, falling in the risk off area in July 2009.

The liquidity distress persists until August 2011 when US markets crashed following the credit rating downgrade of the U.S. sovereign debt by Standard and Poor's. The LRI retreats since then, it is in a risk off area in February 2012 and remains stable until October 2014, the period of the large collapse in oil prices. Financial markets dynamics have been significantly affected by the around 60% decline in oil prices. Furthermore, the collapse influences the global inflation and affected the oil-importing economies. Indeed the Equity US LRI recorded two other relevant spikes in January and August 2015, the month one of the so called financial flash crashes. The sell-off in the US markets was fuelled by the Chinese market crash that triggered high volatility in the world market. A period of liquidity stress starts and a new sharp increase in the LRI is registered in January 2016, triggered by a new sell-off in China's stock market. From 4 to 15 January 2016, the Chinese market lost nearly 18% and quickly sent stocks tumbling globally.

The LRI starts its decline in March 2017 and registers a new significant increase in March 2018, when an important risk area starts to then last until February 2019. Concerns about a possible slowdown of the expansionary monetary policy of the FED and the world's other major central banks (e.g. Bank of England, European Central Bank, Bank of Japan) caused a liquidity crunch. Moreover some developed and emerging countries have been affected by other events, such as the political tensions in Italy, concerns about a trade war, worries about debt vulnerabilities in emerging economies caused by the rise of the Dollar. A new sharp increase occurred in February 2020, with the widespread of Covid-19 pandemic.

Finally, for the Equity US the LRI shows a spike in the last quarter of 2021, but the magnitude of the liquidity event is lower if compared with European asset classes. The Euro area, if compared with other economic region, has been particularly vulnerable to the economic consequences of Russia's invasion of Ukraine, mainly because Europe heavily depends on energy imports and the important role played by Russia and Ukraine in euro area as far as the import of food and fertilisers is concerned. However, even if US trade with Russia and Ukraine was minimal, the war triggered high inflation and slow growth in consumer spending. In the US, the headline inflation rate (1.4% at the end of 2020) took off drastically pushed mainly by demand-side factors and solid GDP growth, reaching 7.0% at the end of 2021 and a maximum of 9.1% in June 2022. Central banks, though with some delay, react vigorously: in March 2022, the Federal Reserve (FED) brings the official rate from 0.25% to 5.50%, the highest level since 2001, with ten consecutive rate hikes, and four consecutive moves of 75bps, never experienced before. Moreover, the FED started to reduce the size of its balance sheet (more than doubled to about $9 trillions in two years) by reversing its Quantitative Easing policy, namely quantitative tightening (QT). In June 2022, the Fed stopped reinvesting up to $47.5 billions in maturing securities every month; the pace of the unwinding was increased to $95 billions starting from September. Despite the negative shape affected also the US government market, giving a signal of potential restrictive policies and global recession, the US economy appears resilient and now embarked on a path of soft-landing and declining inflation but above 3%.

3.2.5 Bond corporate investment grade USD

The first relevant spike for the Bond corporate investment grade USD occurs in August 2007, with the start of subprime crisis and lasting until August 2009. The LRI achieves its maximum levels between September 2008 and April 2009. A liquidity distress phase lasts from September 2009 until July 2011, when the Euro area sovereign crisis drives global financial markets and declining expectations of global economic growth cause a decrease in growth-sensitive asset prices in September 2011. A new

liquidity stress period is experienced between 2015 and 2016, when high volatility triggered by the Chinese slowdown, uncertainties about FED's monetary policy, slowdown of economic growth in the United States and crash of raw material. Since March 2017 the LRI started a descending phase and registered a new sharp spike in March and April 2018, when concerns about a possible slowdown of the expansionary monetary policy of the FED and other central banks caused a liquidity crunch. Moreover some developed and emerging countries are affected by other events, such as the political tensions in Italy, concerns about a trade war, worries about debt vulnerabilities in emerging economies caused by the rise of the Dollar. The LRI moves into a risk off regime until the upturn of March 2020 when there is a deterioration of liquidity conditions triggered by the Covid-19 pandemic crisis. LRI experienced the same trend of Equity US LRI since the last quarter of 2021, but more persistent in term of level joint by the index in the second half of 2022, due to specific impact on corporate bond market, that is widening of bid ask spread and increase in yield to maturity.

3.2.6 Short term US government bond

Figure 1 shows a first downgrading trend since 2007, during the subprime mortgage crisis, for Short Term US Government Bond. Indeed, Treasury bond prices rise in response to negative shocks to the sub-prime market, due to the flight to quality behaviour of investors, facing high volatile collateralized debt obligation's markets, paralysis of the structured credit market and catastrophic losses in financial markets. In 2008, the sub-prime crisis deepens and becomes the catalyst for a broader global financial crisis that affected also Treasury bond market. A liquidity distress period persists until the last quarter of 2014, when the market of US Treasury securities, futures and other closely related experience a remarkably high level of volatility and, although trading volumes were consistent, liquidity conditions become strained. Furthermore, the large collapse in oil prices impacts on the global inflation and affects the oil-importing economies. LRI for Short Term US Government Bond persists in an high risk level during 2015, when the so called financial flash crashes is fuelled by the Chinese market crash and during 2016, triggered by a new sell-off in China's stock market. LRI registers the same decreasing trend of Equity US LRI during the first quarter of 2017 and then another remarkable spike in the first quarter 2018, when an important risk area starts to then last until February 2019, caused by concerns about a possible slowdown of the expansionary monetary policy of the FED. A new sharp increase occurs in February 2020, with the widespread of Covid-19 pandemic and then, after a distress period, the events of the last quarter of 2021 triggered a new risk pattern which persists also as consequence if the high inflation and the Russia's invasion of Ukraine, as reported in Table C11 where we observe a relevant peak (68.54%) in January 2022.

3.3 Robustness check and alternative stress indexes

The liquidity risk indicators we propose are able to signal liquidity risk in presence of stress with high level of correlations. They extend the stress indicators by Hollo et al. (2012) and Garabedian and Inghelbrecht (2015, 2020), and relate to a body of existing financial stress indexes proposed by Illing and Liu (2006), Arsov et al. (2013), Manamperi (2015), Oet et al. (2015), Broto and Lamas (2016), Iachini and Nobili (2016), Kremer (2016), Monin (2016), Kim et al. (2020), Boyarchenko et al. (2021), and Xu et al. (2023), among others, constructed either incorporating information only from financial markets, or equity returns of listed banking institutions, or investor sentiments.

As already stressed above, one of the main novelty of the liquidity risk indicators proposed in this paper consists in adding monetary and credit variables to financial variables, the latter being the conventionally used to represent the dimensions of the market liquidity discussed by Kyle (1985). Moreover, liquidity has its interlinkage with monetary, credit and macroeconomic worlds. Thus, while building a theoretical framework falls outside the scope of the paper, however we conduct a robust empirical analysis to establish why the inclusion of monetary and credit variables is of importance in measuring asset class liquidity. We empirically show that our indicator, constructed by aggregating financial, credit and monetary variables via their dynamic correlations, is able to capture in full the "resilience" of each asset classes (Bond US, for instance) over specific stress periods (post sub-prime crisis and Covid-19, for instance) able to capture both flights to quality/flights to safety (Baele et al, 2020) of investors behaviour and the countercyclical impact of monetary policy interventions. In general, and contrary to Adrian et al. (2017) measure based on the sole price impact, a correct detection of liquidity stress is possible only with the inclusion also of credit and monetary variables able to account for the impact of the intervention of the policy authority via credit and monetary instruments in ameliorating/exacerbate market stress. The full set of results is not reported in this paper but available upon request from authors.

4 MEASURING THE TIME-VARYING CONTRIBUTION FROM FINANCIAL, CREDIT AND MONETARY VARIABLES TO LIQUIDITY RISK

One important novel feature of the approach we propose in this paper is to provide a time-varying measure of the relative contribution of the raw financial, credit and monetary drivers on the liquidity risk indicator, which we discuss in this section. To simplify the presentation, we aggregate the full set

of drivers into four main groups: *financial-non volatility index*, *financial volatility index*, *credit index*, and *moneraty index*, which may be specific to the each of the six LRIs, as reported below.

In the light that the liquidity measure LRI_t^i refers to the ith asset class at time t, we can estimate the liquidity risk contribution at time t of the gth group of liquidity indices, with $g = 1, ..., G_i$. Thus, we can rewrite (6) as follows:

$$LRI_t^i = \sum_{h=1}^{G_i} \sum_{j=1}^{G_i} w_{t,h}^i l_{t,h}^i w_{t,j}^i l_{t,j}^i C_{t;h,j} \tag{8}$$

where $C_{t;h,j}$ is the element of position (h, j) of matrix C_t of correlations. The contribution of group g to the ith unified liquidity measure L_t^i at time t can be written as follows:

$$LRC_{t,g}^i = \sum_{j=1}^{G_i} w_{t,g}^i l_{t,g}^i w_{t,j}^i l_{t,j}^i C_{t;g,j} \tag{9}$$

The liquidity risk contribution in percentage is:

$$LRC_{t,g}^i\% = \frac{\sum_{j=1}^{G_i} w_{t,g}^i l_{t,g}^i w_{t,j}^i l_{t,j}^i C_{t;g,j}}{\sum_{h=1}^{G_i} \sum_{j=1}^{G_i} w_{t,h}^i l_{t,h}^i w_{t,j}^i l_{t,j}^i C_{t;h,j}} \tag{10}$$

Figure 3 reports the plots of the contribution of the four groups of variables to the Equity Europe Liquidity Risk index during some exemplary periods of liquidity stress. The top panel reports the liquidity risk contribution from January 2008 to December 2009, with an overview on the financial crisis. Panel b plots the contribution to liquidity risk index during the sovereign debt crisis with a window running from June 2010 to June 2013. In the third panel, we report the contribution of the four indices during Covid-19 period.

[INSERT SOMEWHERE HERE FIGURE 3]

For this asset class, the *financial-non volatility index* includes the Amihud, bid ask spread and the cluster with volume, turnover and turnover ratio; the *financial-volatility index* covers all the volatility proxies, namely futures volatility and the group V2X/VIX; the *credit index* includes the cluster of cost of borrowing, domestic credit and Libor OIS spread; and, the *monetary index* include the base money, broad money and aggregate M1.

The first signal of worsening of liquidity conditions in Europe was mainly provided by credit indicators in August 2007, when concerns about subprime mortgages were confirmed. In March 2008, with the collapse of Bear Stearns, the LRI sharply increases with an equal contribution of volatility and credit indices. As reported in Figure 3a, the credit index is the largest contributor to LRI over several months until October 2008, when the financial indicator contributes around 60%. Between

October and November 2008, the LRI reaches its maximum despite bailout programs and rate cuts across major central banks. In particular, as reported in Table C1 in the Internet Appendix, the main contributors in October 2008 are Libor OIS spread (22.46%), implied volatility indices (16.95%), the Amihud ratio (16.94%), and borrowing rates with a contribution of 15.83%. Further, between November and December 2009, the financial indices contribute for more than 80%. As shown in Figure 3b, the main contribution to the liquidity risk index during the sovereign debt crisis was that of credit variables: on average over the period from June 2010 to June 2013 the contribution is around 40% with a pick of 60% in June 2013. The Covid 19 crisis we report in Figure 3c triggered the worsening of liquidity conditions with a main driver that was the volatility on financial markets, that since February 2020 joint stably high contribution to the Equity Europe LRI [9]. In February 2020 implied volatility index sharply increased their contribution, from 1.10% of January to 31.31% of February, as detailed in Table C3 in the Internet Appendix. The volatility of futures moves from -0.11% to 9.78% between January and February 2020 to reach a contribution of 36.18% in March 2020.

Figure 4 plots the contribution to Long Term Italian Government Bond LRI during some relevant periods of liquidity stress.

[INSERT SOMEWHERE HERE FIGURE 4]

The top panel reports the liquidity risk contribution from January 2011 to January 2013, with an overview on sovereign debt crisis. The second panel plots the contribution to liquidity risk index during the 2018 crisis. For this asset class, the *financial-non volatility index* includes bid ask spread and listed liquidity indicator GVLQIT Index provided by Bloomberg; the *financial-volatility index* is represented by BTP-Futures volatility[10]; the *credit index* includes the cluster of cost of borrowing, domestic credit and Libor OIS spread and 10 years government bonds YTM; and the *monetary index* include the base money, broad money and aggregate M1. Panel 4a shows that during the sovereign debt crisis the first signal of liquidity stress comes from both monetary and credit risk indicators, with The Long Term Italian Government Bond LRI recording a series of sharp increases that triggered a risk on area.

From June 2011 onwards, the main contributor becomes the credit risk index, while monetary index takes a residual contribution from August onwards, when ECB extended the Securities Markets Programme (SMP) to Italy and Spain. If we focus on credit risk index during the sovereign debt crisis, as shown in Panel 4b, the first signal of liquidity stress comes from 10-Year Government Bond YTM

[9] Recent related literature on the topic includes Chakrabarty and Pascual (2022), Ebsim et al. (2022), O'Hara and Zhou (2021), Kargar et al. (2021), Helwege and Wang (2021).

[10] Euro-BTP Italian Government Bond futures was introduced on 14th September 2009 and therefore the standardized liquidity index trough ECDF is only available in December 2014.

that shows a series of sharp increases from late (October) 2010 onwards. On average, the 10-Year Government Bond YTM was 381 basis points in October 2010, while its level was 474 basis points in January 2011, 529 basis points in July 2011, with a peak of 680 basis points in November 2011. The increasing level and the increasing volatility cause a spike in the contribution of 10-Year Government Bond YTM to LRI, that in July 2011 reaches its maximum contribution of 51.44% over the sovereign debt crisis[11].

Figure 5 plots the contribution to Short Term Euro Government Bond LRI during the energy crisis since the last quarter of 2021. For this asset class, the *financial-non volatility index* includes bid ask spread, yield to maturity and listed liquidity index provided by Bloomberg; the *financial-volatility index* includes the futures volatility index; the *credit index* includes the cluster of cost of borrowing, domestic credit and Libor OIS spread and 10 years government bonds YTM; and *Monetary index* include the base money, broad money and aggregate M1. The figure shows that from October 2021 to February 2022, the main contributors to Short Term Euro Government Bond are the two financial indices with a signal of deterioration coming from the liquidity index that sharply increases. When liquidity conditions are unfavourable, the index assumes high level because misalignments from fair value implied by the Bloomberg curve fitter can remain persistent and resulting in wide average yield errors. From March to April 2022, the liquidity stress is mainly driven by futures volatility, while from May onwards liquidity crunch becomes mainly the result of a credit crunch driven by worsening credit conditions, both in the interbank market and in the private credit market. As the European Central Bank tightens monetary policy, credit to the private sector become more expensive, bank lending to firms decelerates sharply, household borrowing continues to weaken, as a consequence of rising lending rates, tighter credit standards and the fall in demand for mortgages. As lending activity decelerates, money growth decelerates with a significant decline in overnight deposits.

[INSERT SOMEWHERE HERE FIGURE 5]

[11] In Table C4 in the Appendix, we report further details about the monthly contribution of 10-Year Government Bond YTM to LRI. Since March 2011 onwards the domestic credit's contribution becomes relevant, joining a peak of 36.92% in May 2011, as indicated in Table C4. The credit crunch during the sovereign debt crisis was the result of European banks' exposure to sovereign debt, through three ways. The reduction in private lending was a consequence of decline in the value of bank's assets that reduced the access to funding, as reported in Bocola (2016) and Gennaioli, Martin, and Rossi (2018). Furthermore the decrease in government bond prices caused a limited access to interbank markets, given that sovereign bonds represent collateral assets, highlighted in Engler and Steffen (2016). Third, as we explained in Acharya and Steffen (2015) and Becker and Ivashina (2018), banks may change the composition of balance sheets during a crisis, reducing private lending activity. The third panel shows the contribution to Long Term Italian Government Bond LRI during the 2018 crisis with a focus on the period from June 2018 to July 2019, when liquidity conditions in the Italian sovereign bond market deteriorates sharply. In the second half of 2018 bid ask spreads increased to levels not seen in the previous five years and reached a peak of 27.41% of liquidity risk contribution in June 2018, as indicated in Table C5. Another signal of liquidity deterioration came from listed liquidity index, that sharply increased because the average yield errors sharply rose. This means that dislocations from fair value implied by the curve fitter were persistent, causing large average yield errors in Italian sovereign bond market. In June 2018 listed liquidity index joint a contribution of 20.66%, as shown in Table C5. Other main contributors over the 2018 crisis are BTP-Futures volatility and 10 years government bonds YTM. For more details, we refer to Bouveret, Haferkon, Marseglia, and Panzarino (2022).

Figure 6 shows the contribution of the four groups of variables to Equity US liquidity risk index over some relevant periods of liquidity stress. For this asset class, the *financial-non volatility index* includes Amihud, bid ask spread and the cluster with volume, turnover and turnover ratio; the *financial-volatility index* covers all proxies, namely futures volatility and VIX; the *credit index* includes the cluster with mortgage rate on Treasury Yield and commercial paper outstanding, Libor OIS spread and TED spread; and finally the *monetary index* includes the base money and monetary aggregates M1 and M3. Panel 6a shows that during the global financial crisis the first signal of liquidity stress comes from credit index, and especially from interbank indicators, namely Libor OIS spread and TED spread. Interbank credit index achieves its maximum level between September and December 2007 despite the FED reaction to concerns about the subprime lending crisis[12]. Panel 6b plots the liquidity risk contribution to Equity US index during the Covid 19 crisis and show that the four groups have a constant flat contribution to LRI[13]. The main contributors over the period is the financial-volatility index, with a contribution of 47.45% on average. The other contributors are the financial-non volatility and credit indices, 29.38% and 23.13%, respectively.

[INSERT SOMEWHERE HERE FIGURE 6]

Figure 7 reports the contribution to Bond Corporate IG USD liquidity risk index. In this case, the *financial-non volatility index* includes bid ask spread and yield to maturity IG USD; the *financial-volatility index* includes the futures volatility index; the *credit index* includes the mortgage rate on T-yield index, the commercial paper outstanding, the Libor OIS spread and the TED spread; and finally *monetary index* includes the base money, broad money and aggregate M1. Figure 7a plots the contribution to Bond Corporate IG USD liquidity risk of the fours indices during the liquidity stress events in 2018. Since November 2017, LRI started an ascending phase, with a sharp spike in March and April 2018, when concerns about possible slowdown of the expansionary monetary policy of central banks caused a reaction of credit indicators. The main contribution comes especially from the interbank credit indicators (Libor OIS spread and the TED spread)[14]. The contribution of the credit index remains relevant until April, when the contribution starts to decrease until September 2018, when improvements in short-term credit availability leads to a narrowing of interbank spreads:

[12] In September 2007, the Libor OIS spread and TED spread show a 31.43% and 32.55% of liquidity risk contribution, respectively, as reported in Table C7, and in December 27.68% and 32.84%, respectively. In August the FED cut discount rate half a percentage point, with a consequent lowering of monetary index contribution to Equity US liquidity risk index, from 34.99% to −4.86%, as reported in Table C7. Since September 2008 the three groups of financial-non volatility, financial-volatility and credit indices show a more aligned contribution to the liquidity risk index: 34.34% on average for financial indicators volatility, 26.14% for financial indicators non volatility and 40% for credit indicators.

[13] See Ebsim et al. (2022), O'Hara and Zhou (2021), Kargar et al. (2021), Chakrabarty and Pascual (2022), Helwege and Wang (2021).

[14] As can be seen in Table C10, in March 2018 the contribution amounts to 26.06% and 27.62%, respectively, while in April of 24.59% and 30.15%, respectively.

Libor OIS spread and TED spread stands at around 19 and 22 basis points, respectively. Between August and October 2018, the main contribution comes from monetary and financial-non volatility indicators, but since then major concerns about balance sheet reduction causes in the markets a cost of credit rising and interbank spread widening. Credit index continues an ascending phase until January 2019 and then normalized causing a liquidity distress of Bond Corporate IG USD market. Panels 7b and 7c plot the contribution to Bond Corporate IG USD liquidity risk index during Covid 19 events. As far as Panel 7b is concerned, from March 2020 to April 2020 the main contribution to Bond Corporate IG USD LRI was that of credit indicators, while since may 2020 financial and credit indices equally contributed to the LRI. In December 2020, the contribution of credit lowered, with a simultaneous increase in the contribution of financial indicators. Panel 7c shows the contribution of some constituents of credit indicators, dividing them into two groups: *credit to private non bank sector indicators*, that includes mortgage rate on T-yield index and commercial paper outstanding, and *credit to private bank sector indicators*, namely Libor OIS spread and TED spread. From March to April 2020 the highest contribution comes from the credit to private bank sector, while from then onwards the credit index contribution is fully explained by credit to non bank sector.

[INSERT SOMEWHERE HERE FIGURE 7]

Figure 8 shows the contribution to Short Term US Government Bond liquidity risk index during the energy crisis that affects global markets since the last quarter of 2021. The *financial-non volatility index* include bid ask spread and yield to maturity; the *financial-volatility index* include the futures volatility index; the *credit index* includes the mortgage rate on T-yield index, the commercial paper outstanding, the Libor OIS spread and the TED spread; and finally the *monetary index* includes the base money, broad money and aggregate M1. Since the last quarter of 2021, the LRI starts an ascending phase, with a sharp spike mainly driven by financial indices, with as main contributors bid ask spread and futures volatility index. Financial indicators' main contribution persists until the second quarter of 2022, when credit indicators register a spike in contribution, primarily caused by Libor OIS spread and TED spread. From the second semester of 2022, the financial-non volatility index is back to being the main contributor, with an equal contribution of bid ask spread and yield to maturity. During the whole period, monetary indicator register an increasing trend.

[INSERT SOMEWHERE HERE FIGURE 8]

5 DYNAMICS AND TIMING OF LIQUIDITY RISK

In this section, for each of the six liquidity risk indicators we formally identify alternative liquidity risk regimes by implementing the endogenous Markov-switching model (Section 5.1) and then tests whether the presence of bubbles is in correspondence of specific stress periods (Section 5.2).

5.1 Markov-switching framework

Economic variables often exhibit structural changes, which are induced by events such as price shocks, financial crises, and policy reforms.

Following the seminal contribution by Hamilton (1989), economists' have widely used Markov-switching models in the field of empirical macroeconomics and finance[15]. One limitation of the early Markov-switching models based on Hamilton (1989) is the restriction of fixed transition probabilities (FTP), in that the probability of switching from one regime to the other is constant over time thus ruling out the effect of extra information (e.g., economic fundamentals) on the prediction of the regimes. Markov-switching models with time-varying transition probabilities (TVTP) address this limitation, the transition probabilities now vary depending on some exogenous or predetermined variables[16]. However, both the Hamilton (1989)'s fixed transition probability model and the TVTP extensions impose a strong assumption such as that the regime changes are independent of the contemporaneous value of the regression disturbance (the Markov regime-switching process is exogenous, as defined in Hwu et al. (2021)). Exogenous switching models are highly restrictive in many empirical applications. For instance, a common application of the Markov regime-switching process in the business cycle dating literature is to models where the variables to model are some aggregate indicators of economic fluctuations, and the regimes correspond to the economic expansion and recession (see, Hamilton (2011), Duprey et al (2017)). Thus, it seems reasonable that the shocks to these aggregate variables, such as industrial production growth and unemployment rates, would contribute simultaneously to changes in the business cycle regimes. Moreover, the business cycle regimes are likely to be influenced by some unobserved factors, such as monetary and fiscal policies. If these factors are not modelled in the regression, then the disturbance would be instantaneously correlated with the regime shifts, and the regime shifts become endogenous.

[15] A sample of interesting applications include stock volatility studied by Billio and Pellizon (2003), exchange rates investigated by Engel and Hamilton (1990), asset allocation in Ang and Bekaert (2002), and monetary policy examined by Sims and Zha (2006), among many others. For a survey of this empirical literature, we refer the readers to see, e.g., Ang and Timmermann (2012) and Hamilton (2016).

[16] For instance, Diebold, Lee, and Weinbach (1994) and Filardo (1994) allow the transition probabilities to be partly determined by leading economic indicators. Durland and McCurdy (1994), Filardo and Gordon (1998) and Lam (2004) allow the transition probabilities to evolve as a function of the duration of the current regime. Piger (2009) argues that the predetermined variables may also include lagged values of the dependent variable, and thus lagged values of the regression disturbance.

In this paper, we implement/adopt the univariate N-state endogenous Markov-switching process approach proposed in Hwu et al. (2021), where the authors describe regime shifts between the N states as the outcome of a set of auxiliary variables, which is in contrast with the preceding literature

5.1.1 Endogenous Markov-switching model

The regime dependence of the liquidity risk indicator LRI_t can be formalized as follows:

$$LRI_t = c(s_t) + \phi LRI_{t-1} + \sigma(s_t)u_t \tag{11}$$

where u_t is assumed to be standard, normal and identically distributed, and s_t represents the state at time t. In our estimates, the number of states/regimes are searched from three up to five, where $s_t \in \{1, 2, ..., N\}$ is a discrete regime indicator indicating which of N different regimes is realised at time t.

We formulate the state process s_t based on the Markov regime-switching model of Hwu et al. (2021). The unique feature of their approach is that they allow for endogeneity in the regime transitions, which means that future transition between regimes depends on the current regime as well as two sources of information: (i) the information coming from some exogenous variables expected to influence the regime transitions, and (ii) the information contained in the regression error as it may include the missing regressors that are correlated with the regime transitions. This is in sharp contrast to the conventional Markov switching model based on Hamilton (1989), in which the future transition is completely determined by the current regime. Hwu et al. (2021) show that neglecting endogeneity in regime-switching incurs not only a substantial bias, but also a significant information loss, in estimating model parameters.

In the Markov regime-switching model of Hwu et al. (2021), s_t takes the following form

$$s_t|s_t^*, s_{t-1} = \begin{cases} 1 & \text{if } 0 = \max\left\{0, s_{1,t}^*, s_{2,t}^*, ..., s_{N-1,t}^*\right\}|s_{t-1} \\ 2 & \text{if } s_{1,t}^* = \max\left\{0, s_{1,t}^*, s_{2,t}^*, ..., s_{N-1,t}^*\right\}|s_{t-1} \\ \vdots & \\ N & \text{if } s_{N-1,t}^* = \max\left\{0, s_{1,t}^*, s_{2,t}^*, ..., s_{N-1,t}^*\right\}|s_{t-1} \end{cases} \tag{12}$$

This equation parametrises N possible outcomes of s_t as the outcome of the values of $N-1$ auxiliary continuous random variables, denoted by $s_t^* = (s_{1,t}^*, s_{2,t}^*, ..., s_{N-1,t}^*)'$. For instance, consider the case of

two regimes (i.e., $N = 2$), we have

$$s_t|s_t^*, s_{t-1} = \begin{cases} 1 & \text{if } s_{1,t}^* \leq 0|s_{t-1} \\ 2 & \text{if } s_{1,t}^* > 0|s_{t-1} \end{cases} \tag{13}$$

and consider the case of four regimes (i.e., $N = 4$), we have

$$s_t|s_t^*, s_{t-1} = \begin{cases} 1 & \text{if } (s_{1,t}^* < 0, s_{2,t}^* < 0, s_{3,t}^* < 0)|s_{t-1} \\ 2 & \text{if } (s_{1,t}^* > 0, s_{1,t}^* > s_{2,t}^*, s_{1,t}^* > s_{3,t}^*)|s_{t-1} \\ 3 & \text{if } (s_{2,t}^* > 0, s_{2,t}^* > s_{1,t}^*, s_{2,t}^* > s_{3,t}^*)|s_{t-1} \\ 4 & \text{if } (s_{3,t}^* > 0, s_{3,t}^* > s_{1,t}^*, s_{3,t}^* > s_{2,t}^*)|s_{t-1} \end{cases} \tag{14}$$

To incorporate the first source of information into the state process, each of the $N-1$ auxiliary random variables is defined by

$$\begin{aligned} s_{i,t}^* &= \bar{\gamma}_{i,s_{t-1}} + z_t' \gamma_{i,s_{t-1}}^z + \eta_{i,t}, \\ \eta_{i,t} &\sim \text{ i.i.d. } \mathcal{N}(0,1), \\ i &= 1, 2, ..., N-1, \end{aligned} \tag{15}$$

where z_t is a vector of exogenous variables affecting the regime transitions. The parameter $\bar{\gamma}_{i,s_{t-1}}$ denotes the average value of the ith auxiliary variable $s_{i,t}^*$. The parameter $\gamma_{i,s_{t-1}}^z$ denotes a vector of coefficients of z_t. For both $\bar{\gamma}_{i,s_{t-1}}$ and $\gamma_{i,s_{t-1}}^z$, the subscript s_{t-1} suggests that the parameters take different values, depending on the past regime. $\eta_{i,t}$ denotes an error term, which is drawn from an independently distributed standard normal distribution.

Based on equation (15), the information variables z_t indirectly influences the realisation of s_t through $s_{i,t}^*$. Specifically, with a positive $\gamma_{i,s_{t-1}}^z$, a higher value of z_t leads to a higher value of $s_{i,t}^*$. Thus, $s_{i,t}^*$ is more likely to become the maximum among all the $N-1$ auxiliary random variables. As a result, there is an increased probability that the regime at time t shifts to $(i+1)$ according to equation (12). The interpretation for a negative $\gamma_{i,s_{t-1}}^z$ is similar. In general, the effects of z_t on the regime transitions are associated with combinations of $\gamma_{i,s_{t-1}}^z$, for $i = 1, 2, ..., N-1$ and $s_{t-1} = 1, 2, ..., N$.

To account for endogeneity arising from the regression error term, all the $N-1$ elements in s_t^* and the regression error term u_t are assumed to be generated simultaneously from a joint Gaussian distribution. We denote by θ the collection of model parameters, including all the parameters in equations (11) and (15) and those in the Gaussian distribution specified below. We denote by $\mathbf{Y}_t$ the observations of the dependent variables through time t, i.e., $\mathbf{Y}_t = \{LRI_{p,i}\}_{i=1}^t$. Then, the joint

distribution of s_t^* and u_t, given $(s_{t-1}, \mathbf{Y}_{t-1}, z_t, \theta)$, is simply given by

$$\begin{bmatrix} s_t^* \\ u_t \end{bmatrix} | s_{t-1}, \mathbf{Y}_{t-1}, z_t, \theta \sim \mathcal{N}\left(\begin{pmatrix} \bar{\gamma}_{s_{t-1}} + z_t' \gamma^z_{s_{t-1}} \\ 0 \end{pmatrix}, \begin{pmatrix} \Omega & \rho \\ \rho' & 1 \end{pmatrix} \right), \tag{16}$$

where $\bar{\gamma}_{s_{t-1}} = (\bar{\gamma}_{1,s_{t-1}}, \bar{\gamma}_{2,s_{t-1}}, ..., \bar{\gamma}_{N-1,s_{t-1}})'$ and $\gamma^z_{s_{t-1}} = (\gamma^z_{1,s_{t-1}}, \gamma^z_{2,s_{t-1}}, ..., \gamma^z_{N-1,s_{t-1}})'$. ρ is an $(N-1)\times 1$ vector of conditional correlations, i.e., $\rho = (\rho_1, \rho_2, ..., \rho_{N-1})'$, where $\rho_i = \text{corr}(s^*_{i,t}, u_t | s_{t-1}, \mathbf{Y}_{t-1}, z_t)$ is the conditional correlation between the ith auxiliary variable and the regression error term. Ω is an $(N-1)\times(N-1)$ conditional variance-covariance matrix of s_t^*, which can be obtained as follows

$$\Omega = \begin{pmatrix} 1 & \rho_1\rho_2 & \cdots & \rho_1\rho_{N-1} \\ \rho_2\rho_1 & 1 & & \vdots \\ \vdots & & \ddots & \rho_{N-2}\rho_{N-1} \\ \rho_{N-1}\rho_1 & \cdots & \rho_{N-1}\rho_{N-2} & 1 \end{pmatrix}. \tag{17}$$

Based on equation (16), the presence of some non-zero correlation coefficients in ρ implies endogeneity in the regime transitions. In particular, when ρ_i is positive, the regression error term $\varepsilon_{p,t}$ at time t becomes positively correlated with the ith auxiliary variable. This means that a largely positive u_t is associated with a higher value of $s^*_{i,t}$, and thus results in an increased probability of $s_t = i+1$. The converse is also true. Similar to the case of z_t, endogenous regime shifts are associated with combinations of ρ_i, for $i = 1, 2, ..., N-1$.

In summary, the timing model in Equation (11) and the Markov regime-switching model of Hwu et al. (2021) in equations (15)-(17) constitute the Markov regime-switching framework used in the empirical analysis. Our framework is estimated with a simulation-based Bayesian procedure. We refer to seminal paper Hwu et al. (2021) for more details.

5.1.2 Timing liquidity stress regimes in the six liquidity risk indicators

We conducted an extensive econometric analysis considering all combinations of constant and/or switching intercept, slope and variance and the final selected preferred specification is chosen considering $MS(N)$-$DR(1)$, that is we explored up N=4 regimes and an autoregressive process of order 1 with switching intercept and variance and with non switching slope.

The preferred MS-DR model is selected using the log-likelihood, the AIC and BIC criteria, and the Regime Classification Measure (RCM) of Ang and Bekaert (2002). For all assets, the $MS(3) - DR(1)$ is the preferred model, which implies the identification of low, medium and high risk regimes[17]. It is

[17] A useful benchmark is how the attained regime classification and parameter estimates compare with those of standard

worth stressing that the three regimes model is coherent with the practice in the financial industry in managing portfolio risk with respect to the identification of market cycles that in general are associated to low equity, medium (balanced) and high- risk (equity based) portfolios.

In Figures 9-14, we report the smoothed probabilities of the preferred specifications for all asset classes, allowing to identify the number of regimes. For *Equity Europe*, Figure 9 shows that the first high-risk regime is identified for the period July 2008 to April 2009, starting in correspondence of the failure of the Indy Mac Bank and the worsening of financial condition due to the federally backed home mortgage companies Fannie Mae and Freddie Mac, with its maximum in November 2008. The next large increase is observed in May 2010, reflecting the concerns about credit risk in the Euro area, with 30.91% probability to be attributed to the high risk regime. As far as the period, June-December 2011, all spikes shown by the LRI during the sovereign debt crisis of the peripheral countries of the Eurozone are classified as high-risk regime, in which it is also the period August-November 2013, but in particular August-September 2015 and January-February 2016, which captures the relevant events of second half of 2015, when the drop in the Asian market triggered a fall in equity index futures in the European market and the subsequent events of the first half of 2016, when the Chinese equity market experienced a sharp sell off with spillover effects on European and U.S. stock markets, respectively. March-June 2020 and May 2022-January 2023 highlight the Covid-19 and Ukraine invasion period persisting up to January 2023. The LRI for Equity Europe is classified as medium-risk regime for June 2017-February 2020, September-December 2020 (since June 2020, liquidity distress period started, with LRI decreasing by -2.2% in June, by -12.2% in July and by -3.0% in August) and November 2021-April 2022.

For the *Long Term Italian Government Bond*, Figure 10 shows that from May 2008 to August 2009 the preferred specification $MS(3) - DR(1)$ classifies the indicator in the medium and high risk regime, with a subsequent distress area of low risk which lasts until February 2011, when the LRI reacts to sovereign debt crisis events. Since the beginning of 2011, the LRI sharply increases, and we note peaks in August 2011, with spread sailing straight over 400 basis points and the Italian public debt under heavy scrutiny. A distress period of low liquidity risk starts in the last quarter of 2013 and lasts until the second half of 2016, when a medium and high risk regime start, triggered by market turmoil caused by the outcome of the Brexit referendum in UK. From the second quarter of 2018 to August 2020, the Long Term Italian Government Bond swings between medium and high liquidity risk regime, thus capturing investors' uncertainty awed by the prospect of the Italian exit from the Euro following the

exogenous Markov-switching models. The empirical regularity we observe is that the endogenous MS models (always preferred by the model selection criteria) identify with more precision well established situations of high-risk which the exogenous MS used to classify as medium-risk. The comparison between the two MS approaches is beyond the scope of this paper, we do not report the results which however are available upon request.

formation of the yellow-green government, and the surge of Covid-19 crisis.

For the *Short Term European Government Bond*, Figure 11 the high risk period is around the four main crises: from the build up (June 2007) to the cool down (October 2008) of the sub-prime crisis; sovereign debt crisis in 2011; the surge of the Covid-19 pandemic in 2020; and, the latest crises period due to both the Russian invasion of Ukraine and the surge of Inflation and interest rates from mid-2022 onwards. As above, it is worth noticing medium risk regime from August 2018 to early 2019.

For *Equity US*, Figure 12 shows that Global Financial crisis is classified by the selected model $MS(3) - DR(1)$ as high and very high risk regimes. The first spikes in the second half of 2007, when it becomes apparent that the financial markets could not solve the sub-prime crisis, are classified as high risk regime. This continues until August 2008, when the index registers its biggest increase, warning a very high liquidity risk regime triggered by the collapse of Lehman Brother and one of the deepest market crash ever experienced. The very high risk regime persists until April 2009, when the Equity US market experiences a liquidity distress condition, classified by the model as low risk regime. A liquidity distress period prevails until August 2011, identified as high risk regime due to the US markets crash following the credit rating downgrade of the US sovereign debt by Standard and Poor's. Then the LRI gradually retreats and a low risk phase persists until October 2014, when an high risk regime starts, triggered by the large collapse in oil prices. This persists for several years until January 2020, capturing the so-called financial flash crash in August 2015, the stock markets turmoil triggered by the sell-off in China's stock market of January 2016, the liquidity crunch experienced in 2018 and 2019 caused by concerns about a possible slowdown of the expansionary monetary policy of the FED and the world's other major central banks (e.g. Bank of England, European Central Bank, Bank of Japan). The Covid-19 crisis triggers a high liquidity risk regime from February to November 2020, the LRI persists in a medium risk regime since early 2014.

For the *Bond Corporate Investment Grade USD*, Figure 13 shows that from July 2008 are classified as high risk months by preferred $MS(3) - DR(1)$ model. From May 2009 to October 2014, the LRI steadily remains in the low risk regime, and reacts in November 2014 to markets turmoil triggered by the Chinese slowdown, uncertainty about the FED's monetary policy, the slowdown of economic growth in the United States and the crash of raw material. The index stays at a medium risk regime (the only exception being January 2017) until November 2017, when it reaches a high liquidity risk level (which persists up to mid-2018) caused by concerns about a possible slowdown of the expansionary monetary policy of the FED and the world's other major central banks (e.g. Bank of England, European Central Bank, Bank of Japan). The LRI moves into a medium-low risk regimes until March 2020 when (an up to June 2020) a new high risk beginnings, triggered by the Covid-19 pandemic. Since August 2022 to

present, the LRI is again in the high regime due to interest rates and inflationary pressures.

Finally, for the *Short Term US Government Bond*, Figure 14 shows that following a floating between high to medium risk regime from the end of 2014 to end of 2015, this asset class is almost permanently in the high risk regime from December 2015 mid-2019, when move back again to medium risk up to the upsurge of the Covid-19 pandemic in early 2020. Finally, we are again in the high risk regime from February 2022 to January 2023, the end of the sample period.

[INSERT SOMEWHERE HERE FIGURES 9-14]

5.2 Measuring bubble episodes

In this section, we complement our analysis by defining bubbles and measuring the presence of bubbles in six liquidity risk indicators. We then map the three regimes Markov-switching model presented above with the bubble episodes we identify using recursive testing procedures.

5.2.1 Measuring price bubbles and test for explosive behaviour

The deviation of asset prices from market fundamentals and the subsequent collapse are considered as financial bubbles (Blanchard, 1979; Diba & Grossman, 1988; Evans, 1991; Lee & Phillips, 2016; Chen et al., 2023). A bubble can be defined as a period in which asset prices surge far beyond their intrinsic value; this is typically associated with exuberant behaviour. In the history of financial markets and economic development, bubbles are fairly common occurrences and are well documented in the literature (Quinn & Turner, 2020; Vogel, 2022). Speculation is a feature of all bubbles, but the presence of speculation alone is not sufficient to make an asset price bubble (Lei et al., 2001). Bubbles are characterised by the interplay between speculation money and credit (fuel for the bubble), which collectively invites, stimulates and enables broad and extreme participation by the public at large. Bubbles are not unique to any time or place. They have existed in every market, including stocks and bonds, real estate, gold and other commodities and asset classes. In addition, there have often been long periods without any important bubbles or chases, and other periods in which such episodes have occurred frequently. However, for all the contributions trying to investigate bubble phenomena by studying price changes into fundamental values and bubble components, many challenges lie ahead.

Explosive behaviour in asset prices are a primary indicator of market exuberance during the phase of a bubble. These episodes may be subjected to econometric testing using recursive procedures, like the right-sided unit root tests in Phillips et al. (2011). Recursive right-sided unit root tests seem to be particularly effective as real-time detection mechanisms for slightly explosive behavior and market exuberance. We apply the Backward Supremum Augmented Dickey Fuller (BSADF) approach

of Phillips et al. (2015a; 2015b) that allows to identify multiple bubble episodes within a data set (Homm & Breitung, 2012 , Phillips et al. 2015a)[18].

The BSADF testing procedure is defined as follows:

$$BSADF_{r2}(r_0) = \sup_{r_1 \in [0, r_2 - r_0]} \left\{ BADF_{r_1}^{r_2} \right\} \tag{18}$$

where r_1 and r_2 denote the starting and the ending fraction of the sample, respectively, implying that $r_1 < r_2$; r_0 is the fractional threshold and it is chosen on a lower bound of 1% of the full sample with the following functional form: $r_0 = (0.01 + 1.8/\sqrt{T})$, where T refers to the number of observations in the sample. We denote r_w, the window size of the regression, as $r_1 - r_2$.

Phillips et al. (2015a) suggest to implement the BSADF test on a sample sequence where the end point is fixed at r_2, and expands backwards to the starting point, r_1, which varies between 0 and $(r_2 - r_0)$. Let r_e the fraction of the sample at which the bubble starts, r_f the fraction of the sample at which it ends, and $\hat{r}_e$ and $\hat{r}_f$ the estimators of both. The origination and termination points of a bubble, i.e. r_e and r_f, are calculated according to the Equations (19) and (20):

$$\hat{r}_e = \inf_{r_2 \in [r_0, 1]} \left[r_2 : BSADF_{r_2}(r_0) > scv_{r_2}^{\beta} \right] \tag{19}$$

$$\hat{r}_f = \inf_{r_2 \in [\hat{r}_e + \delta log(T), 1]} \left[r_2 : BSADF_{r_2}(r_0) < scv_{r_2}^{\beta} \right] \tag{20}$$

where T is the number of observations, $scv_{r_2}^{\beta}$ is the critical value of the BSADF statistic based on $\lfloor Tr_2 \rfloor$ observations and confidence level β. $\lfloor Tr_2 \rfloor$ refers to the largest integer smaller than or equal to Tr_2. Phillips et al. (2015a) impose a condition that for a bubble to exist its duration must exceed a slowly varying (at infinity) quantity such as $L_T = log(T)$. This condition helps to exclude short lived blips in the fitted autoregressive coefficient and can be adjusted to consider the data frequency. Thus, $\delta log(T)$ is a minimal bubble length, and δ is a frequency-dependent parameter chosen freely.

[18] Further extant work on the topic to acknowledge is in several contributions such as Shi and Song (2016), Jarrow and Kwok (2021), Fusari, Jarrow, and Lanichhane (2020), and Chinco (2023) some of which propose similar approaches. In particular, Shi and Song (2016) propose a new infinite hidden Markov model to integrate the detection, date-stamping, and estimation of bubble behaviours in a coherent Bayesian framework, particularly useful to conduct real-time forecasting of bubble probability and capture the complex non linear dynamics of bubbles with sufficient flexibility in estimation. On the other hand, unlike time series techniques, Jarrow and Kwok (2021), Fusari, Jarrow, and Lanichhane (2020) follow the local martingale framework proposed in Jarrow et al (2010) to infer bubbles using cross-section option data, with the main difference being the use of non-parametric vs parametric estimation methods for the identification of bubbles in US stock market. Finally, Chinco (2023) proposes a theoretical framework to model speculative bubbles enabling researchers to forecast the likelihood of a future bubble episode based on information observed during normal times.

5.2.2 Empirical results

Figures 16-21 report the BSADF statistics and critical values at 90% (first column) and 95% (second column), while Tables 2-3 report the time periods when the t-statistics signals presence of bubbles at 90% and 95% significance level, respectively and the corresponding Markov-Switching regimes. We identify several episodes of bubble periods across the six assets, with interesting common and idiosyncratic features. All those episodes of "episodes of explosive behaviour" occur in the high risk regime identified by the MS model. It is worth stressing that the initial minimum window size to calculate the BSADF statistics is $r_0 = 26$, which means that by construction for all assets we cannot check whether the sub-prime crisis periods considered bubble episodes. We use 10,000 Monte Carlo simulation iterations to calculate the finite sample critical values.

The period of high instability for *Equity Europe* is in early 2009, mid-2020, and quite persistent in second half of 2022, in all case corresponding to the high risk regime identified by the MS. For the *Long Term Italian Government Bond*, the bubbles periods start with the explosion of the sovereign debt crisis in the second half of 2011 to August 2012, plus the second half of 2018, and from the second half of 2022 to the last period of the sample. For the *Short Term European Government Bond*, the bubble periods, corresponding to the high-risk regime identified by the MS model, occur in the second half of 2011, and from July 2022 to January 2023, periods of inflationary and interest rate pressures. For *Equity US*, the bubbles period is concentrated in the early 2009, though in 2015 and at the beginning of 2016 there bubble episodes lie in the medium risk regime. The *Bond Corporate Investment Grade USD* class shows significant bubble episodes for most of 2015 and a very relevant part of 2016, corresponding to the Chinese stock market crash, though all bubble episodes fall into the medium-risk regime. The only exception being January 2017, classified as high-risk episode. Finally, for the *Short Term US Government Bond* bubble episodes characterise the second half of 2016 to February 2017 only when we consider a critical value of 90% (we may interpret this as a sort of early warning episodes). The second half of 2022 up to January 2023, all explosive bubble periods fall into the high-risk regime, mainly due to inflationary and interest pressures.

[INSERT SOMEWHERE HERE FIGURES 15-20 & TABLES 2-3]

6 CONCLUSIONS

The contribution of this paper is threefold. First, we proposed novel asset class liquidity risk indicators by aggregating financial, monetary and credit liquidity variables via a time-varying correlation

approach. We constructed liquidity indicators for a wide range of very representative equity and bond markets such as Equity Europe, Long Term Italian Government Bond, Short Term European Government Bond, Equity US, Bond Corporate Investment Grade USD, Short Term US Government Bond over the period January 2007 to January 2023. Second, the framework we proposed allows to measure the specific time-varying contribution of the constituents of the asset class indicators. Third, low-medium-high risk regimes were identified via endogenous Markov-switching models and the presence of explosive episodes affecting the asset class liquidity risk indicators classified using the recursive testing procedure.

The liquidity risk indicators we propose for the six asset classes are able to incorporate the relevant episodes of distress experienced over the last decades. As far as the contributions to risk on events for Equity Europe, the group of non-volatility financial variables showed the highest impact during the global financial crisis with respect to the major role played by the credit variables during the sovereign debt crisis and the monetary indicator during the Covid-19 period. For the Long Term Italian Government Bond, during the sovereign debt crisis the highest contribution came from the credit market, which also played a crucial role as main driver for Equity US over the global financial crisis though for this market the monetary variables dominate the event associate to the Covid-19 crisis. As far as the Bond Investment Corporate USD market is concerned, the main contribution comes from the credit market over the crisis period we consider; for the Short Term Euro Government Bond there is a strong evidence of the crucial role played by the credit indicators from the last quarter of 2021, while the Short Term US Government Bond were mainly affected by financial indicators, the only exception being the second quarter of 2022 when again the credit indicators showed a dominant spike. In general, bubble episodes are found in correspondence of a high-risk regime charactering the Eurozone debt crisis of 2011 and 2012, the Chinese stock market crash in 2015/6, the Covid-19 pandemic and the invasion of Ukraine in 2022.

The findings in this paper suggest some interesting extensions. First, it will be useful to extend our analysis to a wide range of asset classes beyond the six considered in this paper and include misspecification analysis as recently proposed by Pouzo, Psaradakis, and Sola (2022). Second, it will be interesting to construct a global portfolio liquidity risk indicator which may be able provide investors warning signals of liquidity stress for the hypothetical invested portfolios. Third, compare the regimes identified in the portfolio risk indicator with those obtained via the implementation of the multivariate Markov-switching approach to the asset classes as recently proposed in Kim and Kang (2023), who extend the univariate approach of Hwu et al. (2021) to a multivariate case. While there are some important curse of dimensionality issues to be solved, the multivariate endogenous Markov-

switching model may enable to detect the common regime shifts affecting several markets thus tracing the propagation of shocks between markets. Finally, a formal validation of the liquidity risk indicators could be undertaken by means of surveys [see Illing and Liu (2016), Louzis and Vouldis (2013), and Iachini and Nobili (2014, 2016)], or signal-to-noise ratios [see Garabedian and Inghelbrecht (2015, 2020)]. The validation could also prove useful in the empirical justification for the use of credit and monetary variables in measuring liquidity risk. This is part of an ongoing research agenda.

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Table 1: **Descriptive statistics**

Equity Europe	Mean	Median	Min	Max	StDev	Skw	Krt
Libor OIS (bps)	27.964	11.614	-8.753	283.286	44.447	3.064	14.393
Domestic credit (%)	3.504	2.708	-2.223	12.109	3.425	0.708	3.009
Cost of borrowing corp (%)	2.740	2.670	1.350	6.030	1.265	1.102	3.401
Cost of borrowing hh (%)	2.819	2.660	1.300	5.550	1.215	0.592	2.308
Volume (€-mil)	4.774	4.371	2.450	9.953	1.469	1.136	3.669
Turnover (€-mil)	236.742	84.012	52.492	1348.390	350.731	1.970	5.163
Bid ask (%)	0.128	0.111	0.066	0.257	0.047	0.909	2.901
V2X (%)	23.397	21.936	12.172	63.272	8.594	1.858	7.824
VIX (%)	20.299	17.871	10.121	62.639	8.847	2.173	9.376
Amihud (%)	17.975	15.068	1.892	60.618	12.284	0.786	3.108
Turnover ratio (%)	0.003	0.003	0.001	0.007	0.001	1.083	3.312
Futures volatility (%)	1.310	1.167	0.488	4.266	0.609	2.007	8.222
Base money (%)	16.348	10.999	-28.259	75.252	22.295	0.232	2.595
Broad money (%)	4.932	4.854	-2.108	12.789	3.482	0.262	2.480
M1 (%)	7.635	7.472	-0.242	15.407	3.469	0.013	2.591
Long Term Italian Govt Bond	**Mean**	**Median**	**Min**	**Max**	**StDev**	**Skw**	**Krt**
Libor OIS (bps)	27.964	11.614	-8.753	283.286	44.447	3.064	14.393
Domestic credit (%)	3.504	2.708	-2.223	12.109	3.425	0.708	3.009
Cost of borrowing corp (%)	3.017	2.910	1.200	6.390	1.408	0.645	2.452
Cost of borrowing hh (%)	2.981	2.910	1.250	5.910	1.299	0.598	2.421
YTM bond govt 10y (%)	3.146	3.246	0.574	6.796	1.559	0.037	1.849
Bid ask spread (%)	0.101	0.062	0.013	0.777	0.127	3.325	14.782
BTP-Futures volatility (%)	0.562	0.464	0.256	1.440	0.272	1.089	3.157
Liq. Index (%)	5.638	4.934	2.152	22.519	3.028	2.073	9.763
Base money (%)	16.348	10.999	-28.259	75.252	22.295	0.232	2.595
Broad money (%)	4.932	4.854	-2.108	12.789	3.482	0.262	2.480
M1 (%)	7.635	7.472	-0.242	15.407	3.469	0.013	2.591
Short Term Euro Govt Bond	**Mean**	**Median**	**Min**	**Max**	**StDev**	**Skw**	**Krt**
Libor OIS (bps)	27.964	11.614	-8.753	283.286	44.447	3.064	14.393
Domestic credit (%)	3.504	2.708	-2.223	12.109	3.425	0.708	3.009
Cost of borrowing corp (%)	2.740	2.670	1.350	6.030	1.265	1.102	3.401
Cost of borrowing hh (%)	2.819	2.660	1.300	5.550	1.215	0.592	2.308
YTM bond govt 1y (%)	0.235	-0.117	-0.998	4.21	1.381	1.848	5.279
Bid ask spread (%)	0.018	0.010	0.000	0.160	0.022	3.690	19.724
Bund-Futures volatility (%)	0.376	0.348	0.188	0.802	0.124	1.391	5.077
Liq. Index (%)	2.399	1.510	0.757	11.515	2.075	2.213	7.972
Base money (%)	16.348	10.999	-28.259	75.252	22.295	0.232	2.595
Broad money (%)	4.932	4.854	-2.108	12.789	3.482	0.262	2.480
M1 (%)	7.635	7.472	-0.242	15.407	3.469	0.013	2.591

Equity US	Mean	Median	Min	Max	StDev	Skw	Krt
Libor OIS (bps)	29.196	17.831	3.521	293.967	32.332	4.210	28.517
TED spread (%)	0.421	0.286	0.069	3.353	0.429	3.253	16.721
Mortgage rate to T-Yield	1.394	1.356	1.026	2.616	0.253	1.739	7.678
Commercial paper out (%)	-1.814	-0.942	-37.396	24.063	12.179	-0.373	3.160
Volume ($-mil)	15.466	14.051	6.864	32.343	6.200	0.570	2.348
Turnover ($ - mil)	1122.048	876.585	475.269	2919.352	580.377	1.502	4.186
Bid ask (%)	0.048	0.043	0.023	0.099	0.017	0.836	2.896
VIX (%)	20.299	17.871	10.121	62.639	8.847	2.173	9.376
Amihud (%)	2.830	1.738	0.615	14.589	2.486	1.619	6.110
Turnover ratio (%)	0.008	0.008	0.005	0.016	0.002	1.017	3.467
Futures volatility (%)	1.102	0.906	0.327	4.741	0.684	2.613	11.601
Base money (%)	15.419	3.710	-15.713	112.663	27.369	1.719	5.864
Broad money (%)	7.459	6.339	-2.043	26.887	4.948	2.154	8.128
M1 (%)	29.008	8.575	-4.371	358.847	79.955	3.612	14.151
Bond Corporate IG USD	**Mean**	**Median**	**Min**	**Max**	**StDev**	**Skw**	**Krt**
Libor OIS (bps)	29.196	17.831	3.521	293.967	32.332	4.210	28.517
Commercial paper out (%)	-1.814	-0.942	-37.396	24.063	12.179	-0.373	3.160
TED spread (%)	0.421	0.286	0.069	3.353	0.429	3.253	16.721
Mortgage rate to T-Yield	1.394	1.356	1.026	2.616	0.253	1.739	7.678
Bid ask (%)	0.427	0.402	0.231	1.128	0.156	2.202	8.507
Futures volatility (%)	0.408	0.328	0.209	2.093	0.271	2.881	16.154
YTM IG USD (%)	3.901	3.437	1.844	8.765	1.407	1.236	4.394
Base money (%)	15.419	3.710	-15.713	112.663	27.369	1.719	5.864
Broad money (%)	7.459	6.339	-2.043	26.887	4.948	2.154	8.128
M1 (%)	29.008	8.575	-4.371	358.847	79.955	3.612	14.151
Short Term US Govt Bond	**Mean**	**Median**	**Min**	**Max**	**StDev**	**Skw**	**Krt**
Libor OIS (bps)	29.196	17.831	3.521	293.967	32.332	4.210	28.517
Commercial paper out (%)	-1.814	-0.942	-37.396	24.063	12.179	-0.373	3.160
TED spread (%)	0.421	0.286	0.069	3.353	0.429	3.253	16.721
Mortgage rate to T-Yield	1.394	1.356	1.026	2.616	0.253	1.739	7.678
Bid ask (%)	0.003	0.002	0.001	0.022	0.003	3.598	17.949
Futures volatility (%)	0.646	0.588	0.312	1.482	0.225	1.203	4.312
YTM bond govt 1y (%)	0.894	0.157	-0.015	5.129	1.316	1.729	5.197
Base money (%)	15.419	3.710	-15.713	112.663	27.369	1.719	5.864
Broad money (%)	7.459	6.339	-2.043	26.887	4.948	2.154	8.128
M1 (%)	29.008	8.575	-4.371	358.847	79.955	3.612	14.151

Note: The table reports summary statistics of the liquidity measures, and monetary and credit variables used to construct each asset class liquidity risk indicator. Sample period: January 2007-January 2023.

Table 2: **Bubble Periods and Markov-Switching (MS) Regimes.**

Equity Europe				Long Term Italian Government Bond				Short Term European Government Bond			
Date	**90%**	**95%**	**MSRegime**	**Date**	**90%**	**95%**	**MSRegime**	**Date**	**90%**	**95%**	**MSRegime**
18-Feb-2009	1	1	3	18-Jun-2011	1	0	2	18-Sep-2009	1	0	1
18-Mar-2009	1	0	3	18-Sep-2011	1	1	3	18-Oct-2009	1	0	1
18-Apr-2009	1	0	3	18-Oct-2011	1	1	3	18-Nov-2009	1	1	1
18-Dec-2018	1	0	2	18-Nov-2011	1	1	3	18-Dec-2009	1	0	1
18-May-2020	1	0	3	18-Dec-2011	1	1	3	18-Jan-2010	1	1	1
18-Aug-2022	1	1	3	18-Jan-2012	1	1	3	18-Feb-2010	1	0	1
18-Sep-2022	1	1	3	18-Feb-2012	1	1	3	18-Mar-2010	1	1	1
18-Oct-2022	1	1	3	18-Mar-2012	1	0	3	18-Apr-2010	1	0	1
18-Nov-2022	1	1	3	18-Apr-2012	1	1	3	18-May-2010	1	0	1
18-Dec-2022	1	1	3	18-May-2012	1	1	3	18-Jun-2010	1	0	1
18-Jan-2023	1	1	3	18-Jun-2012	1	1	3	18-Jul-2010	1	0	1
				18-Jul-2012	1	1	3	18-Aug-2010	1	0	1
				18-Aug-2012	1	1	3	18-Sep-2010	1	0	1
				18-Dec-2014	1	0	1	18-Sep-2011	1	1	3
				18-Jan-2015	1	0	1	18-Oct-2011	1	1	3
				18-Feb-2015	1	0	1	18-Nov-2011	1	1	3
				18-Feb-2017	1	0	2	18-Dec-2011	1	1	3
				18-Jul-2018	1	1	3	18-Jan-2012	1	1	1
				18-Aug-2018	1	1	3	18-Feb-2012	1	1	1
				18-Sep-2018	1	1	3	18-Feb-2015	1	1	1
				18-Oct-2018	1	1	3	18-Jul-2022	1	0	3
				18-Nov-2018	1	1	3	'18-Aug-2022	1	1	3
				18-Dec-2018	1	1	3	18-Sep-2022	1	1	3
				18-Jun-2022	1	1	3	18-Oct-2022	1	1	3
				18-Jul-2022	1	1	3	18-Nov-2022	1	1	3
				18-Aug-2022	1	1	3	18-Dec-2022	1	1	3
				18-Sep-2022	1	1	3	18-Jan-2023	1	1	3
				18-Oct-2022	1	1	3				
				18-Nov-2022	1	1	3				
				18-Dec-2022	1	1	3				
				18-Jan-2023	1	1	3				

Note: The table reports the Dates of the bubbles identified via the BSADF statistics at 90% and 95% confidence levels, and the regimes (MSRegime) identified via the endogenous Markov-Switching model where Low-Risk Regime=1, Medium-Risk Regime=2, and High-Risk Regime=3

Table 3: **Bubble Periods and Markov-Switching (MS) Regimes.**

Equity US				Bond Corporate Investment Grade USD				Short Term US Government Bond			
Date	**90%**	**95%**	**MSRegime**	**Date**	**90%**	**95%**	**MSRegime**	**Date**	**90%**	**95%**	**MSRegime**
18-Feb-2009	1	0	3	18-Jan-2012	1	0	1	18-Jun-2016	1	0	3
18-Mar-2009	1	0	3	18-Sep-2014	1	1	1	18-Jul-2016	1	0	3
18-Sep-2015	1	1	2	18-Oct-2014	1	1	1	18-Aug-2016	1	0	3
18-Jan-2016	1	1	2	18-Dec-2014	1	1	2	18-Sep-2016	1	0	3
18-Feb-2016	1	1	2	18-Jan-2015	1	1	2	18-Nov-2016	1	0	3
				18-Feb-2015	1	1	2	18-Dec-2016	1	0	3
				18-Mar-2015	1	1	2	18-Jan-2017	1	0	3
				18-Apr-2015	1	1	2	18-Feb-2017	1	0	3
				18-May-2015	1	1	2	18-May-2018	1	0	3
				18-Jun-2015	1	1	2	18-Jul-2022	1	0	3
				18-Jul-2015	1	1	2	18-Sep-2022	1	1	3
				18-Aug-2015	1	1	2	18-Oct-2022	1	1	3
				18-Sep-2015	1	1	2	18-Nov-2022	1	1	3
				18-Oct-2015	1	0	2	18-Dec-2022	1	1	3
				18-Nov-2015	1	1	2	18-Jan-2023	1	0	3
				18-Dec-2015	1	1	2				
				18-Jan-2016	1	1	2				
				18-Feb-2016	1	1	2				
				18-Mar-2016	1	1	2				
				18-Apr-2016	1	1	2				
				18-Sep-2016	1	0	2				
				18-Oct-2016	1	1	2				
				18-Jan-2017	1	0	3				
				18-Feb-2017	1	1	2				

Note: The table reports the Dates of the bubbles identified via the BSADF statistics at 90% and 95% confidence levels, and the regimes (MSRegime) identified via the endogenous Markov-Switching model where Low-Risk Regime=1, Medium-Risk Regime=2, and High-Risk Regime=3

LIST OF FIGURES

Figure 1: **Asset Class Liquidity Risk Indicators**

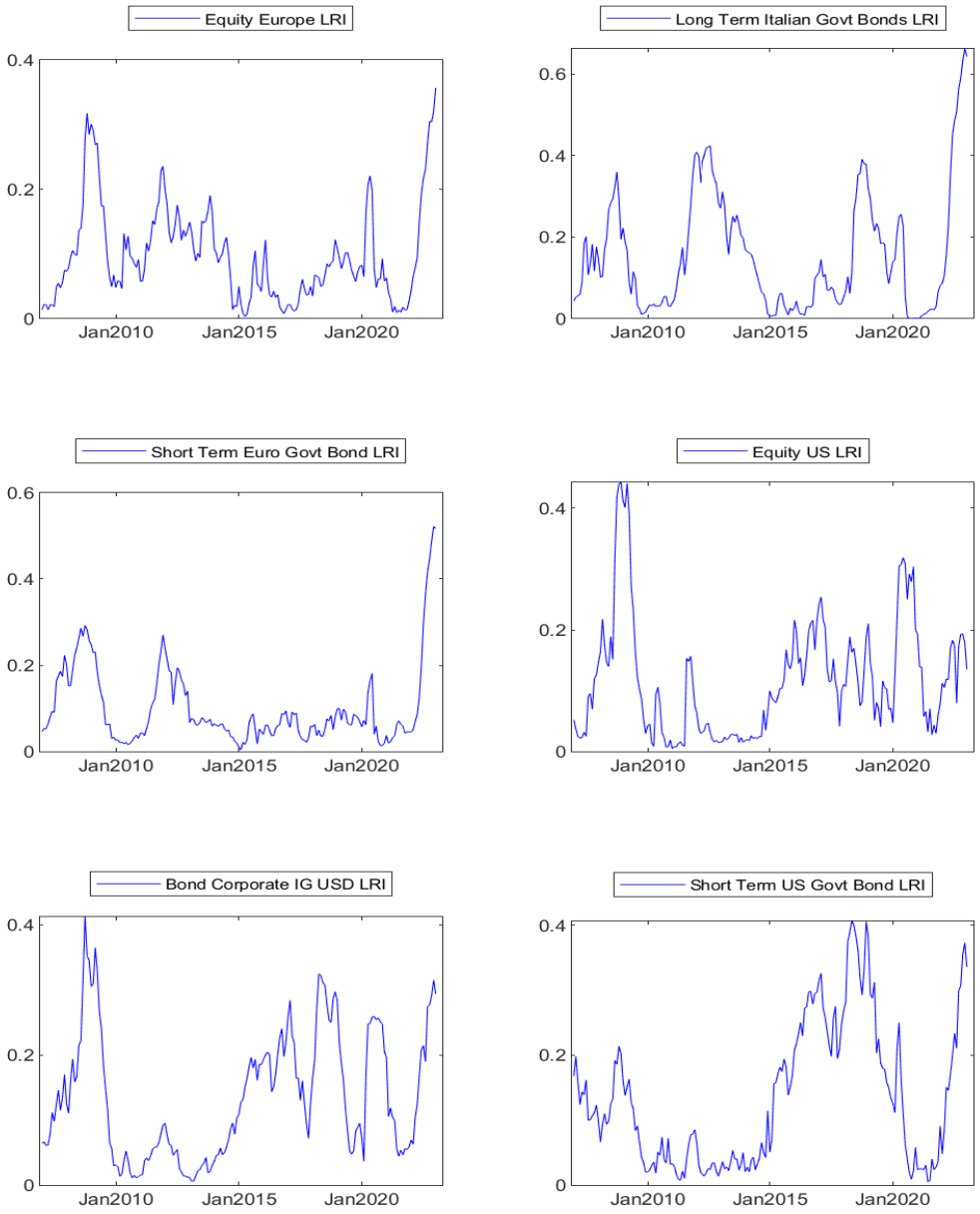


Figure 2: **Equity Europe and Short Term Euro Government Liquidity Risk Indicators**

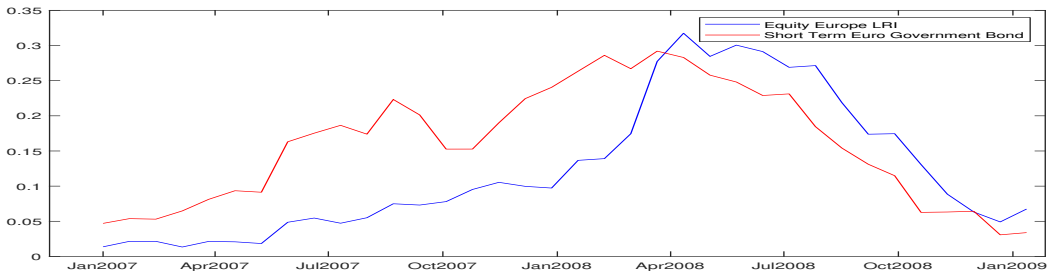
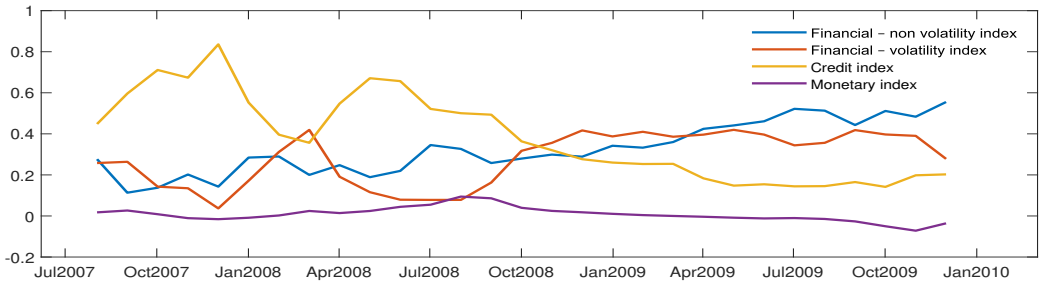
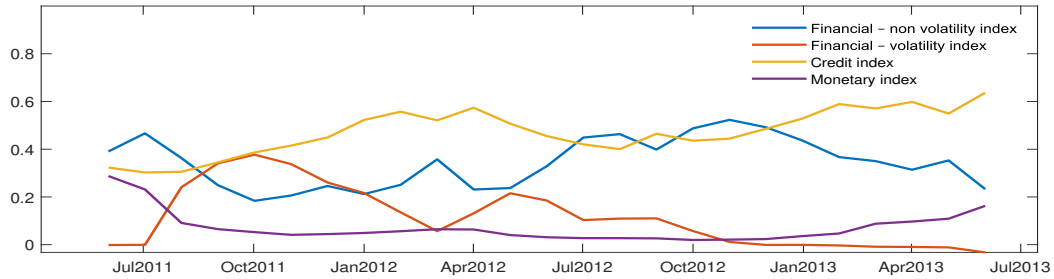


Figure 3: **Contribution to Equity Europe Liquidity Risk Index**

(a) Global financial crisis



(b) Sovereign debt crisis



(c) Covid 19 crisis

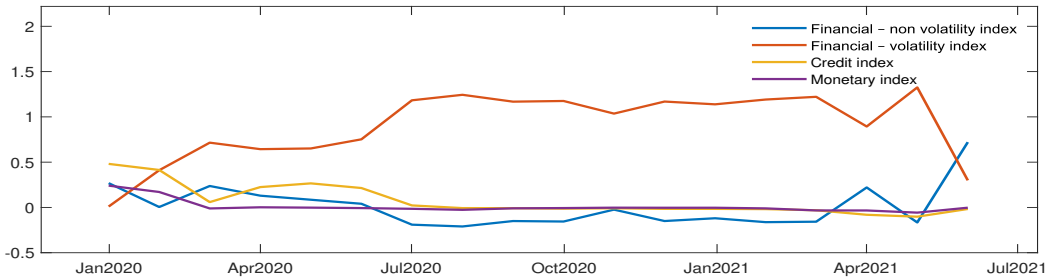
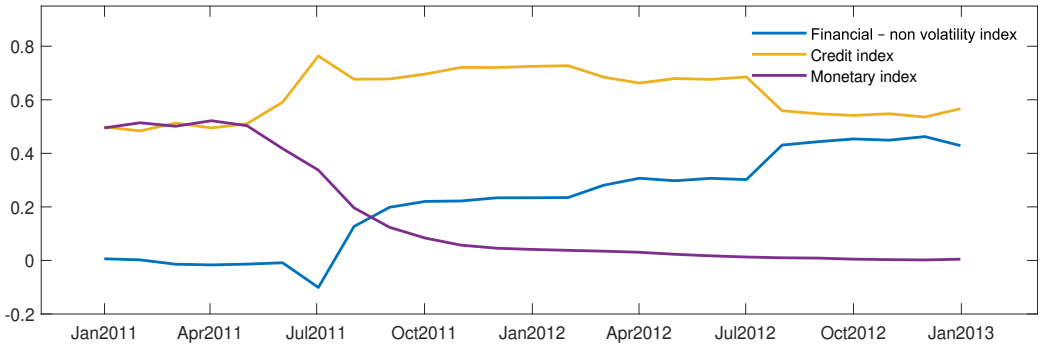
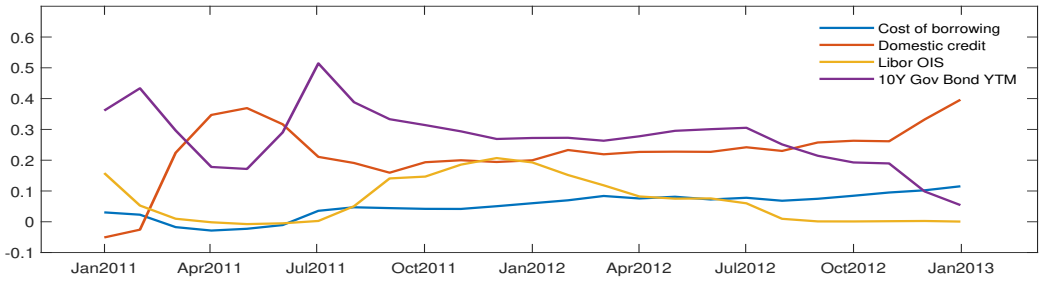


Figure 4: **Contribution to Long Term Italian Government Bond Liquidity Risk Index**

(a) Sovereign Debt Crisis



(b) Sovereign Debt Crisis - Focus Credit Indices



(c) 2018 Crisis

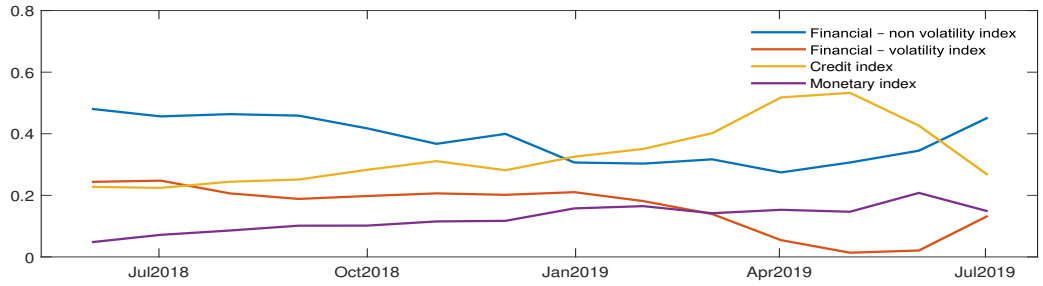


Figure 5: **Contribution to Short Term Euro Government Bond Liquidity Risk Index**

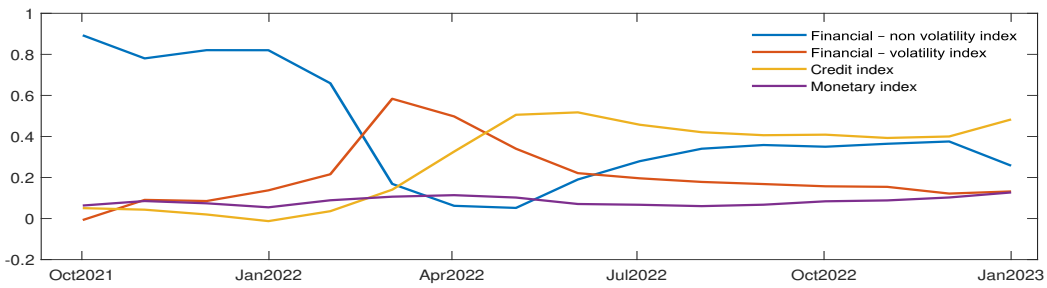
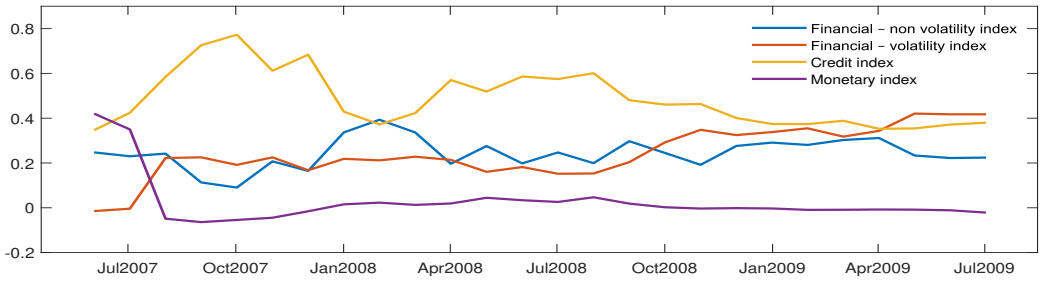


Figure 6: **Contribution to Equity US Liquidity Risk Index**

(a) Global Financial Crisis



(b) Covid-19 Crisis

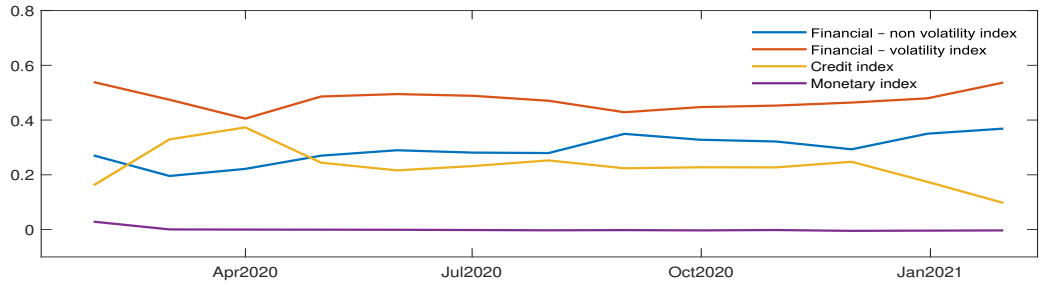
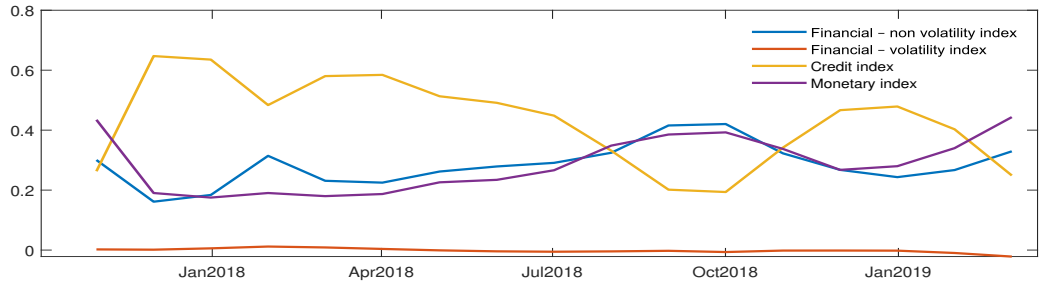
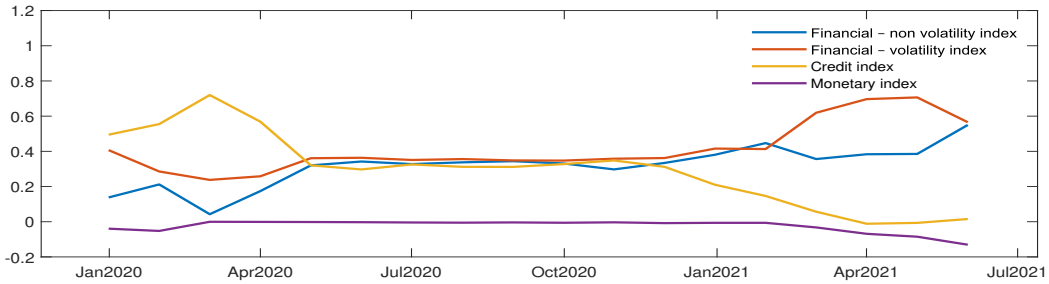


Figure 7: **Contribution to Bond Corporate IG USD Liquidity Risk Index**

(a) 2018 Crisis



(b) Covid-19 crisis



(c) Covid-19 Crisis - Detail on Credit Indicators

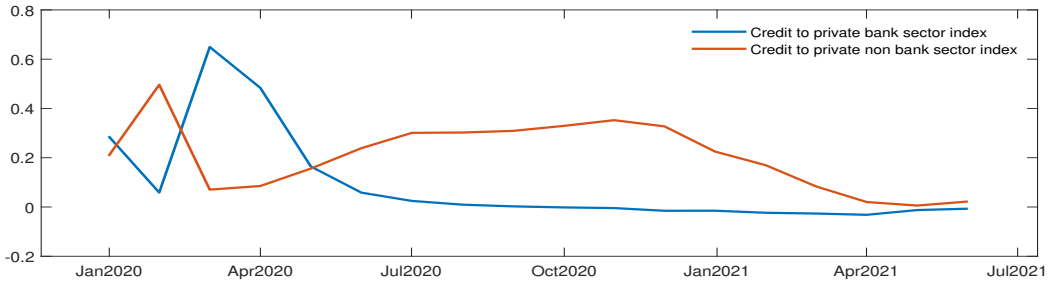


Figure 8: **Contribution to Short Term US Government Bond Liquidity Risk Index**

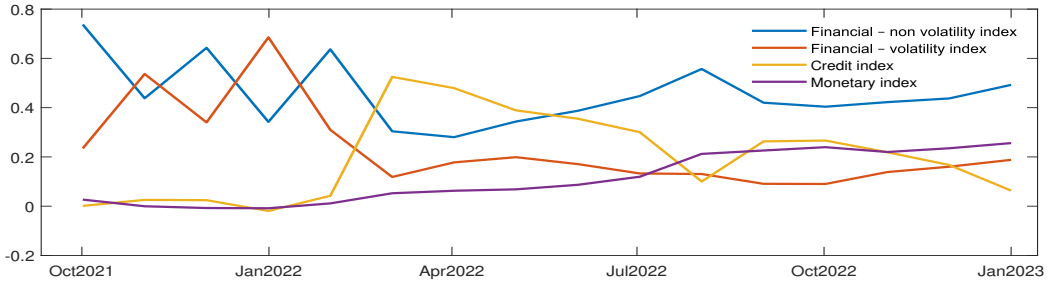


Figure 9: **Equity Europe - Smoothed probabilities for low (=1), medium (=2), and high (=3) risk regimes.**

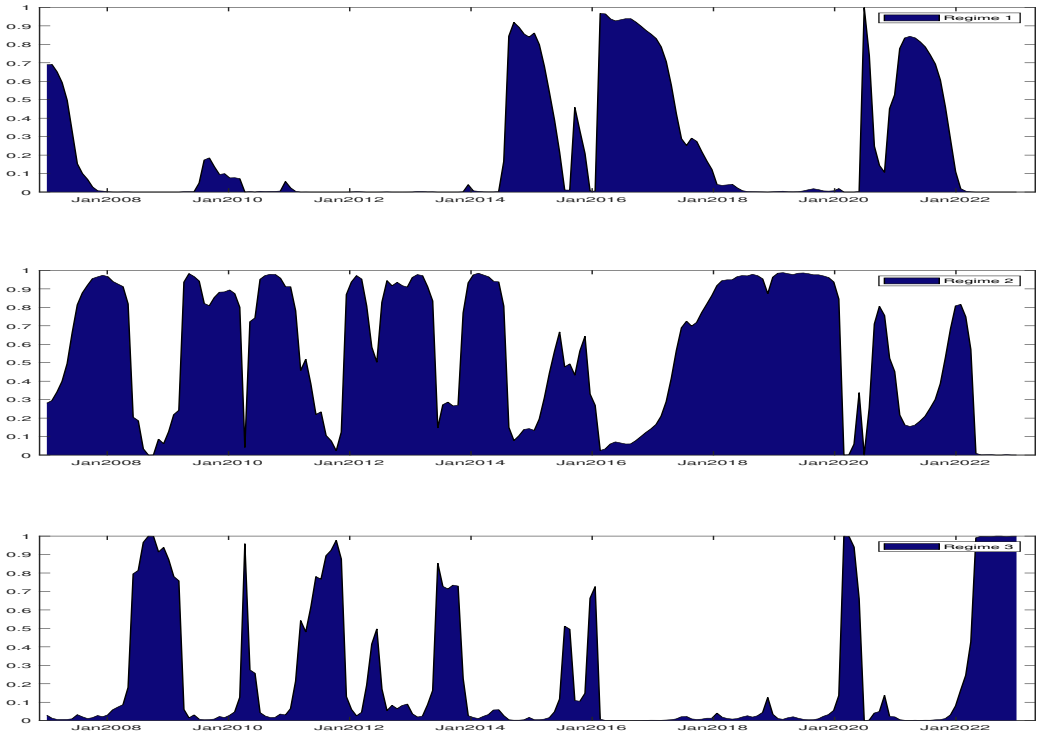


Figure 10: **Long Term Italian Government Bond - Smoothed probabilities for low (=1), medium (=2), high (=3) risk regimes, respectively.**

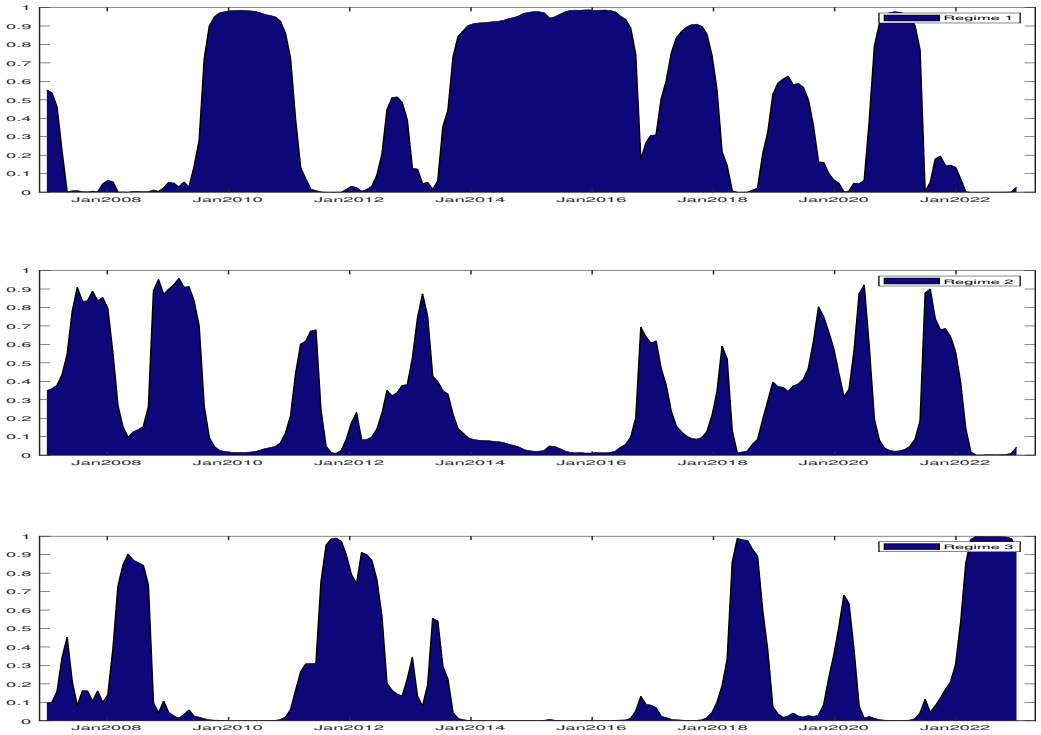


Figure 11: **Short Term European Government Bond - Smoothed probabilities for low (=1), medium (=2), and high (=3) risk regimes.**

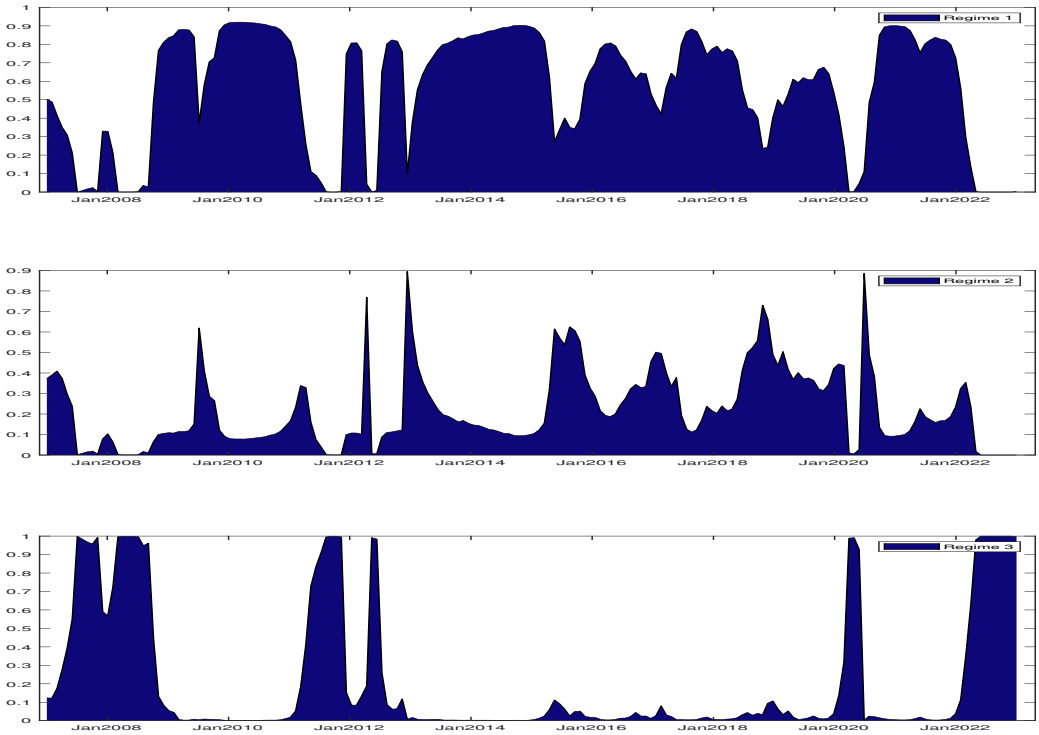


Figure 12: **Equity US - Smoothed probabilities for low (=1), medium (=2), and high (=3) risk regimes.**

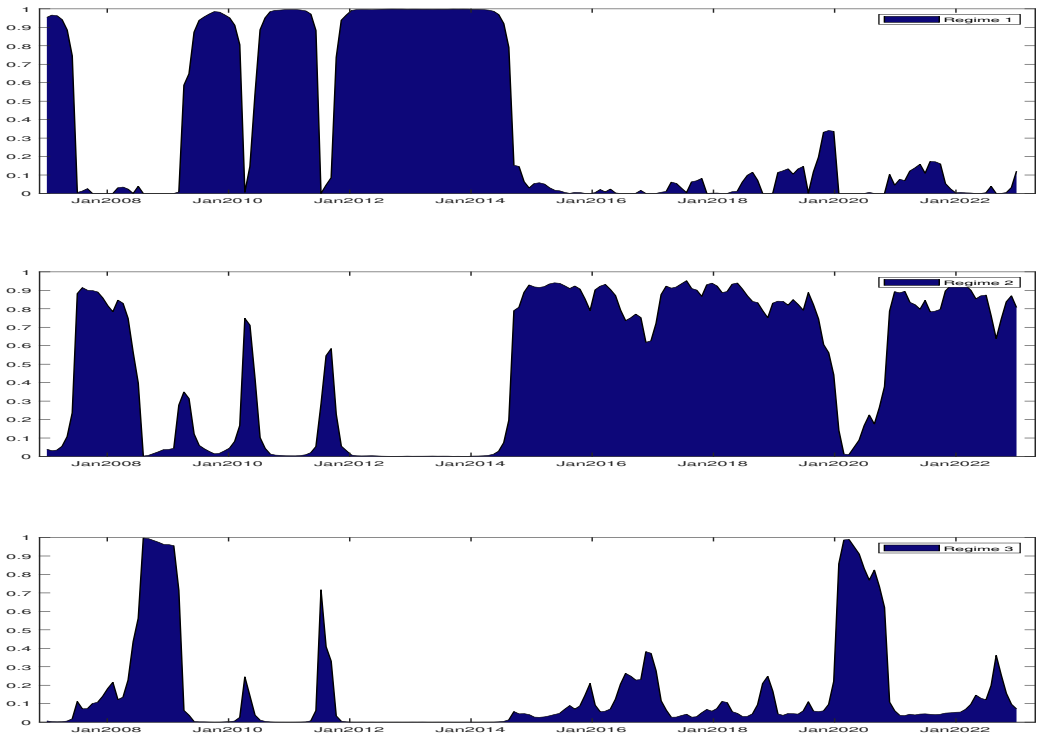


Figure 13: **Bond Corporate Investment Grade USD - Smoothed probabilities for low (=1), medium (=2), and high (=3) risk regimes.**

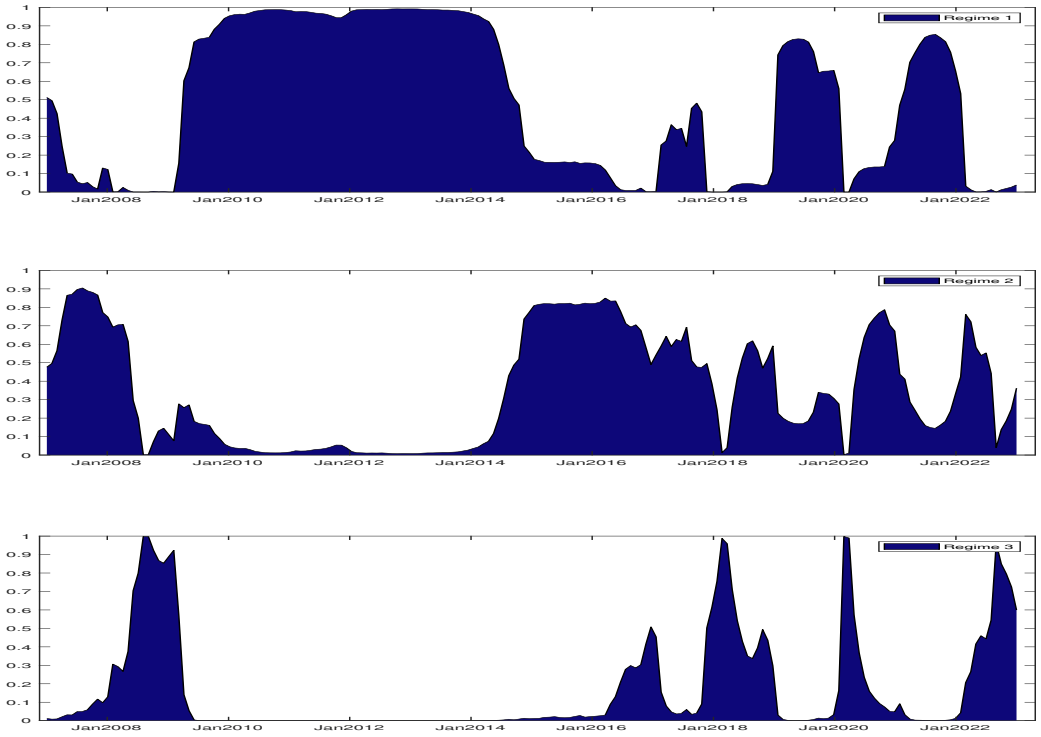


Figure 14: **Short Term US Government Bond - Smoothed probabilities for low (=1), medium (=2), and high (=3) risk regimes.**

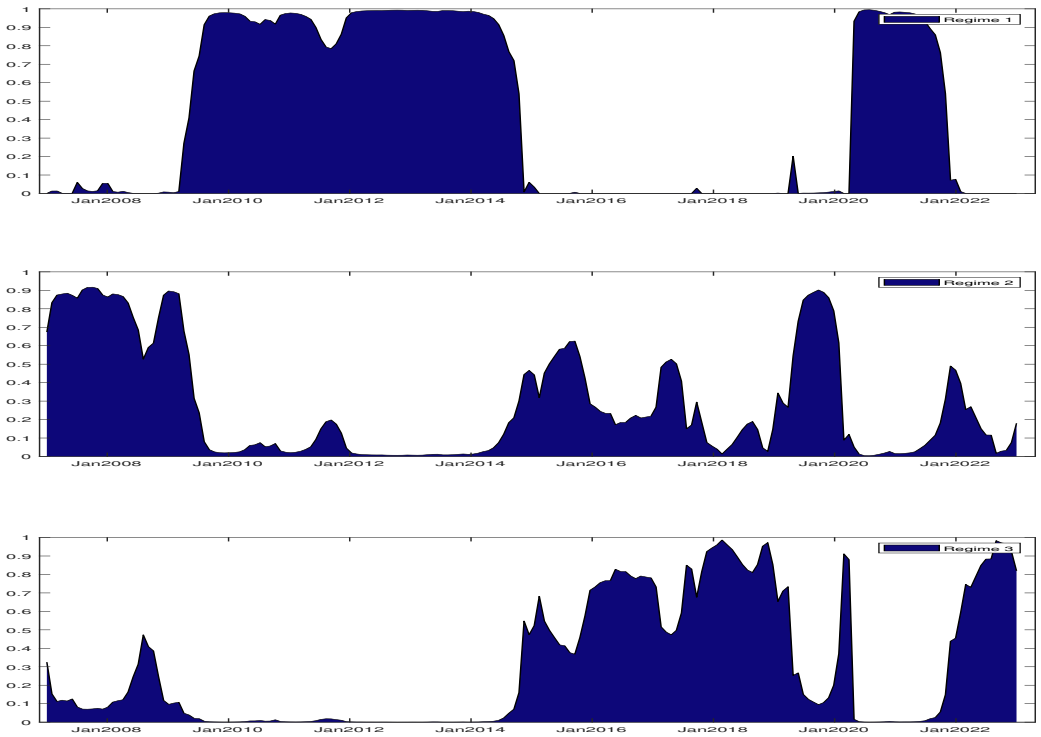
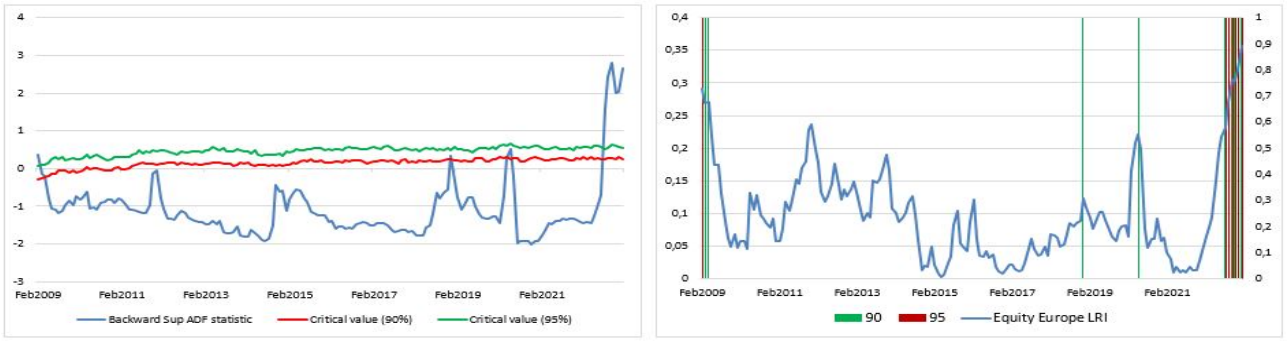
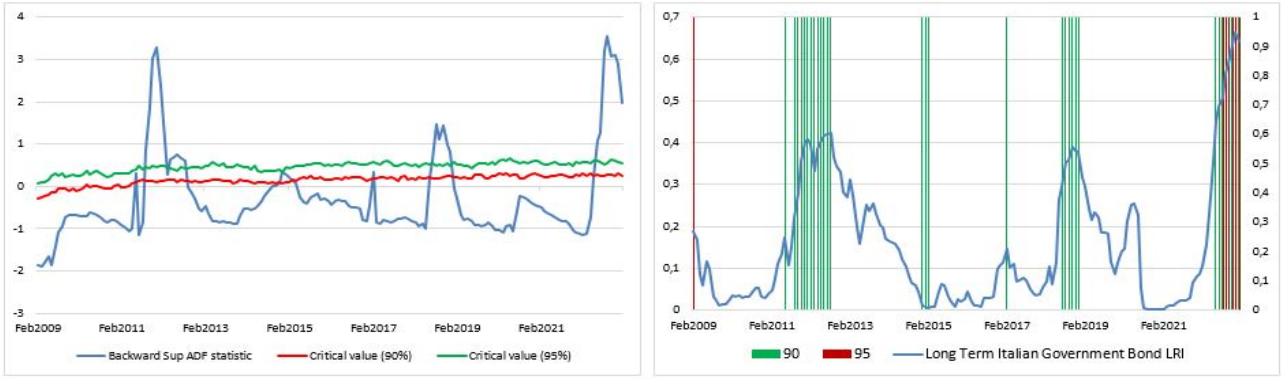


Figure 15: **Equity Europe - BSADF Statistics and Critical Values.**



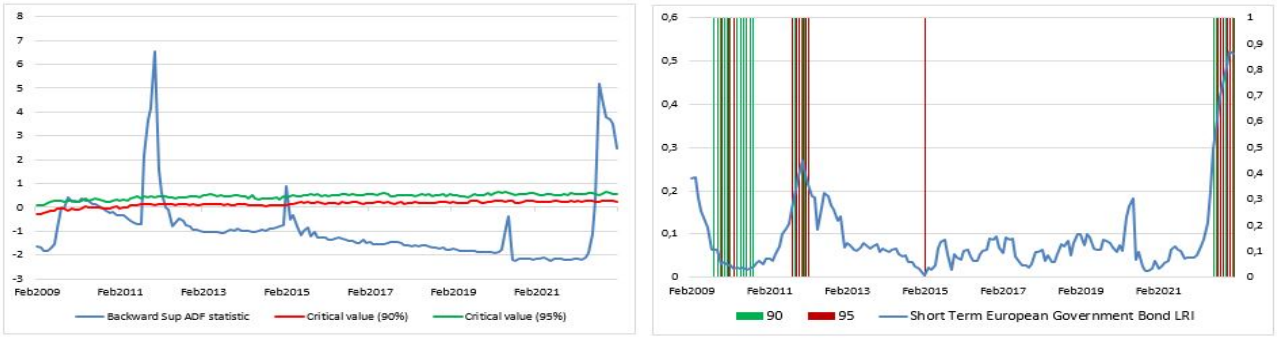
Note: This figure reports the results for Equity Europe. In the left panel, the sequence of the Backward Supremum Augmented Dickey Fuller (BSADF) statistics and respective finite sample critical values at both 90% and 95% confidence levels, respectively, are reported. Finite sample critical values are obtained by Monte Carlo simulation with 10,000 iterations. In the right panel, the identified bubble periods are highlighted against the liquidity risk indicator for the equity Europe asset class, the colour green indicates the periods identified with the 90% confidence level and in red the ones at 95% confidence level

Figure 16: **Long Term Italian Government Bond - BSADF Statistics and Critical Values.**



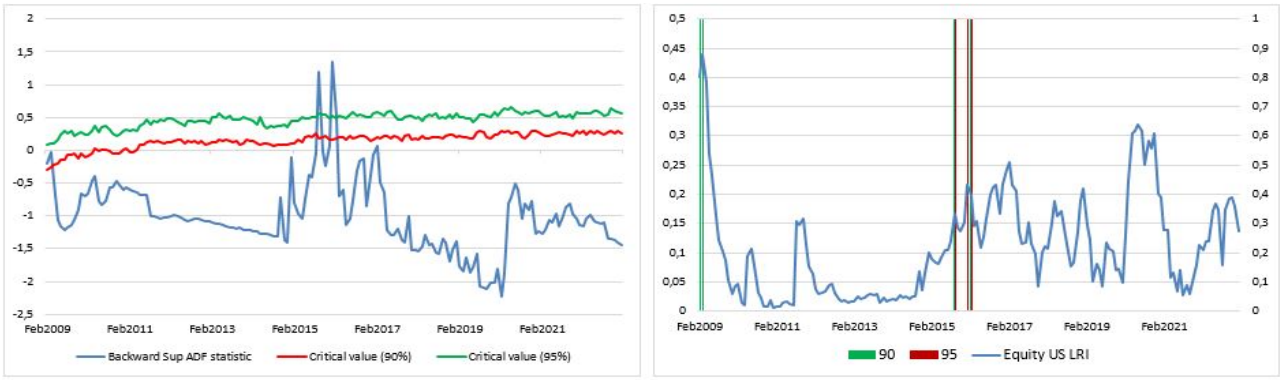
Note: This figure reports the results for Long Term Italian Government Bond. In the left panel, the sequence of the Backward Supremum Augmented Dickey Fuller (BSADF) statistics and respective finite sample critical values at both 90% and 95% confidence levels, respectively, are reported. Finite sample critical values are obtained by Monte Carlo simulation with 10,000 iterations. In the right panel, the identified bubble periods are highlighted against the liquidity risk indicator for the equity Europe asset class, the colour green indicates the periods identified with the 90% confidence level and in red the ones at 95% confidence level

Figure 17: **Short Term European Government Bond - BSADF Statistics and Critical Values.**



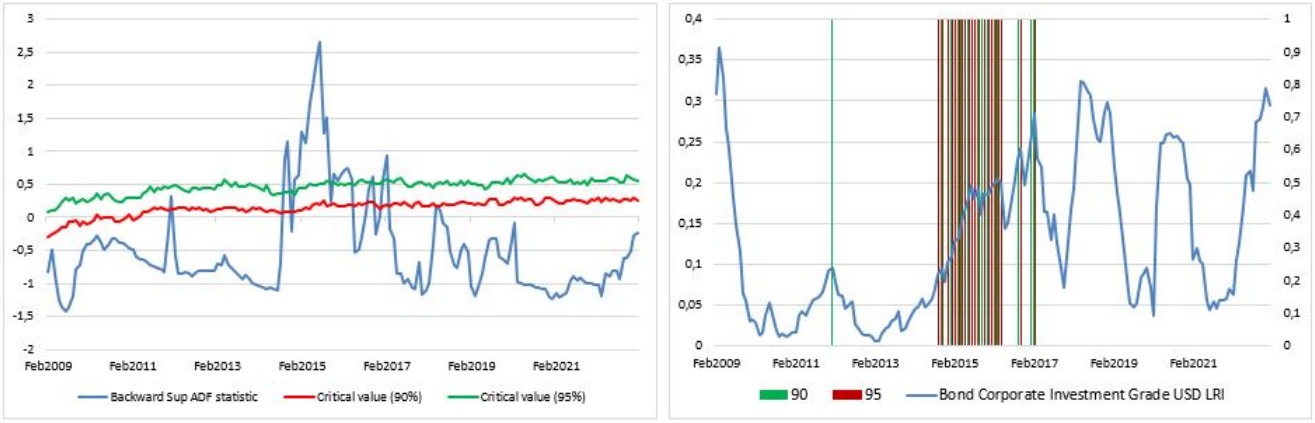
Note: This figure reports the results for Short Term European Government Bond. In the left panel, the sequence of the Backward Supremum Augmented Dickey Fuller (BSADF) statistics and respective finite sample critical values at both 90% and 95% confidence levels, respectively, are reported. Finite sample critical values are obtained by Monte Carlo simulation with 10,000 iterations. In the right panel, the identified bubble periods are highlighted against the liquidity risk indicator for the equity Europe asset class, the colour green indicates the periods identified with the 90% confidence level and in red the ones at 95% confidence level

Figure 18: **Equity US - BSADF Statistics and Critical Values.**



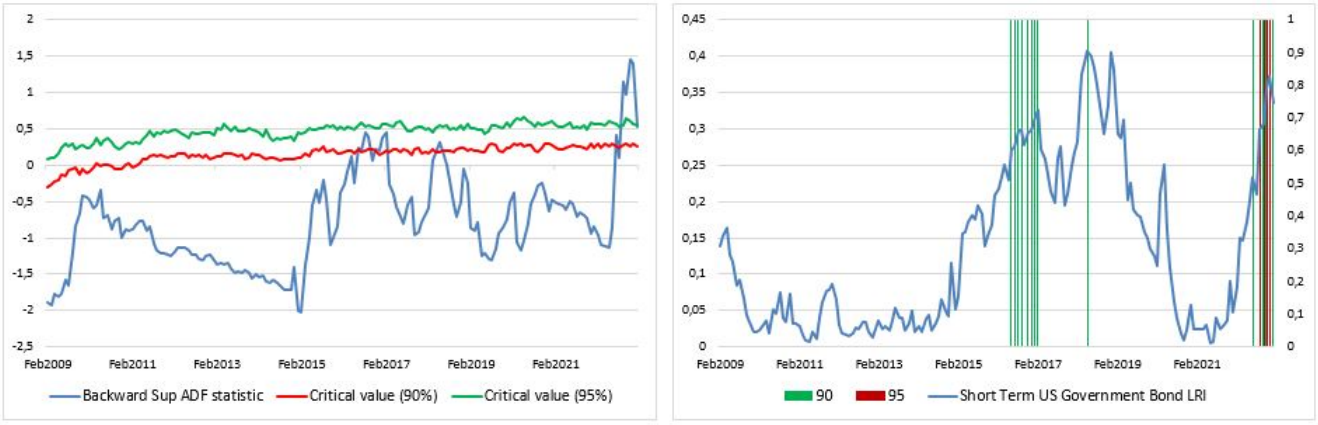
Note: This figure reports the results for Equity US. In the left panel, the sequence of the Backward Supremum Augmented Dickey Fuller (BSADF) statistics and respective finite sample critical values at both 90% and 95% confidence levels, respectively, are reported. Finite sample critical values are obtained by Monte Carlo simulation with 10,000 iterations. In the right panel, the identified bubble periods are highlighted against the liquidity risk indicator for the equity Europe asset class, the colour green indicates the periods identified with the 90% confidence level and in red the ones at 95% confidence level

Figure 19: **Bond Corporate Investment Grade USD - BSADF Statistics and Critical Values.**



Note: This figure reports the results for Bond Corporate Investment Grade USD. In the left panel, the sequence of BSADF statistics and respective finite sample critical values at both 90% and 95% confidence levels, respectively, are reported. Finite sample critical values are obtained by Monte Carlo simulation with 10,000 iterations. In the right panel, the identified bubble periods are highlighted against the liquidity risk indicator for the equity Europe asset class, the colour green indicates the periods identified with the 90% confidence level and in red the ones at 95% confidence level

Figure 20: **Short Term US Government Bond - BSADF Statistics and Critical Values.**



Note: This figure reports the results for Short Term US Government Bond. In the left panel, the sequence of BSADF statistics and respective finite sample critical values at both 90% and 95% confidence levels, respectively, are reported. Finite sample critical values are obtained by Monte Carlo simulation with 10,000 iterations. In the right panel, the identified bubble periods are highlighted against the liquidity risk indicator for the equity Europe asset class, the colour green indicates the periods identified with the 90% confidence level and in red the ones at 95% confidence level

INTERNET APPENDICES

A Liquidity measures, credit and monetary variables

Table A: Raw liquidity measures, credit and monetary variables

Variables	Transformation	Sign change	Source
Equity Europe			
Libor OIS	level	no	ECB
Domestic credit	yoy gr	yes	ECB
Cost of borrowing corporate	level	no	ECB
Cost of borrowing households	level	no	ECB
Volume	level	yes	BBG
Turnover	level	yes	BBG
Bid ask spread percent	level	no	BBG
Implied volatility index V2X	level	no	BBG
Implied volatility index VIX	level	no	BBG
Amihud	level	no	BBG
Turnover ratio	level	yes	BBG
Futures volatility on index	level	no	BBG
Base money	yoy gr	yes	ECB
Broad money	yoy gr	yes	ECB
Monetary aggregate M1	yoy gr	yes	ECB
Long Term Italian Government Bond			
Libor OIS	level	no	ECB
Domestic credit	yoy gr	yes	ECB
Cost of borrowing corporate	level	no	ECB
Cost of borrowing households	level	no	ECB
YTM bond govt 10y	level	no	BBG
Bid ask spread percent	level	no	BBG
BTP-Futures volatility	level	no	BBG
Listed liquidity index	level	no	BBG
Base money	yoy gr	yes	ECB
Broad money	yoy gr	yes	ECB
Monetary aggregate M1	yoy gr	yes	ECB
Variables	Transformation	Change of sign	Source
Short Term European Government Bond			
Libor OIS	level	no	ECB
Domestic credit	yoy gr	yes	ECB
Cost of borrowing corporate	level	no	ECB
Cost of borrowing households	level	no	ECB
YTM bond govt 1y	level	no	BBG
Bid ask spread percent	level	no	BBG
Bund-Futures volatility	level	no	BBG
Listed liquidity index	level	no	BBG
Base money	yoy gr	yes	ECB
Broad money	yoy gr	yes	ECB
Monetary aggregate M1	yoy gr	yes	ECB
Equity US			
Libor OIS	level	no	FRED
TED spread	level	no	FRED
Mortgage rate to Treasury Yield Ratio	level	no	FRED
Commercial paper outstanding	yoy gr	yes	FRED
Volume	level	yes	BBG
Turnover	level	yes	BBG
Bid ask spread percent	level	no	BBG
Implied volatility index VIX	level	no	BBG
Amihud	level	no	BBG
Turnover ratio	level	yes	BBG
Futures volatility on index	level	no	BBG
Base money	yoy gr	yes	FRED
Broad money	yoy gr	yes	FRED
Monetary aggregate M1	yoy gr	yes	FRED
Bond Corporate Investment Grade USD			
Libor OIS	level	no	FRED
Commercial paper outstanding	yoy gr	yes	FRED
TED spread	level	no	FRED
Mortgage rate to Treasury Yield Ratio	level	no	FRED
Bid ask spread percent	level	no	BBG
Futures volatility on index	level	no	BBG
YTM Investment Grade USD	level	no	FRED
Base money	yoy gr	yes	FRED
Broad money	yoy gr	yes	FRED
Monetary aggregate M1	yoy gr	yes	FRED
Variables	Transformation	Change of sign	Source
Short Term US Government Bond			
Libor OIS	level	no	FRED
Commercial paper outstanding	yoy gr	yes	FRED
TED spread	level	no	FRED
Mortgage rate to Treasury Yield Ratio	level	no	FRED
Bid ask spread percent	level	no	BBG
Futures volatility on index	level	no	BBG
YTM bond govt 1y	level	no	FRED
Base money	yoy gr	yes	FRED
Broad money	yoy gr	yes	FRED
Monetary aggregate M1	yoy gr	yes	FRED

Note: The table reports the list of financial, credit and monetary variables used to construct the liquidity risk indicators for each of the six markets, the transformation if any (yoy gr indicates year on year growth rate) and sign change implemented on the raw variables such that all variables measure increases in the absolute value when illiquidity is high. The last column indicates the source of data.

B Clusters of raw liquidity measures, credit and monetary variables

Table B: Clusters	
ID Cluster	Variables
	Equity Europe
1	Volume-Turnover-Turnover ratio
2	Bid Ask
3	Amihud
4	VIX - V2X
5	Futures volatility
6	Cost of borrowing corp - Cost of borrowing households
7	Domestic credit
8	Libor OIS
9	Base money - Broad money - M1
	Long Term Italian Government Bond
1	Bid Ask
2	BTP-Futures volatility
3	Liquidity Index
4	YTM bond govt 10y
5	Cost of borrowing corp - Cost of borrowing households
6	Domestic credit
7	Libor OIS
8	Base money - Broad money - M1
	Short Term European Goverment Bond
1	Bid Ask
2	Bund-Futures volatility
3	Liquidity Index
4	YTM bond govt 1y
5	Cost of borrowing corp - Cost of borrowing households
6	Domestic credit
7	Libor OIS
8	Base money - Broad money - M1
	Equity US
1	Volume-Turnover-Turnover ratio
2	Bid Ask
3	Amihud
4	VIX
5	Futures volatility
6	TED spread
7	Mortgage rate to T-Yield- Commercial paper out
8	Libor OIS
9	Base money - Broad money - M1
	Bond Corporate Investment Grade USD
1	Bid Ask
2	Futures volatility
3	TED spread
4	Mortgage rate to T-Yield- Commercial paper out
5	YTM IG USD
6	Libor OIS
7	Base money - Broad money - M1
	Short Term US Government Bond
1	Bid Ask
2	Futures volatility
3	TED spread
4	Mortgage rate to T-Yield- Commercial paper out
5	YTM bond govt 1 y
6	Libor OIS
7	Base money - Broad money - M1

Note: The table shows how original variables are aggregated in g clusters, as described in Equation (5).

C Time-varying contribution of the raw liquidity measures, credit and monetary variables to liquidity risk indicators

Table C1: Liquidity Risk Contribution. Equity Europe - Global Financial Crisis

ID Cluster	1	2	3	4	5	6	7	8	9
2007Aug	-1.23%	25.41%	3.48%	19.69%	6.09%	24.93%	-3.58%	23.44%	1.76%
2007Sep	-1.12%	9.56%	2.89%	13.18%	13.21%	20.54%	-2.99%	42.08%	2.66%
2007Oct	-3.86%	14.40%	3.21%	4.20%	10.07%	34.53%	-3.13%	39.71%	0.85%
2007Nov	-1.36%	18.85%	2.71%	11.35%	2.14%	40.55%	-4.00%	30.82%	-1.07%
2007Dec	-7.08%	19.14%	2.24%	3.06%	0.63%	40.10%	-1.28%	44.76%	-1.57%
2008Jan	-0.27%	23.38%	5.34%	13.26%	3.94%	33.80%	-0.23%	21.66%	-0.87%
2008Feb	-1.10%	26.35%	3.72%	17.95%	13.24%	22.02%	-0.55%	18.12%	0.24%
2008Mar	-0.88%	15.24%	5.64%	22.18%	19.75%	14.44%	-0.55%	21.75%	2.44%
2008Apr	-4.22%	26.26%	2.72%	5.99%	13.12%	23.36%	-0.39%	31.75%	1.41%
2008May	-6.25%	23.48%	1.66%	2.32%	9.25%	31.77%	-1.47%	36.80%	2.43%
2008Jun	-5.25%	24.08%	3.13%	4.06%	3.86%	37.26%	-2.49%	30.90%	4.45%
2008Jul	-3.05%	32.78%	4.83%	4.90%	2.92%	33.41%	-1.77%	20.50%	5.49%
2008Aug	-5.61%	27.37%	10.90%	2.72%	5.11%	30.84%	-1.33%	20.55%	9.44%
2008Sep	-0.83%	21.17%	5.44%	9.25%	7.02%	29.72%	-1.87%	21.48%	8.60%
2008Oct	-0.13%	11.14%	16.94%	16.95%	14.79%	15.83%	-1.95%	22.46%	3.97%
2008Nov	-0.79%	10.65%	20.03%	18.33%	17.27%	11.79%	-1.79%	22.04%	2.47%
2008Dec	-3.22%	9.84%	22.27%	20.27%	21.40%	8.24%	-2.36%	21.77%	1.79%
2009Jan	-2.87%	15.43%	21.64%	18.83%	19.92%	7.21%	-2.56%	21.36%	1.04%
2009Feb	-2.13%	14.93%	20.47%	20.62%	20.38%	6.60%	-2.68%	21.38%	0.42%
2009Mar	-2.18%	23.16%	15.03%	21.22%	17.38%	6.80%	-3.30%	21.88%	0.01%
2009Apr	-2.08%	24.43%	20.09%	19.66%	19.96%	5.27%	-3.07%	16.14%	-0.38%
2009May	-3.77%	22.45%	25.42%	19.89%	22.06%	4.95%	-3.06%	12.89%	-0.84%
2009Jun	-6.62%	30.34%	22.41%	19.62%	20.02%	5.27%	-3.09%	13.25%	-1.20%
2009Jul	-7.33%	27.56%	31.96%	17.63%	16.77%	3.72%	-2.10%	12.82%	-1.02%
2009Aug	-4.11%	27.28%	28.13%	17.87%	17.76%	3.01%	-1.23%	12.76%	-1.46%
2009Sep	-0.62%	22.56%	22.36%	20.23%	21.60%	2.22%	0.31%	13.99%	-2.65%
2009Oct	1.65%	24.51%	25.00%	21.92%	17.77%	2.01%	3.17%	8.98%	-5.01%
2009Nov	22.67%	10.22%	15.46%	20.40%	18.63%	-1.25%	16.89%	4.17%	-7.18%
2009Dec	28.92%	4.96%	21.63%	10.56%	17.25%	-0.98%	15.03%	6.21%	-3.59%

Table C2: Liquidity Risk Contribution. Equity Europe - Sovereign Debt Crisis

ID Cluster	1	2	3	4	5	6	7	8	9
2011Jun	20.57%	-0.82%	19.31%	0.11%	-0.27%	-0.69%	32.86%	0.16%	28.77%
2011Jul	23.27%	-0.23%	23.62%	0.38%	-0.44%	0.21%	29.90%	0.16%	23.14%
2011Aug	2.53%	1.67%	32.07%	16.69%	7.40%	3.54%	18.38%	8.62%	9.10%
2011Sep	1.44%	1.39%	22.10%	21.01%	13.06%	3.28%	15.45%	15.76%	6.51%
2011Oct	1.94%	1.62%	14.82%	19.48%	18.24%	3.35%	19.31%	15.99%	5.26%
2011Nov	2.99%	1.47%	16.13%	17.22%	16.55%	2.97%	20.18%	18.36%	4.13%
2011Dec	10.30%	0.85%	13.45%	11.24%	14.80%	3.16%	22.28%	19.49%	4.43%
2012Jan	12.74%	0.77%	7.70%	6.87%	14.77%	3.90%	26.66%	21.70%	4.90%
2012Feb	21.07%	0.13%	3.89%	4.05%	9.49%	4.09%	34.37%	17.26%	5.64%
2012Mar	32.78%	-0.35%	3.34%	1.30%	4.38%	3.91%	35.01%	13.18%	6.47%
2012Apr	16.80%	0.42%	5.90%	5.45%	7.70%	4.67%	40.61%	12.09%	6.36%
2012May	18.73%	1.52%	3.48%	9.72%	11.83%	3.86%	35.79%	11.05%	4.03%
2012Jun	21.06%	1.81%	10.02%	8.00%	10.50%	2.83%	32.43%	10.24%	3.11%
2012Jul	30.85%	0.31%	13.74%	2.03%	8.29%	1.82%	33.26%	6.98%	2.74%
2012Aug	37.43%	0.17%	8.72%	1.01%	9.92%	1.27%	37.31%	1.44%	2.73%
2012Sep	38.65%	0.22%	0.99%	0.36%	10.66%	1.01%	45.28%	0.19%	2.64%
2012Oct	48.10%	-0.14%	0.77%	-0.04%	5.75%	0.72%	42.72%	0.13%	1.97%
2012Nov	51.92%	-0.69%	1.07%	-0.27%	1.41%	0.55%	43.70%	0.19%	2.12%
2012Dec	49.37%	-0.30%	0.13%	-0.39%	0.28%	0.44%	47.94%	0.17%	2.36%
2013Jan	43.82%	-0.29%	0.10%	-0.10%	0.01%	0.37%	52.46%	0.03%	3.60%
2013Feb	36.77%	-0.24%	0.18%	-0.30%	-0.02%	0.31%	58.56%	0.05%	4.68%
2013Mar	35.91%	-1.00%	0.10%	-0.23%	-0.63%	0.44%	56.48%	0.15%	8.78%
2013Apr	31.19%	-0.40%	0.63%	-0.65%	-0.30%	0.81%	58.70%	0.33%	9.70%
2013May	36.13%	-0.92%	0.08%	-0.33%	-0.81%	0.38%	54.45%	0.12%	10.89%
2013Jun	23.63%	-0.53%	0.20%	-2.47%	-0.75%	0.19%	63.48%	-0.01%	16.26%

Table C3: Liquidity Risk Contribution. Equity Europe - Covid 19 Crisis

ID Cluster	1	2	3	4	5	6	7	8	9
2020Jan	27.24%	-0.57%	0.15%	1.10%	-0.11%	-0.74%	16.55%	32.29%	24.09%
2020Feb	0.63%	-0.59%	0.43%	31.31%	9.78%	-0.08%	19.83%	21.63%	17.07%
2020Mar	-0.10%	15.51%	8.28%	35.34%	36.18%	0.11%	1.19%	4.60%	-1.11%
2020Apr	-0.42%	8.38%	5.05%	32.66%	31.69%	-0.04%	0.01%	22.49%	0.17%
2020May	-1.34%	7.28%	2.57%	31.85%	33.28%	-0.12%	-0.06%	26.76%	-0.22%
2020Jun	-0.71%	3.60%	1.17%	38.26%	36.95%	-0.32%	-0.11%	21.87%	-0.71%
2020Jul	-20.97%	1.76%	0.19%	56.57%	61.73%	-0.35%	-0.19%	2.78%	-1.50%
2020Aug	-22.85%	1.53%	0.31%	65.18%	59.19%	-0.76%	-0.27%	0.30%	-2.64%
2020Sep	-16.47%	1.32%	0.13%	69.42%	47.38%	-0.72%	-0.31%	0.22%	-0.98%
2020Oct	-16.24%	0.66%	0.04%	70.59%	46.96%	-1.13%	-0.33%	0.15%	-0.69%
2020Nov	-4.46%	2.05%	0.00%	53.76%	49.86%	-0.77%	-0.31%	0.12%	-0.25%
2020Dec	-15.47%	0.54%	-0.07%	55.45%	61.47%	-1.25%	-0.40%	0.07%	-0.34%
2021Jan	-12.12%	0.37%	-0.19%	59.82%	54.04%	-0.86%	-0.78%	0.04%	-0.33%
2021Feb	-16.21%	0.13%	-0.16%	71.55%	47.59%	-0.86%	-1.01%	0.01%	-1.03%
2021Mar	-15.54%	0.00%	-0.21%	68.10%	54.05%	-0.63%	-2.46%	-0.01%	-3.29%
2021Apr	22.38%	-0.24%	-0.08%	45.45%	43.92%	-3.69%	-3.79%	-0.61%	-3.34%
2021May	-15.45%	-0.50%	-0.62%	77.61%	54.90%	-1.98%	-8.06%	-0.16%	-5.73%
2021Jun	72.70%	-0.53%	-0.08%	18.12%	11.78%	-0.86%	-0.42%	-0.43%	-0.28%

Table C4: Liquidity Risk Contribution. Long Term Italian Government Bond - Sovereign Debt Crisis

ID Cluster	1	2	3	4	5	6	7	8
2011Jan	0.62%	-	-	36.13%	3.05%	-5.09%	15.81%	49.48%
2011Feb	0.22%	-	-	43.35%	2.30%	-2.56%	5.28%	51.41%
2011Mar	-1.41%	-	-	29.64%	-1.74%	22.40%	0.99%	50.12%
2011Apr	-1.67%	-	-	17.80%	-2.85%	34.70%	-0.16%	52.18%
2011May	-1.38%	-	-	17.16%	-2.27%	36.92%	-0.75%	50.33%
2011Jun	-0.87%	-	-	29.02%	-1.07%	31.67%	-0.50%	41.75%
2011Jul	-10.09%	-	-	51.44%	3.56%	21.08%	0.27%	33.74%
2011Aug	12.68%	-	-	38.83%	4.71%	19.09%	5.05%	19.64%
2011Sep	19.86%	-	-	33.31%	4.44%	15.94%	14.08%	12.36%
2011Oct	22.04%	-	-	31.39%	4.20%	19.34%	14.68%	8.35%
2011Nov	22.21%	-	-	29.36%	4.17%	19.98%	18.56%	5.71%
2011Dec	23.39%	-	-	26.89%	5.06%	19.42%	20.69%	4.56%
2012Jan	23.41%	-	-	27.22%	6.02%	19.97%	19.27%	4.11%
2012Feb	23.48%	-	-	27.28%	6.98%	23.31%	15.18%	3.78%
2012Mar	28.08%	-	-	26.32%	8.38%	21.92%	11.84%	3.46%
2012Apr	30.70%	-	-	27.76%	7.57%	22.69%	8.22%	3.05%
2012May	29.76%	-	-	29.54%	8.13%	22.77%	7.51%	2.29%
2012Jun	30.67%	-	-	30.07%	7.24%	22.71%	7.59%	1.72%
2012Jul	30.20%	-	-	30.52%	7.79%	24.20%	6.00%	1.28%
2012Aug	23.86%	-	19.22%	25.12%	6.83%	23.01%	0.97%	0.99%
2012Sep	24.69%	-	19.65%	21.44%	7.47%	25.75%	0.12%	0.88%
2012Oct	25.45%	-	19.92%	19.27%	8.45%	26.32%	0.11%	0.48%
2012Nov	25.29%	-	19.63%	18.95%	9.51%	26.14%	0.19%	0.30%
2012Dec	27.43%	-	18.82%	9.83%	10.22%	33.24%	0.26%	0.19%
2013Jan	26.78%	-	16.11%	5.42%	11.53%	39.63%	0.06%	0.47%

Table C5: Liquidity Risk Contribution. Long Term Italian Government Bond - 2018 Crisis

ID Cluster	1	2	3	4	5	6	7	8
2018Jun	27.41%	24.37%	20.66%	16.88%	0.32%	2.76%	2.80%	4.80%
2018Jul	26.41%	24.77%	19.23%	16.78%	0.29%	2.79%	2.57%	7.17%
2018Aug	24.18%	20.64%	22.19%	18.37%	0.33%	3.67%	2.04%	8.57%
2018Sep	24.68%	18.84%	21.21%	18.66%	0.05%	4.69%	1.73%	10.15%
2018Oct	18.56%	19.79%	23.17%	21.05%	0.01%	5.81%	1.44%	10.18%
2018Nov	13.42%	20.64%	23.30%	21.87%	-0.05%	7.51%	1.77%	11.53%
2018Dec	16.58%	20.17%	23.37%	18.82%	-0.09%	7.32%	2.11%	11.72%
2019Jan	4.25%	21.03%	26.41%	20.51%	-0.28%	9.33%	2.99%	15.76%
2019Feb	2.49%	18.14%	27.81%	23.91%	-0.42%	7.88%	3.71%	16.49%
2019Mar	2.06%	13.93%	29.63%	23.52%	-0.10%	12.19%	4.58%	14.20%
2019Apr	1.86%	5.45%	25.59%	25.90%	-0.33%	19.19%	7.04%	15.30%
2019May	4.62%	1.37%	26.05%	27.40%	-0.25%	19.70%	6.44%	14.67%
2019Jun	10.16%	2.09%	24.34%	21.74%	-0.06%	14.50%	6.44%	20.79%
2019Jul	25.95%	13.31%	19.27%	5.55%	-0.08%	11.46%	9.70%	14.83%

Table C6: Liquidity Risk Contribution. Short Term Euro Government Bond - Energy and Inflation Crisis

ID Cluster	1	2	3	4	5	6	7	8
2021Oct	6.35%	12.40%	0.09%	4.77%	0.22%	77.17%	-0.71%	-0.29%
2021Nov	8.54%	12.83%	0.31%	3.76%	0.26%	65.34%	9.11%	-0.15%
2021Dec	7.43%	12.50%	-0.17%	1.99%	0.17%	71.53%	8.54%	-1.99%
2022Jan	5.48%	-0.33%	-1.50%	-0.21%	0.47%	76.03%	13.75%	6.31%
2022Feb	8.91%	-0.19%	-0.70%	1.08%	3.21%	65.19%	21.58%	0.91%
2022Mar	10.66%	0.53%	3.52%	3.82%	6.73%	17.07%	58.36%	-0.70%
2022Apr	11.40%	2.24%	7.91%	4.33%	20.39%	5.57%	49.76%	-1.60%
2022May	10.24%	3.86%	10.33%	4.31%	35.92%	1.98%	34.01%	-0.65%
2022Jun	7.10%	4.44%	21.86%	2.26%	27.61%	6.15%	22.13%	8.46%
2022Jul	6.72%	5.87%	21.31%	1.44%	22.96%	7.91%	19.61%	14.19%
2022Aug	6.06%	9.50%	20.41%	1.11%	20.55%	9.35%	17.85%	15.18%
2022Sep	6.75%	8.27%	19.92%	0.95%	19.73%	11.47%	16.81%	16.10%
2022Oct	8.41%	5.43%	20.02%	1.06%	19.78%	12.68%	15.72%	16.89%
2022Nov	8.85%	7.93%	19.22%	1.20%	18.85%	12.10%	15.45%	16.41%
2022Dec	10.28%	12.43%	17.65%	4.99%	17.35%	10.53%	12.18%	14.58%
2023Jan	12.73%	0.08%	19.76%	8.97%	19.55%	8.71%	13.22%	16.97%

Table C7: Liquidity Risk Contribution. Equity US - Global Financial Crisis

ID Cluster	1	2	3	4	5	6	7	8	9
2007Jun	-8.58%	20.84%	12.47%	-1.01%	-0.45%	38.82%	-4.05%	-0.07%	42.03%
2007Jul	-10.51%	10.41%	23.10%	-0.45%	0.04%	42.33%	-1.27%	1.36%	34.99%
2007Aug	-5.96%	12.26%	17.90%	13.95%	8.27%	32.08%	7.08%	19.29%	-4.86%
2007Sep	-9.97%	5.04%	16.25%	9.99%	12.54%	32.55%	8.58%	31.43%	-6.41%
2007Oct	-9.16%	3.60%	14.58%	5.16%	13.99%	37.53%	10.87%	28.86%	-5.43%
2007Nov	-2.87%	6.20%	17.40%	14.23%	8.28%	31.02%	8.53%	21.66%	-4.44%
2007Dec	-7.09%	5.57%	17.98%	6.43%	10.33%	32.84%	7.82%	27.68%	-1.56%
2008Jan	-3.38%	14.22%	22.82%	11.52%	10.35%	21.94%	6.06%	14.93%	1.54%
2008Feb	-3.34%	20.93%	21.71%	10.91%	10.26%	16.96%	5.51%	14.77%	2.29%
2008Mar	-1.87%	14.55%	20.96%	12.37%	10.43%	19.87%	6.34%	16.05%	1.30%
2008Apr	-4.24%	6.16%	17.73%	6.25%	15.14%	23.47%	8.97%	24.60%	1.92%
2008May	-6.34%	11.32%	22.61%	3.15%	12.91%	18.50%	10.14%	23.25%	4.46%
2008Jun	-3.73%	6.34%	17.21%	7.38%	10.80%	17.13%	17.16%	24.34%	3.38%
2008Jul	-2.30%	11.27%	15.74%	8.00%	7.20%	19.36%	16.27%	21.86%	2.61%
2008Aug	-13.64%	13.76%	19.80%	4.27%	11.04%	19.40%	16.95%	23.73%	4.69%
2008Sep	-0.53%	13.49%	16.76%	9.52%	10.85%	20.04%	7.08%	20.92%	1.86%
2008Oct	-1.97%	8.24%	18.22%	14.05%	15.15%	16.37%	10.32%	19.38%	0.24%
2008Nov	-1.33%	2.07%	18.45%	16.82%	17.99%	16.77%	9.84%	19.73%	-0.34%
2008Dec	-3.27%	12.91%	17.96%	15.08%	17.38%	15.03%	7.35%	17.70%	-0.16%
2009Jan	-3.22%	13.89%	18.43%	15.49%	18.31%	11.81%	8.15%	17.45%	-0.31%
2009Feb	-2.94%	13.33%	17.68%	17.56%	17.92%	9.35%	10.63%	17.40%	-0.93%
2009Mar	-2.45%	15.23%	17.49%	16.06%	15.71%	10.21%	11.16%	17.48%	-0.89%
2009Apr	-4.78%	18.04%	17.89%	16.53%	17.81%	10.17%	8.11%	17.00%	-0.78%
2009May	-9.02%	5.39%	26.97%	19.44%	22.62%	10.70%	9.13%	15.59%	-0.83%
2009Jun	-6.81%	2.71%	26.32%	18.85%	22.89%	9.27%	13.84%	14.06%	-1.12%
2009Jul	-11.61%	5.38%	28.65%	21.29%	20.45%	7.06%	17.54%	13.39%	-2.14%

Table C8: Liquidity Risk Contribution. Equity US - Covid 19 Crisis

ID Cluster	1	2	3	4	5	6	7	8	9
2020Feb	-1.27%	28.31%	0.04%	40.52%	13.36%	-0.03%	13.28%	2.92%	2.88%
2020Mar	-0.18%	16.66%	3.09%	22.60%	24.83%	7.94%	5.98%	19.03%	0.05%
2020Apr	-0.34%	17.24%	5.26%	19.29%	21.24%	10.95%	7.74%	18.63%	-0.01%
2020May	-0.96%	22.36%	5.60%	23.48%	25.13%	1.30%	11.82%	11.32%	-0.04%
2020Jun	-1.06%	24.43%	5.60%	24.96%	24.53%	0.03%	16.55%	5.04%	-0.09%
2020Jul	-1.59%	25.36%	4.34%	24.67%	24.19%	-0.01%	20.74%	2.46%	-0.17%
2020Aug	-3.50%	28.16%	3.29%	25.07%	21.99%	-0.07%	23.86%	1.48%	-0.27%
2020Sep	-1.11%	30.21%	5.86%	26.94%	15.92%	-0.05%	21.64%	0.79%	-0.20%
2020Oct	-4.00%	32.13%	4.68%	27.46%	17.28%	-0.07%	22.63%	0.20%	-0.31%
2020Nov	-2.24%	31.48%	2.93%	24.16%	21.12%	-0.16%	22.83%	0.05%	-0.17%
2020Dec	-5.57%	33.66%	1.23%	25.16%	21.24%	-0.62%	25.44%	-0.07%	-0.48%
2021Jan	-1.97%	35.01%	1.98%	31.74%	16.20%	-0.55%	18.19%	-0.21%	-0.39%
2021Feb	-7.28%	42.94%	1.21%	37.40%	16.29%	-1.32%	11.20%	-0.14%	-0.31%

Table C9: Liquidity Risk Contribution. Bond Corporate Investment Grage USD - 2018 Crisis

ID Cluster	1	2	3	4	5	6	7
2017Nov	-1.10%	0.22%	7.53%	18.71%	31.14%	0.05%	43.45%
2017Dec	-0.68%	0.13%	26.79%	14.57%	16.81%	23.36%	19.02%
2018Jan	-0.68%	0.58%	29.89%	8.68%	19.07%	24.95%	17.51%
2018Feb	-0.77%	1.17%	20.28%	4.92%	32.20%	23.16%	19.03%
2018Mar	-0.36%	0.87%	27.62%	4.34%	23.47%	26.06%	17.99%
2018Apr	-0.28%	0.38%	30.15%	3.70%	22.78%	24.59%	18.69%
2018May	-0.34%	-0.10%	23.83%	2.92%	26.54%	24.55%	22.60%
2018Jun	-0.24%	-0.42%	22.46%	2.58%	28.13%	24.08%	23.43%
2018Jul	-0.13%	-0.55%	19.90%	2.52%	29.22%	22.42%	26.63%
2018Aug	-0.17%	-0.44%	11.47%	2.79%	32.62%	18.89%	34.85%
2018Sep	-0.20%	-0.25%	4.89%	3.10%	41.76%	12.16%	38.54%
2018Oct	-0.21%	-0.66%	3.58%	3.44%	42.25%	12.35%	39.26%
2018Nov	-2.54%	-0.17%	12.51%	2.54%	34.80%	19.13%	33.74%
2018Dec	-2.92%	-0.16%	18.22%	4.91%	29.67%	23.54%	26.75%
2019Jan	-4.23%	-0.19%	16.96%	8.33%	28.55%	22.59%	27.98%
2019Feb	-3.60%	-0.97%	8.56%	12.12%	30.29%	19.60%	34.00%
2019Mar	-2.47%	-2.17%	1.30%	10.23%	35.41%	13.35%	44.35%

Table C10: Liquidity Risk Contribution. Bond Corporate Investment Grade USD - Covid 19 Crisis

ID Cluster	1	2	3	4	5	6	7
2020Jan	14.04%	40.68%	11.76%	20.75%	-0.24%	16.97%	-3.95%
2020Feb	21.65%	28.56%	0.18%	49.61%	-0.45%	5.69%	-5.24%
2020Mar	6.37%	23.77%	33.07%	7.06%	-2.11%	31.87%	-0.04%
2020Apr	18.69%	25.82%	24.67%	8.52%	-1.29%	23.71%	-0.10%
2020May	32.27%	36.09%	2.87%	15.60%	-0.24%	13.58%	-0.17%
2020Jun	34.37%	36.34%	0.07%	23.88%	-0.16%	5.76%	-0.26%
2020Jul	32.94%	35.10%	0.01%	30.10%	-0.18%	2.45%	-0.43%
2020Aug	33.95%	35.60%	-0.06%	30.23%	-0.19%	1.01%	-0.54%
2020Sep	34.82%	34.84%	-0.06%	30.90%	-0.42%	0.32%	-0.40%
2020Oct	33.78%	34.74%	-0.09%	32.92%	-0.68%	-0.08%	-0.59%
2020Nov	29.97%	35.80%	-0.23%	35.24%	-0.23%	-0.21%	-0.34%
2020Dec	33.67%	36.19%	-0.73%	32.73%	-0.26%	-0.80%	-0.80%
2021Jan	38.64%	41.57%	-0.63%	22.50%	-0.57%	-0.88%	-0.63%
2021Feb	46.98%	41.30%	-1.83%	16.98%	-2.29%	-0.52%	-0.63%
2021Mar	39.55%	61.93%	-2.24%	8.34%	-3.93%	-0.42%	-3.24%
2021Apr	42.60%	69.68%	-3.01%	2.01%	-4.25%	-0.16%	-6.87%
2021May	43.09%	70.64%	-1.03%	0.59%	-4.56%	-0.21%	-8.52%
2021Jun	61.40%	56.54%	-0.37%	2.22%	-6.41%	-0.32%	-13.07%

Table C11: Liquidity Risk Contribution. Short Term US Goverment Bond - Energy and Inflation Crisis

ID Cluster	1	2	3	4	5	6	7
2021Oct	2.67%	69.82%	3.54%	-4.18%	0.77%	23.46%	3.92%
2021Nov	-0.03%	42.22%	3.94%	-3.47%	2.09%	53.66%	1.59%
2021Dec	-0.75%	63.56%	2.90%	-2.53%	2.07%	34.02%	0.73%
2022Jan	-0.84%	32.41%	1.94%	-6.33%	2.46%	68.54%	1.82%
2022Feb	1.13%	59.91%	1.42%	-3.70%	6.48%	30.99%	3.76%
2022Mar	5.25%	23.84%	20.81%	-2.05%	33.74%	11.85%	6.56%
2022Apr	6.27%	21.68%	11.29%	-0.70%	37.33%	17.78%	6.34%
2022May	6.84%	28.02%	5.46%	0.16%	33.28%	19.89%	6.34%
2022Jun	8.68%	28.12%	1.78%	0.42%	33.29%	17.08%	10.62%
2022Jul	11.96%	23.46%	5.42%	-0.14%	24.77%	13.29%	21.24%
2022Aug	21.23%	23.95%	3.31%	-0.66%	7.37%	13.06%	31.75%
2022Sep	22.61%	15.86%	5.23%	-0.37%	21.44%	9.08%	26.15%
2022Oct	23.96%	13.79%	10.90%	-0.45%	16.19%	9.02%	26.59%
2022Nov	22.00%	17.46%	6.12%	-0.39%	16.17%	13.85%	24.79%
2022Dec	23.51%	18.20%	2.85%	-0.46%	14.33%	16.03%	25.54%
2023Jan	25.61%	20.00%	2.63%	-1.03%	4.73%	18.81%	29.24%

Note: The table reports the contribution for each asset class of the $g-th$ cluster reported Table 1 of the raw liquidity, credit and monetary variables, as explained in Equation (5).