

## ADEMU WORKING PAPER SERIES

# The real effects of Liquidity Shocks in Sovereign Debt Markets: Evidence from Italy

Andrea Gazzani<sup>†</sup>

Alejandro Vicondoa<sup>‡</sup>

June 2016

WP 2016/014

[www.ademu-project.eu/publications/working-papers](http://www.ademu-project.eu/publications/working-papers)

### Abstract

This paper provides the first empirical evidence on the macroeconomic effects of liquidity shocks in secondary sovereign debt markets. We consider the Italian case in a VAR analysis by applying different identification strategies: recursive ordering and Proxy-SVAR. Our findings suggest that liquidity is a major driver for indicators of economic activity. A shock to the Bid-Ask Spread induces a strong (15% of the Forecast Error Variance) and persistent (10 months) effect on unemployment and indicators of confidence. Liquidity shocks are transmitted to the real economy through changes in the lending behaviors of banks. On the one hand, an exogenous fall in liquidity induces a tightening of banks standards, particularly due to the asset and liquidity position of commercial banks. On the other hand, firms report worse credit conditions in terms of higher costs apart from the interest rate. Similar macroeconomic implications hold for Spain, whereas liquidity shocks are not a significant driver for France and Germany.

---

<sup>†</sup> Department of Economics, European University Institute. Email: [andrea.gazzani@eui.eu](mailto:andrea.gazzani@eui.eu)

<sup>‡</sup> Department of Economics, European University Institute. Email: [alejandro.vicondoa@eui.eu](mailto:alejandro.vicondoa@eui.eu)

**Keywords:** Liquidity, Sovereign Debt, Proxy-SVAR, Financial Shocks, Macrofinancial linkages

Jel codes: E44

## Acknowledgments

We are grateful to our advisor Evi Pappa and Fabio Canova for fruitful discussions and suggestions. We also thank Agustin Benetrix, Wei Cui, Juan Dolado, Charles Engel, Yuriy Gorodnichenko, Peter Hansen, Juan Pablo Nicolini, Soren Radde, Kenneth West, and seminar participants at the European Central Bank, European University Institute, and ADEMU Workshop on "Macroeconomic and Financial Imbalances and Spillovers" for useful comments. This project is related to the research agenda of the ADEMU project, "A Dynamic Economic and Monetary Union". ADEMU is funded by the European Union's Horizon 2020 Program under grant agreement N° 649396 (ADEMU).

---

The ADEMU Working Paper Series is being supported by the European Commission Horizon 2020 European Union funding for Research & Innovation, grant agreement No 649396.

This is an Open Access article distributed under the terms of the Creative Commons Attribution License Creative Commons Attribution 4.0 International, which permits unrestricted use, distribution and reproduction in any medium provided that the original work is properly attributed.



# 1 Introduction

The sovereign debt crisis has dramatically affected European countries since 2010. Southern European countries like Greece, Italy, Portugal and Spain (GIPS) have been facing increasing unemployment rates and worsening credit conditions for governments, households and firms. Both the media and economic researchers have focused on the behavior of spreads in yields and credit default swaps (CDS), which are supposed to reflect default risk. However, sovereign bonds are very demanded for their liquidity properties that have also fluctuated during the crisis.

In this paper, we examine liquidity, understood as the ease in releasing an asset quickly without incurring in additional costs, as a different but complementary dimension of financial tensions.<sup>1</sup> Government bonds are the most liquid assets in the economy, after money itself. European banks hold large amounts of these assets in their portfolio due to their historical low default risk and liquidity risk. Abrupt changes in the liquidity of sovereign bonds could affect the lending decisions of banks.<sup>2</sup>

This is the first empirical investigation on the macroeconomic effects of exogenous changes in liquidity in sovereign debt markets, which we call *liquidity shocks*. The Euro crisis constitutes an ideal laboratory for such analysis because indicators of liquidity and default risk display different patterns that can be used for identification. Figure 1 shows the evolution of the *Bid-Ask Spread* (BAS), CDS and yield for Italy, which accounts for 26% of European sovereign debt, between 2004 and 2014.<sup>3</sup> While during 2007-2011 the yield and BAS move in opposite directions, between 2011-2012 both of them increase. Moreover, the CDS displays a different dynamic with respect to the other variables. Considering the fluctuations in Italian business cycle during this period, we identify the effects and transmission channels of liquidity shocks. We base our analysis on Vector Autoregression models (VAR) and our identification strategy relies both on the standard recursive ordering and on the Proxy-SVAR. The latter uses exogenous changes in liquidity identified in a financial daily VAR as an instrument for structural liquidity shocks.

Liquidity, as we show, has been a major driver for the Italian economy during the sovereign debt crisis. The Forecast Error Variance (FEV) decomposition shows that liquidity shocks explain a relevant share of the volatility of unemployment (15%) and confidence indicators like consumer confidence, business confidence and stock prices. A BAS shock generates macroeconomic effects that are at least as strong as the effects generated by a raise in yield spreads.<sup>4</sup> The *Bank Lending Survey* and the *ISTAT Business Confidence Survey* reveal that liquidity shocks affect the lending

---

<sup>1</sup>Notice that we refer to market liquidity, opposed to funding liquidity.

<sup>2</sup>We measure liquidity using the *Bid-Ask Spread* (BAS), the traditional indicator of liquidity. We also build an alternative indicator which takes into account the volumes traded in secondary markets.

<sup>3</sup>European sovereign debt markets are concentrated with Italy and France accounting for roughly 50% of the total public debt. Source: European Central Bank Statistics. Italy: 26.4%, France 22.7%, and Germany 18.3%. The three variables are expressed as monthly averages.

<sup>4</sup>The joint contribution of BAS and yield spread shocks to the FEV of unemployment is 20% across 2004-2014 (15% + 5% respectively) and raises up to 30% aver 2009-2014 (15% + 15% respectively).

behavior of banks due to problems in their asset and liquidity positions. Shocks to sovereign yield spreads do not generate worse lending conditions through the same channels. Our findings are particularly relevant to improve the understanding of the relationship between real economy and financial markets.

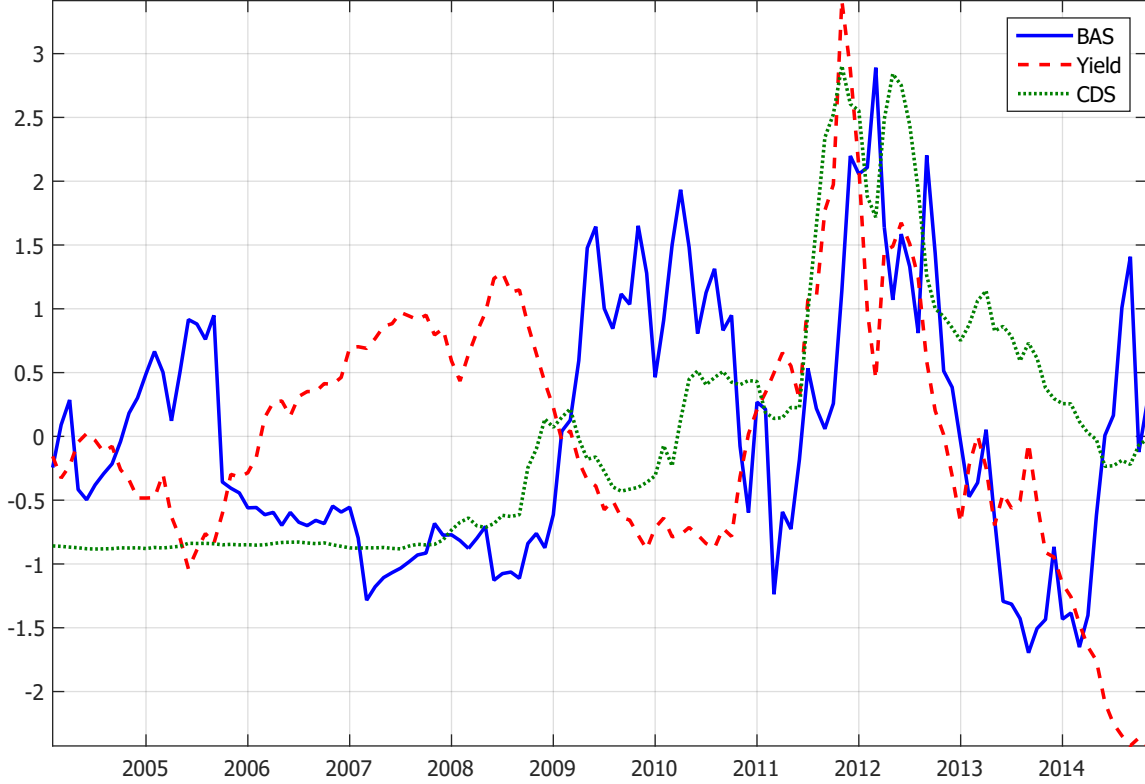


Figure 1: Italian (standardized) BAS, CDS and Yield (monthly average)  
*Each variable corresponds to the first principal components of 2, 5, 10 years bond maturities. Source: Bloomberg (BAS) and Banca d'Italia.*

Our empirical results can be interpreted using the theoretical framework developed by [Cui and Radde \(2015\)](#). They build a real DSGE model with search and matching frictions in asset markets, where the financial sector intermediates between buyers and sellers of financial assets. In this framework, an exogenous increase in financial intermediation costs affects the market participation of buyers more than the one of sellers and induces a fall in the liquidity of financial assets. Market liquidity produces relevant implications for the real economy by tightening the financial constraints of firms and reducing their financing possibilities.<sup>5</sup> [Cui and Radde \(2015\)](#) mainly focus on private assets since, in the U.S., sovereign bonds did not experience a fall in liquidity during the crisis. On the contrary, as [1](#) displays, in the European (Italian) case, the liquidity of sovereign

<sup>5</sup>Notice that, contrary to the outstanding literature, they are able to generate the comovement between asset turnover and asset prices.

bonds has fluctuated significantly.<sup>6</sup> Moreover, their setup can accommodate both market-based and bank-based financial intermediation, with the latter characterizing European economies. Our empirical findings and their theoretical results are consistent in terms of: fall in output, fall in consumption and investment (proxied by business and consumer confidence indicators), turnover (i.e. traded volume relative the outstanding amount of the asset), and asset prices. The only (qualitative) difference consists in their responses being starker than our IRFs because they rely on a model without nominal frictions. In a similar setup to [Cui and Radde \(2015\)](#), [Cui \(2016\)](#) studies monetary and fiscal interactions with market liquidity, and draw conclusions on optimal policies by considering government debt as provider of liquidity services.

Further works have also studied liquidity in a theoretical framework. [Del Negro, Eggertsson, Ferrero, and Kiyotaki \(2011\)](#) and [Benigno and Nistico \(2014\)](#) study the effects of shocks to an exogenous liquidity constraint, which restricts the fraction of an asset which can be used to purchase goods. While [Del Negro, Eggertsson, Ferrero, and Kiyotaki \(2011\)](#) impose this constraint on the fraction of equity holdings that a household can resale, [Benigno and Nistico \(2014\)](#) restrict the fraction of government bonds that can be exchanged for goods. Unlike [Cui and Radde \(2015\)](#), these papers do not endogenize the dynamics of asset liquidity. Both papers conclude that liquidity shocks (i.e a decrease in the release fraction of these assets) produce strong and negative effects on GDP and prices, which in both cases are partially explained by a fall in private consumption. These results differ from our empirical findings since we do not find that liquidity shocks induce a significant effect on CPI inflation. [Passadore and Xu \(2014\)](#) investigate how liquidity risk and credit risk explain sovereign spread through the optimal behavior of buyers and sellers. In an endowment economy with incomplete markets and search and matching frictions in the sovereign debt markets, they find that the liquidity component can explain up to 50% of sovereign spread during the Argentinian crisis in 2001. Although the model matches the correlations and standard deviations of consumption and net exports, they do not consider the effects on output. Overall, we contribute to this literature by characterizing the empirical effects of liquidity shocks and by identifying its transmission through the banking sector. In light of our empirical findings and of the existing models, we believe that financial intermediation and search frictions are a key feature to be taken into account when studying liquidity.

This paper is also related to the strand of the literature that analyzes the macroeconomic effects of shocks to the spread in yields. [Bahaj \(2014\)](#) and [Neri and Ropele \(2015\)](#) study the macroeconomic effects of yield shocks and find that they explain a relevant fraction of business cycle fluctuations in European countries. However, they do not consider sovereign debt liquidity in their analysis and this omitted dimension could affect their conclusions. Regarding the transmission channels, tensions in sovereign debt markets induce a tightening in credit conditions through an increase in the funding

---

<sup>6</sup>Notice that we have also found similar macroeconomic results for the liquidity of corporate bonds and for the spread in liquidity between corporate and sovereign bonds. Nonetheless, in all the specifications, shocks to the liquidity of sovereign bonds produce relevant macroeconomic effects.

costs of banks (De Marco (2016)) or through the Repo market (Boissel, Derrien, Ors, and Thesmar (2014) and Mancini, Ranaldo, and Wrampelmeyer (2014)). In this paper, we show that liquidity shocks have strong macroeconomic effects and identify its transmission through the banking sector. We find that liquidity is at least as relevant as spread in yields to explain fluctuations in economic activity in Italy and Spain and that commercial banks respond to liquidity shocks in a different way than to a yield shock.

The remainder of this paper is organized as follows. Section 2 describes the high frequency variables that characterize Italian sovereign debt market. Section 3 presents the empirical specification and results using different identification schemes. Section 4 investigates the transmission channels by exploiting survey data. Section 5 compares the Italian results to France, Germany and Spain. Finally, Section 6 concludes.

## 2 Data Description

Sovereign debt markets can be characterized by different indicators: Spread in Yields (Spread), Credit Default Swaps (CDS), and Bid-Ask Spread (BAS). The first one captures the difference in yields that a country has to pay in order to issue sovereign debt with respect to a safe asset, which in this case is the German sovereign bond with the same maturity. CDS is a proxy for credit risk. Finally, the third is a widely-used indicator of sovereign debt liquidity (see for example Pericoli and Taboga (2015) and Pelizzon, Subrahmanyam, Tomio, and Umo (2015)).<sup>7</sup> These variables enable us to characterize the sovereign debt markets. For our analysis, we use data from Italy for the period February 2004 until November 2014. The Italian sovereign debt market is one of the most important in Europe, accounting for 26% of the European government debt.<sup>8</sup> Before proceeding to the analysis, we describe briefly the relationship between the three indicators. Table 2 displays the daily correlation between these variables, both in levels and growth rates.<sup>9</sup>

Levels	BAS	Spread	CDS	Growth Rates	BAS	Spread	CDS
BAS	1	0.24***	0.36***	BAS	1	-0.03	-0.03
Spread	0.24***	1	0.91***	Spread	-0.03	1	0.23
CDS	0.36***	0.91***	1	CDS	-0.03	0.23***	1

Table 1: Contemporaneous correlation between financial variables  
*Contemporaneous daily correlation between Italian financial variables at daily frequency: BAS, Spread, CDS. All the variables correspond to 2 years maturity. Left-panel in levels, right-panel in growth rates. \*\*\*, \*\*, \* denote 99%, 95% and 90% confidence intervals.*

<sup>7</sup>Alternatively, people also look at the volume traded or at a combination of both. Figure A1 in Appendix B displays the evolution of the volume traded together with the BAS. We use the BAS for our empirical analysis and present the results using the *Liquidity Index*, which incorporates both BAS and Turnover, in Appendix E.1.

<sup>8</sup>Source: European Central Bank Statistics.

<sup>9</sup>The daily correlations correspond to trading (business) days only.

CDS is highly correlated (0.91) with the Spread while the BAS displays a relative low correlation with the other two variables. This fact also holds if we consider the variables in daily growth rates instead of in levels. In particular, the daily changes of the BAS are uncorrelated with the other financial variables while CDS and Spread are positively correlated. From this preliminary description, we can see that movements in Spread are more associated with credit risk (proxied by the CDS) than liquidity risk, a similar finding to [Pericoli and Taboga \(2015\)](#).<sup>10</sup> However, these variables maybe correlated with other financial ones like stock prices, interest rates or the equity implied volatility from options. Figure 2 displays the evolution of these financial variables at daily frequency.<sup>11</sup>

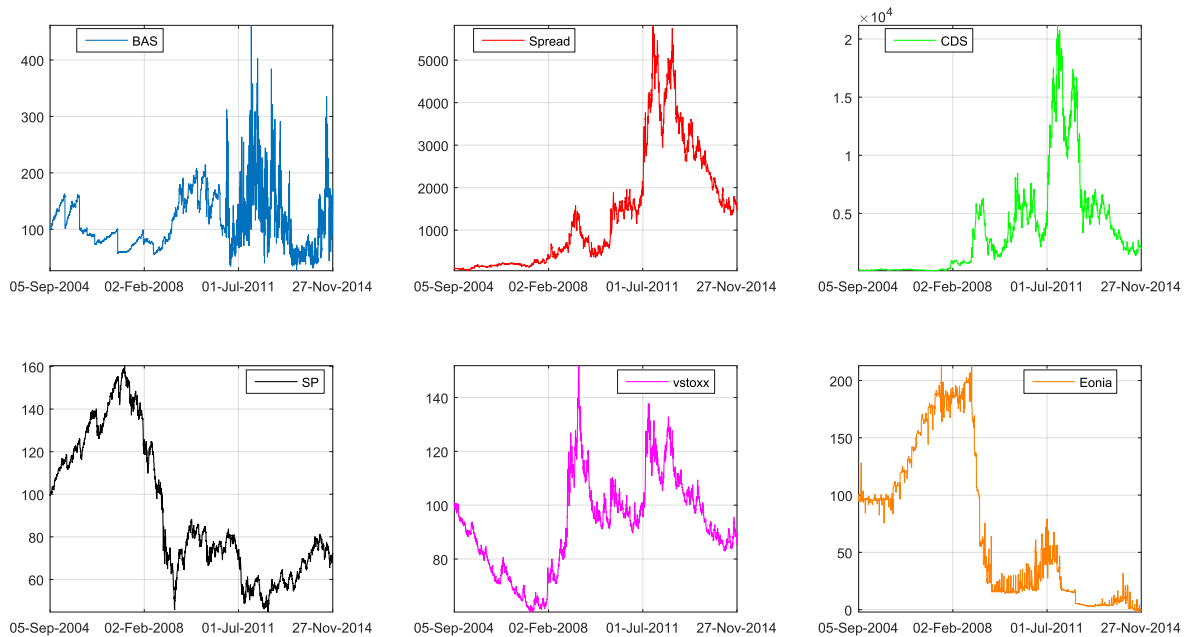


Figure 2: Daily dynamics of the main financial variables

*Financial variables: BAS Italy, Spread Italy, CDS Italy, FTSE MIB (main Italian Stock Price index), Vstoxx (European Implied Volatility Index), Euro Overnight Index Average (Eonia). All variables are expressed in levels for all the business days since September 2004 to November 2014. All variables but the Spread are expressed as an index=100 at the beginning of the sample. Spread is computed as the difference between German and Italian yields and expressed in basis points times 10.*

The peaks in the VSTOXX index reflect the two main periods of financial stress: the second part of 2008, associated with the collapse of Lehman Brothers, and between the second half of 2011

<sup>10</sup>Notice that there is still no **consensus** in the finance literature. For example, [Schwarz \(2014\)](#) highlights, through a novel measure of liquidity, that liquidity risk explains a large share of the raising yields during the Euro crisis. [Beber, Brandt, and Kavajecz \(2009\)](#) show that, during period of market stress, investors chase liquidity and not credit quality.

<sup>11</sup>We use the European Volatility Index (VSTOXX) instead of the one based on FTSE MIB index because it is available for the whole period and it is representative also for the Italian economy. Both indexes are highly correlated for the period when they coincide.

and 2012, related to problems in the European Sovereign Debt markets.<sup>12</sup> These periods of stress are reflected in a different way for each financial variable. On the one hand, the Italian stock price index (FTSE MIB) falls with these two events and recover afterwards, without reaching the peak of 2007. The response of the Eonia rate is similar and reflects the interest rate decisions of the ECB and interbank market stress. On the other hand, financial variables associated with sovereign debt markets display different dynamics. The BAS spikes in 2009 and exhibits an abrupt change in volatility after January 14, 2011, when Fitch agency downgraded Greek sovereign debt to junk status.<sup>13</sup> The dynamics of CDS and Spread are similar during 2012, in line with the correlations reported in Table 2, but the Spread declines at a lower pace after the spikes than the CDS. During 2014, we observe some spikes in the BAS whereas Spread and CDS decline steadily. The key point for identification is that the six financial variables display different patterns.

Since in this paper we are going to focus on shocks to BAS, we analyze whether fluctuations in this variable are associated with particular European events. This analysis enables to us to understand better the underlying dynamics of this variable and its sources of variation. Figure 2 displays the dynamics of the BAS together with some key events related to the European Sovereign debt crisis, which are reported in Table 1A included in the Appendix A.

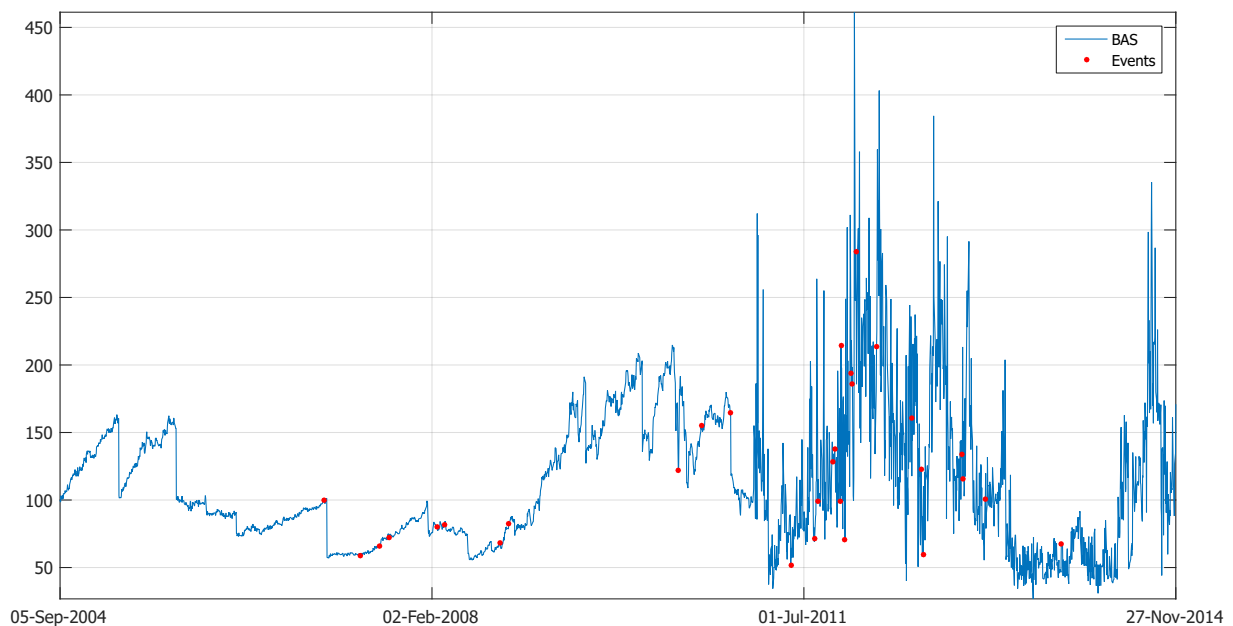


Figure 3: Daily BAS and key European events  
*Daily BAS Italy 2 Years (blue line) and key European events (red dots). Appendix A displays the list of all the events.*

First of all, as we mentioned before, the series displays a clear change in volatility after January

<sup>12</sup>In fact, the decline in the implied volatility happens after the famous speech of Mario Draghi, president of the ECB, on July 26 2012.

<sup>13</sup>This fact holds for Spain only a few days later.



14 2011. After that date, many events related to Portugal, Spain, Greece, and Italy are reflected as spikes in this variable. Additionally, other European events coincide with BAS local maxima or local minima. In particular, the BAS reached a minimum, comparable to pre-crisis levels, when Mario Draghi stated the “Whatever it takes to save the Euro”. Liquidity in the Italian sovereign debt market reflects important economic news, which is key for identification because many of those events can be considered as exogenous with respect to the Italian economy.

### 3 Empirical Analysis

To analyze the effects of liquidity shocks we rely on different VAR specifications. In Section 3.1, we estimate a small scale VAR used to identify the effects of liquidity shocks. Then, we use an enlarged VAR for a better identification of the shocks and to characterize in higher detail the results and the transmission mechanisms (Section 3.2). Both specifications rely on the Cholesky decomposition to identify liquidity shocks. Given that imposing zero contemporaneous restrictions on some financial variables can be controversial, in Section 3.3 we employ a more agnostic identification strategy, the Proxy-SVAR, which places no restrictions on the timing or sign of the responses. Finally, in Section 3.4 we present extensions and additional exercises to further investigate liquidity and assess the robustness of our findings.

#### 3.1 Basic Specification

(In this section) As a first step, we estimate the effect of BAS shocks on Italian business cycles using a small scale VAR. In particular, we specify a VAR that includes the *Unemployment Rate*, as a proxy for economic activity; *Consumer Price Inflation* expressed as an annual rate, to capture price dynamics; *FTSE MIB*, which is the main index of Stock Prices in Italy; *Sovereign Spread*; and *BAS*. While the first two variables are useful to capture the transmission to the real economy, the last three are necessary to identify a liquidity shock. Our sample runs from February 2004 through November 2014. To deal with the different frequencies, we include the financial variables as monthly averages in order to capture all the dynamics during the period.<sup>14</sup> Following Sims, Stock, and Watson (1990), we estimate the model in (log-)levels by OLS, without explicitly modeling the possible cointegration relations among them.<sup>15</sup> In addition to a constant, we also include a deterministic trend. The lag order is selected following the three information criteria and it is always one.<sup>16</sup>

We identify a liquidity shock using a standard Cholesky decomposition, which is based on

---

<sup>14</sup>Table C1 included in the Appendix contains a summary statistic of the main financial variables aggregated at monthly frequency. All the variables are either seasonally adjusted or we adjust them using the Census X-13.

<sup>15</sup>Sims, Stock, and Watson (1990) show that if cointegration among the variables exists, the system’s dynamics can be consistently estimated in a VAR in levels.

<sup>16</sup>We check that the residuals are normally distributed and they do not exhibit autocorrelation.

recursive ordering. The variables are ordered in the VAR from the most exogenous to the most endogenous ones, which are allowed to respond contemporaneously to all structural shocks. Thus, we order Unemployment and Inflation, assuming that they cannot react to the shock on the same month. A severe problem arises from the three financial variables that our VAR incorporates. Obviously, they always react to all the available information and so there is no convincing way of ordering them. Considering this issue, we take a more agnostic stance. Within the financial block, we consider all the possible orderings and we report the median and percentiles of the impulse responses and FEV. In this way, we identify 6 rotations and, for each of those, we compute 100 bootstrap replications. Figure 4 displays the Impulse Response Functions (IRFs) to a one standard deviation BAS shock (i.e. a decrease in liquidity). We report the median together with 68% and 90% confidence bands that include both the identification (from the different Cholesky orderings) and statistical uncertainty.

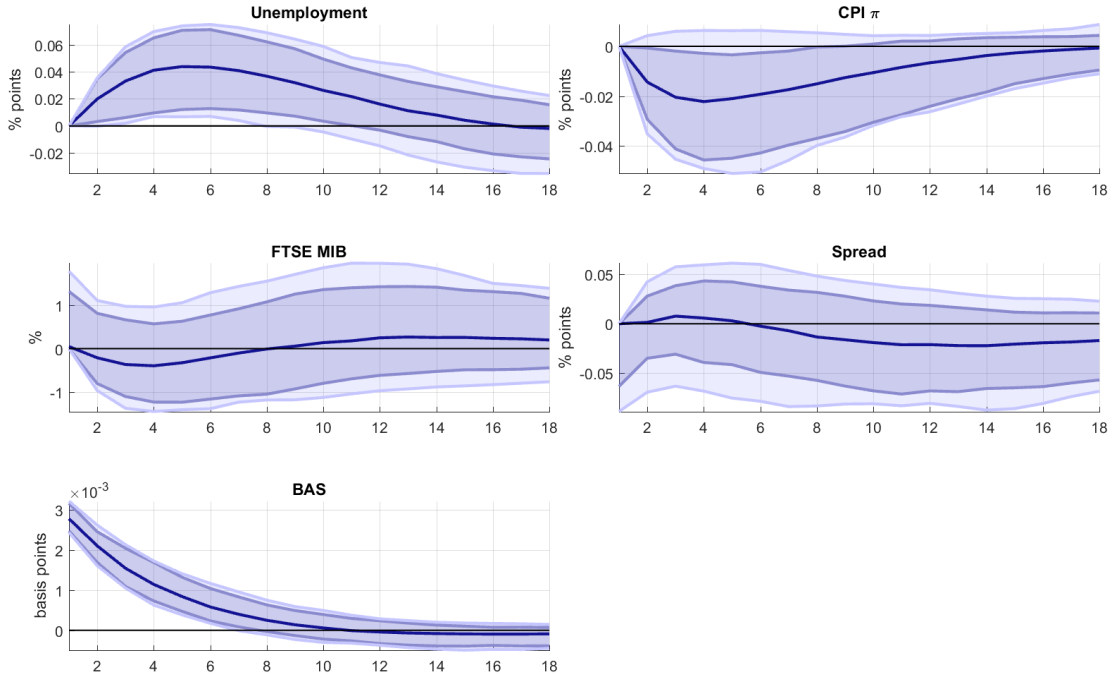


Figure 4: IRF to a BAS shock

*IRFs to a 1 std BAS shock (liquidity deterioration) identified through the following ordering [Unemployment,  $\pi$ , FTSE, Spread, BAS]. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).*

An increase in the BAS induces an increase in Unemployment which lasts 10 months and a slight decrease in CPI inflation. However, the remaining financial variables do not react to the BAS shock. Similar results hold if we estimate the same VAR using the pre-2009 and the crisis

sample.<sup>17</sup> Thus, shocks to the BAS have strong effects on economic activity. In order to understand the channels behind this relationship and to see whether results are robust, in the next section we consider a large scale VAR.

### 3.2 Full Specification

We aim at assessing the macroeconomic effects of BAS shocks, with special emphasis on the comparison with other financial shocks. For this purpose, we enlarge the previous VAR system with other variables. This system features six macroeconomic variables (Unemployment, CPI Inflation, Public Debt, ECB Repo, Italian M2<sup>18</sup>, Consumer and Business Confidence) plus five financial indicators (stock prices, Spread, CDS, BAS and VSTOXX). This set of variables is necessary to identify financial shocks and assess their transmission to the real economy.<sup>19</sup> Like in Section 3.1, we identify the liquidity shock through recursive ordering. In particular, we assume that macroeconomic variables cannot react contemporaneously to the financial shocks and we order them as follows: [UNEMPLOYMENT, CPI, PUBLIC DEBT, M2, CONSUMER CONFIDENCE, BUSINESS CONFIDENCE].

Again, within the financial block, we consider all the possible orderings (120 rotations), compute five bootstrap replications for each of them and report the median and percentiles of the impulse responses and FEV. Different possible orderings across the financial block lead to very similar results, which means that the covariance matrix of the reduced form residuals is close to a diagonal matrix (i.e. the order of financial variables is not dramatically affecting our results).

Figure 3.2 displays the IRFs to a one standard deviation BAS shock, where 68% and 90% confidence bands include both the identification (from the different Cholesky orderings) and statistical uncertainty. The illiquidity shock induces an increase in unemployment that reaches its maximum after four months without a significant effect on inflation, comparable to the findings of the VAR presented in Section 3.1. The stock of government debt falls with a lag whereas there is no reaction in the Repo rate and M2. Both business and consumer confidence indicators decline in response to the shock and reach their trough four months after the shock. The response of confidence is strong across all the specifications and could reflect a fall both in current and future consumption, which may help to explain the strong response of unemployment (Ludvigson (2004)). Moreover, these dynamics are consistent with the findings of Garcia and Gimeno (2014) for flight-to-liquidity episodes. The Forecast Error Variance (FEV) contributions of BAS for consumer confidence, business confidence and stock prices are respectively 15%, 9% and 7% one year after the shock. Moving to the financial block, the equity premium, CDS and spread increase and the FTSE declines by 1%, all of them with a lag. Responses of financial variables are in line expected movements: a decrease in the BAS, which could be interpreted as an increase in the uncertainty regarding the value of the underlying

<sup>17</sup>For ease of exposition, we present these results in the Appendix.

<sup>18</sup>Same results hold employing Italian M3.

<sup>19</sup>As in Section 3.1, we estimate the VAR in (log) levels by OLS. The optimal number of lags is one.

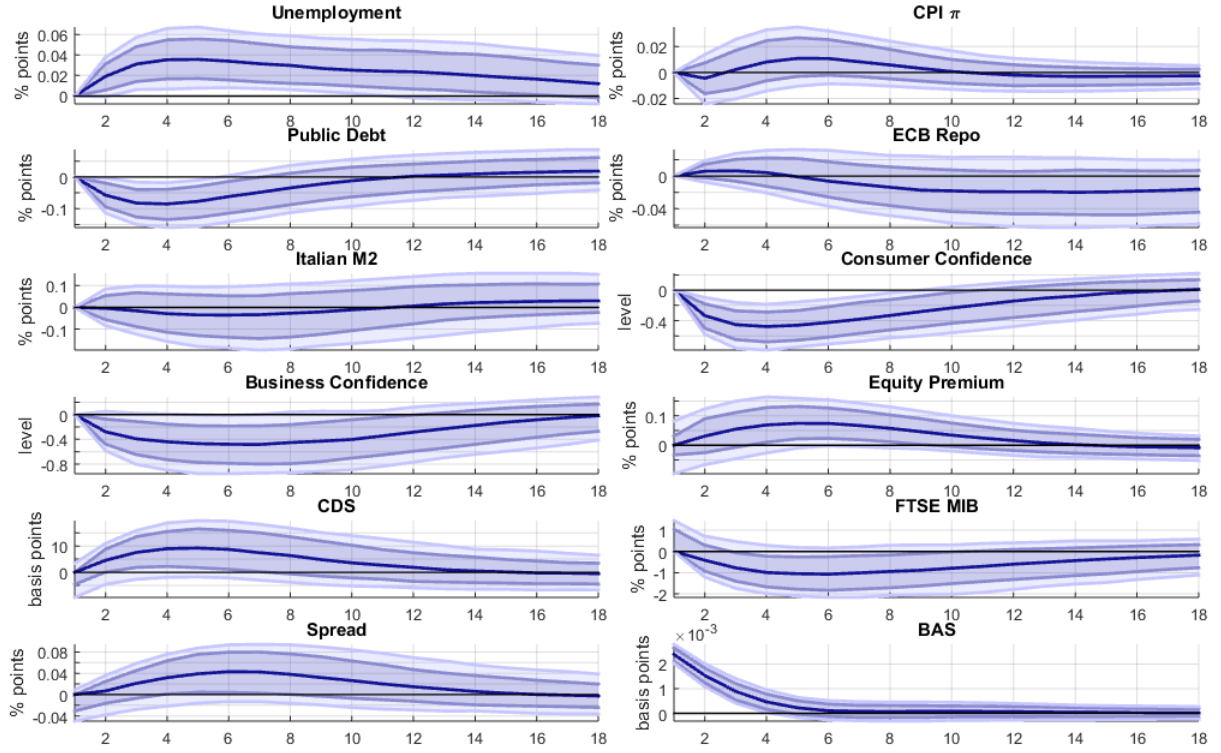


Figure 5: IRF to a BAS shock

IRFs to a 1 std deviation BAS shock (liquidity deterioration) identified through the following ordering [Unemployment,  $\pi$ , Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

asset, reduces prices (i.e. increases the Yield), confidence, and stock prices and increases volatility and CDS.

A key point in our analysis, in light of the outstanding literature on the Euro Crisis, consists of the comparison between BAS (Figure 3.2) and Spread shocks (Figure 3.2). The Spread shock induces a similar effect on unemployment slightly less persistent and significant. However, this shock has a negative effect on CPI inflation, which declines by 0.04% points 2 months after the shock. Even if the response of CPI inflation is different with respect to a BAS shock, in Section 3.3 we show that, by using the Proxy-SVAR, the IRF of CPI to a BAS shock is also negative.<sup>20</sup> Notice that this difference comes from the years 2004-2009 as we display in Figure A2.<sup>21</sup> Unlike in the previous case, consumer confidence and business confidence do not display a significant reaction. Regarding the financial block, the responses are similar in magnitude (even if less significant) but less lagged than the case of a BAS shock. An increase in Spread induces a delayed raise in BAS.

<sup>20</sup>As we show later on, CPI is the only variable whose dynamics changes across the two methodologies.

<sup>21</sup>The response of Spread is robust for the sub-sample 2009-2014.

While the effects on unemployment are similar to the ones reported by [Neri and Ropele \(2015\)](#) using a similar sample, the ones on inflation are the opposite from theirs. This could be explained by the fact that we consider liquidity both for identification and transmission of the shock.

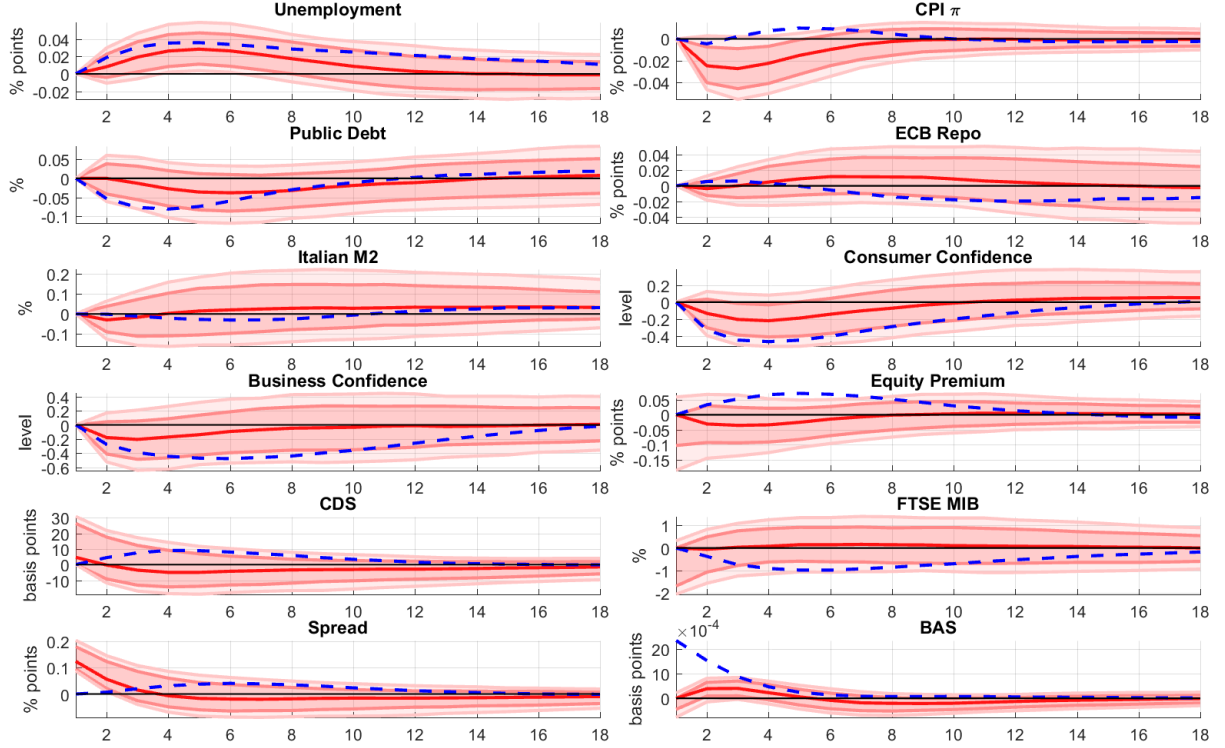


Figure 6: IRF to a Spread shock

IRFs to a 1 std deviation Spread shock identified through the following ordering [Unemployment,  $\pi$ , Public Debt,  $R$ , M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in red and light red, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block). Dotted line denotes the mean response to a 1 std deviation shock to BAS.

For a more comprehensive comparison among financial shocks, in Figure 3.2 we report the FEV decomposition of unemployment (i.e. how much each financial shock explains of unemployment's volatility). BAS shocks explain approximately 15% of unemployment fluctuations at two years horizon. The second largest shock in relevance is the stock prices, accounting for 7%. The remaining financial shocks do not explain a significant fraction of fluctuations in unemployment. All in all, exogenous fluctuations in financial variables explain around 30% of the total variability of unemployment. From this analysis, we can conclude that liquidity is a major driver of unemployment, out of all the financial variables, for the period under analysis.<sup>22</sup>

<sup>22</sup>The relative contribution of each financial shock changes if we consider the sub-sample 2009-2014 (Figure A3 in Appendix E). In this case, the contribution of spread is similar to the one of BAS, which is quantitatively stable over the full sample.

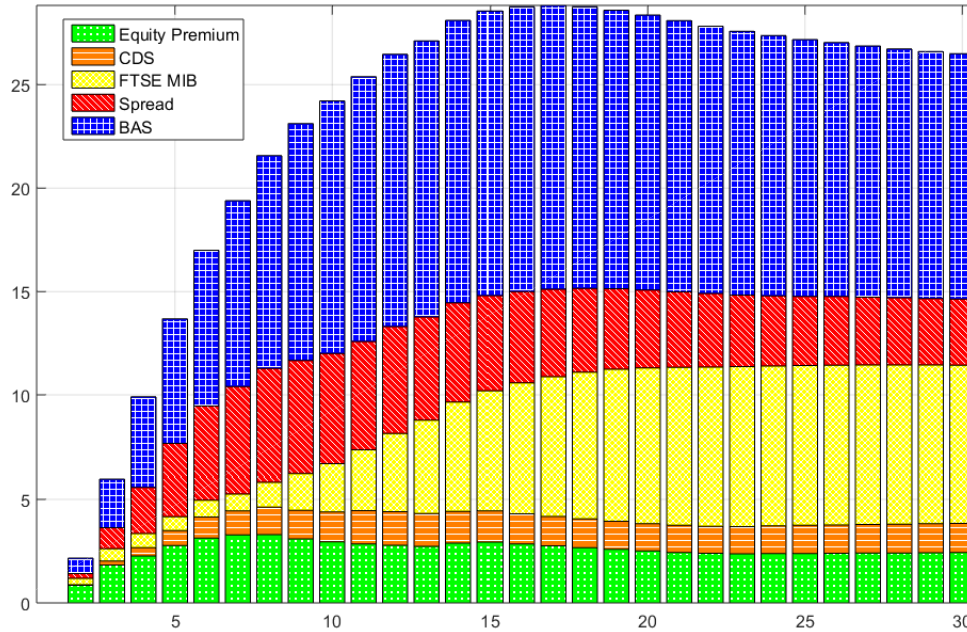


Figure 7: FEV of Unemployment  
FEV of Unemployment in the VAR [Unemployment,  $\pi$ , Public Debt,  $R$ ,  $M2$ ,  $CC$ ,  $BC$ , Financial Block]. The bars denote the contribution of each financial shock in explaining the volatility of Unemployment at each horizon (expressed in months).

### 3.3 Proxy-SVAR

The results in previous section 3.2 are robust to the different Cholesky ordering. Still, in each rotation, we are constraining (some) financial variables not to react on impact to other financial shocks. In this section, we relax this assumption by applying the so called *Proxy-SVAR* identification developed by [Stock and Watson \(2012\)](#) and [Mertens and Ravn \(2013\)](#). The main idea is to use information external to the VAR system as a proxy for the structural shock of interest, the BAS shock in our case. In practice, the proxy constitutes an instrument for the reduced form residuals of the VAR and provides partial identification of the structural shocks. The instrument is assumed to be correlated with the structural shock of interest but not with the remaining ones. An advantage of this technique is that, as long as the proxy is a relevant and valid instrument, the identification relies on a much weaker set of assumptions than the recursive identification scheme.<sup>23</sup> In other words, no assumptions are made on the contemporaneous relationship among the variables in the system. Appendix D contains a detailed explanation of this methodology.

In order to obtain a valid instrument for BAS, we propose a new way to identify the proxy for the Proxy-SVAR at high frequency. We label this identification “*Bridge Proxy-SVAR*” because the Proxy-SVAR links two VAR systems that include data at different frequencies. In [Gazzani and](#)

<sup>23</sup>The proxy is not assumed to be perfectly correlated with the structural shock, but only to be a component of it.

Vicondoa (2016b), we illustrate analytically the properties of *Bridge Proxy-SVAR* the and test it via Monte Carlo simulations. The procedure consists of the following steps:

1. Construct two VARs systems. The first one is a VAR that incorporates daily financial variables relevant for the analysis, defined High Frequency VAR (HF-VAR). This VAR features  $[BAS, CDS, Yield, FTSE, Eonia, VIX]$ . The second one is a VAR, defined Low Frequency VAR (LF-VAR), that includes variables at monthly frequency. In particular, it is the same system that we define in Section 3.2. Again, the financial variables in the LF-VAR are included as monthly averages.
2. Estimate the HF-VAR and identify the structural shock of interest  $\varepsilon_{HF}^{BAS}$  with the most appropriate identification scheme. Given that economic theory does not support any sign restriction identification, we apply the recursive ordering Cholesky decomposition. Notice that the biases implied by Cholesky in the HF-VAR are much lighter than in the LF-VAR. Since we observe a structural break in the daily volatility of financial variables in 2009, we estimate a VAR at daily frequency to identify structural innovations in the BAS during the period 2009m1-2014m11 and we use them as an instrument for the structural BAS shocks at monthly frequency.
3. Aggregate  $\varepsilon_{HF}^{BAS}$  into monthly frequency obtaining  $\bar{\varepsilon}_{HF}^{BAS}$ .
4. Estimate the LF-VAR and apply the Proxy-SVAR identification, where  $\bar{\varepsilon}_{HF}^{BAS}$  is employed as a proxy for the structural shock of interest in the LF-VAR  $\varepsilon_{LF}^{BAS}$ . Namely, the reduced form residual  $u_{LF}^{BAS}$  is instrumented with  $\bar{\varepsilon}_{HF}^{BAS}$ . Again, the underlying assumptions concern the relevance,  $corr(\bar{\varepsilon}_{HF}^{BAS}, \varepsilon_{LF}^{BAS}) \neq 0$ , and the validity,  $corr(\bar{\varepsilon}_{HF}^{BAS}, \varepsilon_{LF}^j) = 0 \quad \forall j \neq BAS$ , of the instrument.

This proxy explains a significant fraction of BAS reduced form residuals from the monthly VAR. The statistics of the first stage are  $F\text{-stat} = 29.465$  and  $R^2 = 0.30231$ , which satisfies the requirements of a strong instrument suggested by Stock and Yogo (2002). This means that a relevant fraction of the reduced form residuals are explained by the daily shocks to the BAS.<sup>24</sup> Figure 7 reports the IRFs to an instrumented shock to the BAS. The BAS shock induces a significant and persistent effect on unemployment, very similar both quantitatively and qualitatively to the ones described in Section 3.2. Unlike with the recursive ordering, CPI inflation decreases by 0.02% after the shock. As displayed in Figure A2, this difference is not due to the methodology but to the shorter sample used. The remaining variables in the macroeconomic block display a comparable reaction to the recursive ordering case. In particular, the BAS shock generates a strong response in the indicators of confidence. All the financial variables display a significant lagged response, except for Equity Premium that reacts on impact.

---

<sup>24</sup>Figure 8 in Appendix D includes a figure with the first stage results.



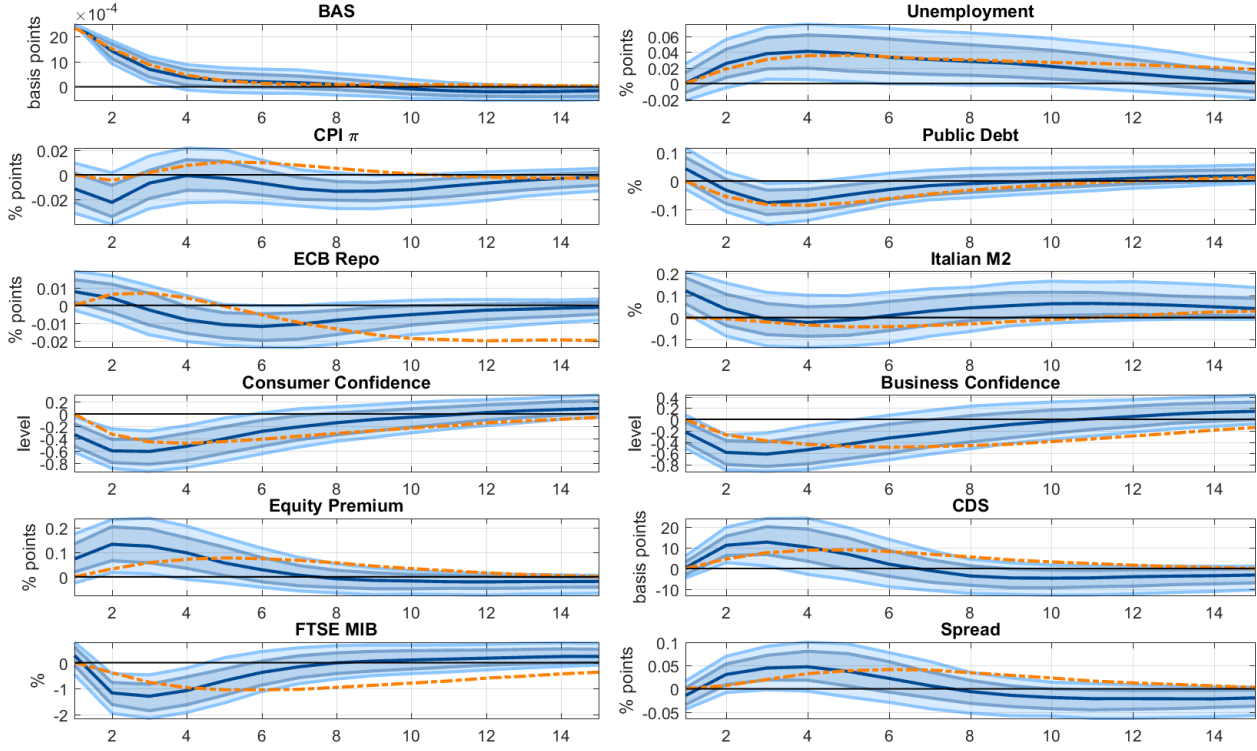


Figure 8: IRF to a BAS shock

IRFs to a 1 standard deviation BAS shock (liquidity deterioration) in the VAR [Unemployment,  $\pi$ , Public Debt,  $R$ , M2, CC, BC, Financial Block]. The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Jan:2009-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications.

Dotted lines denote the mean responses of each variable to a 1 standard deviation BAS shock identified via recursive ordering.

Even if the Proxy-SVAR relies on a weaker set of assumptions, we include it only as an alternative because this approach just reaches partial identification. This implies that we cannot explicitly compare liquidity and spread shocks. Nonetheless, the results from Proxy-SVAR confirm the validity of the recursive ordering identification previously applied, that is the standard methodology. Notice that, with the Proxy-SVAR, even without imposing any contemporaneous restriction, financial variables do not display a significant response on impact (apart from the Equity Premium). However, under this methodology, we can still compute the historical contribution of liquidity shocks to unemployment, which help us to assess the relevance of these shocks during the recent crisis. In fact, Figure 3.3 provides the historical interpretation of our results by displaying the component of unemployment explained by the BAS. In the upper panel, unemployment is expressed in deviation from the trend whereas, in the lower one, at the business cycle frequency.

The BAS explains the initial increase of unemployment, with respect to its trend, in 2010 and 2013 and also the reduction observed in 2014. Finally, it is also relevant to explain the increase



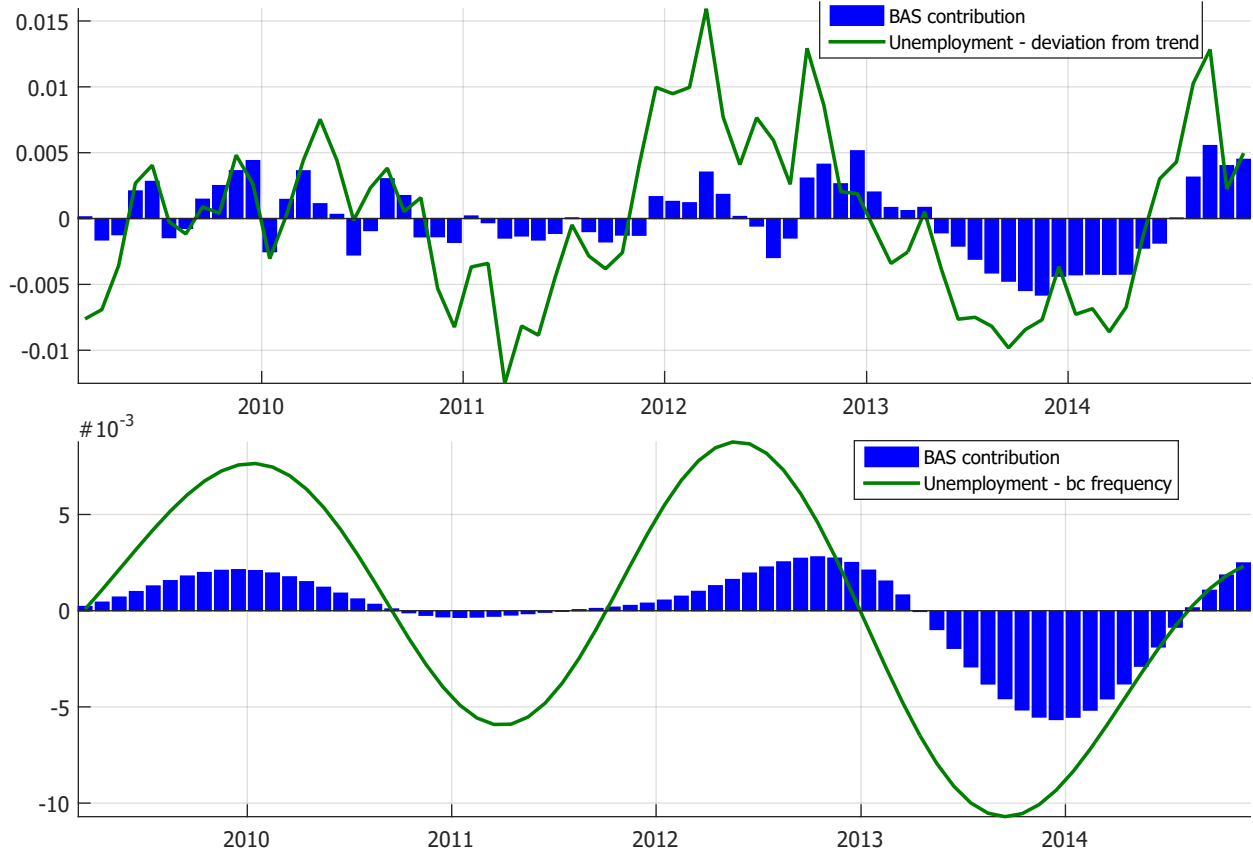


Figure 9: Historical Contribution of BAS to Unemployment  
*Historical contribution of BAS to Unemployment. Identified in the VAR [Unemployment,  $\pi$ , Public Debt, R, M2, CC, BC, Financial Block] through the unpredictable variation of the BAS in a daily VAR system. Upper panel - Unemployment in deviation from trend. Lower panel - Unemployment at the business cycle frequency (18 to 96 months).*

observed during the last stage of 2014. Similar conclusions hold if we look the contribution at business cycle frequencies.

Our findings, which are robust across the two different identification strategies, suggest that liquidity shocks have significant effects on unemployment. These results also hold if we consider industrial production and the *ITA-coin*.<sup>25</sup> A question that may arise naturally is why this peculiar financial variable, not even on the focus of media's attention, has so strong real effects. First, we find that all the measures of confidence decline significantly in response to the decrease in liquidity. This could point to a decrease in aggregate demand that explains the decrease in economic activity (Ludvigson (2004)). Second, in Section 4, we show that commercial banks change their lending conditions in response to liquidity shocks.

<sup>25</sup>Appendix E displays the IRFs using each indicator.

### 3.4 Alternative VAR Specifications

Shocks to the BAS are a major driver of unemployment for the period under analysis. In this subsection, we consider additional specifications to assess the validity of previous findings. For the ease of exposition, the IRFs of the exercises performed in this section are presented in the Appendix E.

#### 3.4.1 Indicator of Liquidity

The BAS is one of the most popular indicators of liquidity. However, it captures only the price dimension of liquidity while another relevant feature is the quantity side. A fall in liquidity equally distributed across price and quantities would generate an increase in the BAS and a fall in the quantity traded. In order to explore whether this relationship holds in our analysis, we estimate the Full VAR including the Turnover, volume traded normalized by the stock of the outstanding asset, as an additional variable in the system. While responses of macroeconomic variables to a BAS shock remain unchanged, the turnover displays a significant reduction. This result conforms with the theoretical predictions of the model proposed by Cui and Radde (2015).

In order to explicitly take this double dimension of liquidity into account, we compute a liquidity index indicator that is defined as the ratio between the Turnover and the BAS.<sup>26</sup> Thus, when the liquidity index is higher (lower), the asset can be considered more (less) liquid. We estimate the same baseline VAR but replacing the BAS with the Liquidity Index. Both responses of variables in the system and the contribution of liquidity to explain fluctuations in unemployment remain unchanged.

#### 3.4.2 Measures of Economic Activity

All the results presented so far rely on Unemployment as a proxy for economic activity. Alternatively, we estimate the VAR including Industrial Production and a Coincident Indicator of Economic Activity (*Indicatore Ciclico Coincidente (ITA-coin)*), a monthly indicator of economic activity published by the Bank of Italy.<sup>27</sup> Results are comparable with the ones using Unemployment.

#### 3.4.3 Different Samples

Figure 2 shows that financial variables display a change in volatility at daily frequency after 2009. Moreover, in the same window there is also a stark fall in interest rates that can constitute another source of structural break. To see whether this fact affects our findings, we estimate our baseline VAR for the sub-sample 2009-2014. The main results remain unchanged. To tackle the possibility

---

<sup>26</sup>The correct measure would employ the quantity bid and asked, but unfortunately we cannot access this data. Therefore, we use the actual number of trades (turnover on the secondary market) compiled by MTS.

<sup>27</sup>See <https://www.bancaditalia.it/statistiche/tematiche/indicatori/indicatore-ciclico-coincidente/> for more information about *ITA-coin*.

that our results are driven only by the Euro crisis, we run the same analysis in 3.1 over the sample 2004-2009. Once again, we find very similar results in this short sample.

#### 3.4.4 Corporate Liquidity

The finance literature that has reported sizable fluctuations of the market liquidity of corporate bonds in the U.S during the financial crisis (see Dick-Nielsen, Feldhutter, and Lando (2012)). Even if Italian firms rely more on banks as a source of finance, we analyze the interrelation between sovereign and corporate liquidity. For this aim, we use the BAS of a representative corporate bond and include it in the VAR instead of the Equity Premium.<sup>28</sup> A couple of interesting facts emerge. First, the effects of sovereign BAS shocks remain unchanged. Second, an exogenous increase in the private BAS generates a significant effect on Unemployment, which is comparable to the one induced by the sovereign BAS. Finally, an exogenous change in the private BAS does not affect significantly the sovereign BAS. These findings suggest that both BAS are relevant to explain economic activity. Finally, we also consider the BAS as a spread between the corporate and sovereign. A shock to this spread induces also sizable effects on economic activity.

#### 3.4.5 Market Stress Index

As we show in Figure 2, the BAS reflects some relevant European events, which may be regarded as periods of Market Stress. To assess potential omitted variable biases, we replace the Equity Premium with the *Composite Indicator of Systemic Stress* (computed by the ECB) in our VAR. IRFs are comparable with respect to the baseline specification. Thus, these results confirm that our results are not biased by omitting other measures of stress in financial markets.

#### 3.4.6 Financial Volatility

Financial variables display a time varying volatility at high frequency which is not reflected at monthly frequency. To control for these changes, we compute the monthly volatility of BAS, CDS and Spread using daily data. We build the first principal component that explains 78% of the variability of these three measures. Then, we include this index in the VAR instead of the Equity Premium. The IRFs and the FEV are unaffected. This suggests that previous findings are not driven by changes in volatility.

---

<sup>28</sup>We use the BAS of a bond issue by Telecom (*TELECOM ITALIA TITIM 5 3/8 01/19*) which is the longest series available. Moreover, it is highly correlated with the liquidity of the other bonds (e.g. 0,91 with Unicredit - *UCGIM 4 3/8 01/20* and 0,65 with ENI - *ENI INTERNATIONAL FINANCE ENIIM 5 1/27/19*. Source: Bloomberg.

## 4 Transmission Channels

The easiness of trading sovereign bonds is particularly relevant for Italian banks because they hold exceptional amounts of Italian sovereign debt. [Gennaioli, Martin, and Rossi \(2014\)](#) show that banks hold large amounts of public bonds due to their liquidity properties. The *European Stress Test* carried out in 2010 provides some insights on the amount of these assets held by the main Italian commercial banks: Banca Popolare, Intesa San Paolo, Monte dei Paschi, UBI Banca and Unicredit. Italian banks' holding of national securities accounts for 74% of their total government bond holdings. This share is even higher if we consider only the trading book: 84%.<sup>29</sup> Moreover, Italian sovereign bonds constitute 6.13% of the total assets owned by those five Italian banks ([Gennaioli, Martin, and Rossi \(2014\)](#)). In this Section, we assess whether and how changes in sovereign debt liquidity and spread affect banks' lending decisions using two official surveys. First, we employ the *ISTAT Business Confidence Survey*, which is carried out at monthly frequency. Second, we use the *Bank Lending Survey* from the Bank of Italy, which is available at quarterly frequency. Unlike statistics about total amount of loans that include both demand and supply effects, survey data allows us to disentangle more precisely the transmission channels.

### 4.1 ISTAT Business Confidence Survey

We employ data from the *ISTAT Business Confidence Survey* to assess the effects of liquidity and spread shocks on firms' credit conditions. This survey, which is carried out by ISTAT at a monthly frequency since March 2008, covers a representative sample of 4,000 firms in the manufacturing sector and includes information about firms' assessments and expectations on the Italian economic situation.<sup>30</sup> To assess how changes in sovereign debt liquidity and spread affect the credit market, we focus on questions regarding credit supply and demand and include them as an additional variable in our baseline VAR.<sup>31</sup> Given that the sample is shorter, we estimate the baseline VAR described in section 3.2 since August 2009, when all the variables are available, including one variable at the time to avoid losing degrees of freedom. In particular, we assume that credit decisions cannot react on impact to a financial shock and place these credit variables before the consumer confidence, business confidence and the financial block.<sup>32</sup> Figure 10 displays the IRF to a liquidity deterioration and a positive sovereign spread shock.

Liquidity and sovereign spread shocks have different effects on the credit market. On the one

---

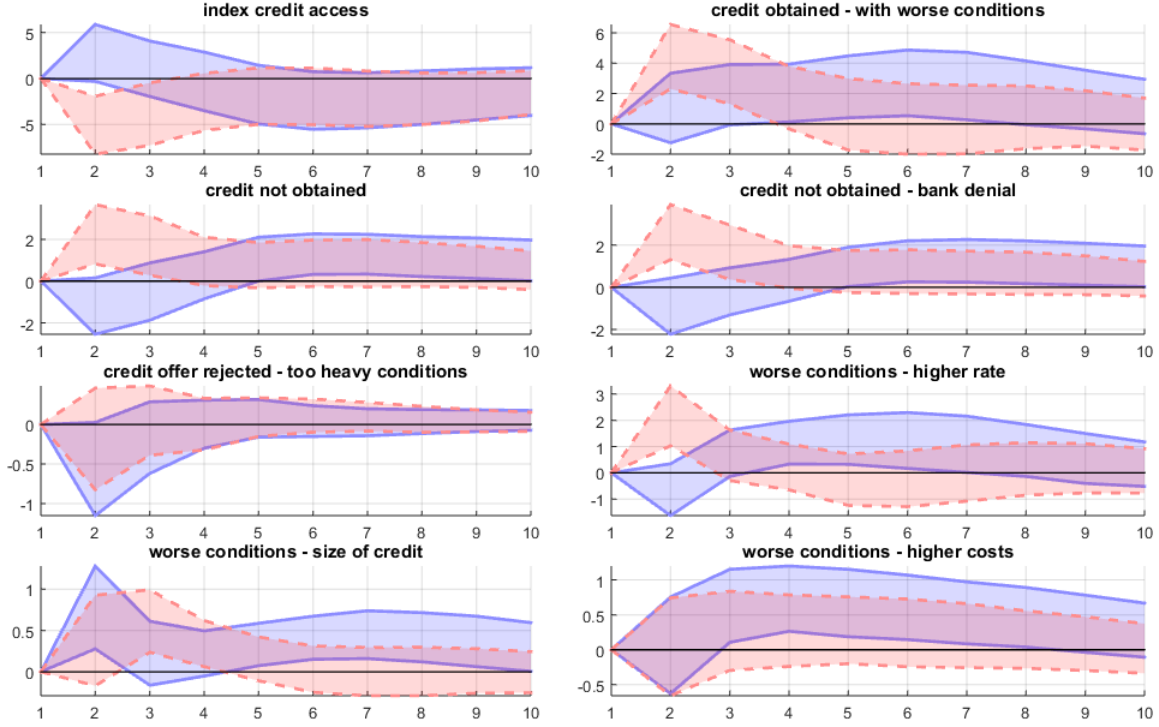
<sup>29</sup>For regulatory purposes, banks divide their activities into two main categories: banking and trading. The trading book was devised to house market-related assets rather than traditional banking activities. Trading book assets are supposed to be highly liquid and easy to trade.

<sup>30</sup>See <http://siqual.istat.it/SIQual/visualizza.do?id=8888945&refresh=true&language=UK> for a detailed description of this survey. There is an analogous survey for the service sector but the sample is shorter. However, results are similar to the ones reported in this section.

<sup>31</sup>The Data Appendix A contains the questions we consider from the ISTAT Business Confidence Survey.

<sup>32</sup>Results remain unchanged if we place this variable last in the VAR.

Figure 10: Changes in credit market conditions for manufacturing firms



NOTE. Changes in the credit market for manufacturing firms in response to a one standard positive BAS (blue) and sovereign spread (red) shocks. All figures denote change in the corresponding index reported by ISTAT. Blue and red areas denote the 68% confidence intervals computed using bootstrap and include both identification and statistical uncertainty.

hand, a BAS shock (i.e. a decrease of liquidity) does not change the index on perceived credit conditions but induces worse conditions in terms of interest rate, size of the credit, and costs other than the interest rate. Moreover, the BAS leads to an rise in the number of denied loans by banks with a lag. On the other hand, a spread shock immediately reduces the credit access and increases the number of denied loans by banks and a rise in the interest rate charged by banks. Notably, the reason why credit is not obtained by firms (*credit not obtained*) is not related with firms rejecting the loans offered by the banks (*credit not obtained - too heavy conditions*), but due to banks denying the loan (*credit not obtained - bank denial*). In other words, credit supply is driving the lower access to credit. While the spread shock affects mostly the interest rate and the size of the credit, a liquidity shock also induces higher costs (apart from the interest rate). These higher costs reflect higher commissions, extra-costs and tighter deadlines. For what concerns the timing, we observe a more lagged response to a liquidity shock than to a spread one. This is consistent with the delayed response of financial variables presented in Section 3.3.

After analyzing firm's survey responses, in the next subsection we assess whether these results are consistent with bank's replies. Additionally, we investigate the reasons that drive banks behavior.

## 4.2 Bank Lending Survey

We exploit the *Bank Lending Survey (BLS)* on Italian commercial banks to determine the effects of liquidity and spread shocks. This survey, which is carried out by *Banca d'Italia* in collaboration with the *European Central Bank* at quarterly frequency since January 2003, contains very detailed information about bank's decisions on different dimensions.<sup>33</sup> Unlike in the previous subsection, we cannot include the replies to the survey in the baseline VAR due to the differences in frequencies. For this reason, we aggregate the monthly BAS and spread shocks identified in section 3.2 to quarterly frequency and estimate the following equation:

$$\Delta BLS_t^i = \alpha + \sum_{j=1}^8 \delta_j \Delta BLS_{t-j}^i + \sum_{j=0}^{12} \beta_j shock_{t-j}^k \quad (1)$$

where  $\Delta BLS_t^i, shock_t^k$  denote the change in bank's behavior and quarterly BAS and spread shocks, respectively. We follow [Romer and Romer \(2004\)](#) and choose eight lags for the autoregressive part and twelve for the effect of the shock. Then, we compute the IRF to a BAS and spread shock for the main bank decisions available in the Survey (Figure 4.2).<sup>34</sup>

Banks increase their credit standards to firms in response to liquidity and spread shocks with a similar magnitude. However, the reasons for increasing standards differ. On the one hand, in response to a illiquidity shock, banks react due to issues with their own asset and liquidity position. On the other hand, banks do not report changes in the relevance of the asset and liquidity position in response to a spread shock. These differences in behavior suggest that banks increase their focus on their own balance sheet in case of a liquidity deterioration in sovereign debt markets. Moreover, banks adjust immediately their standards for mortgage loans while they do not change it for the case of spread shocks. Mortgages are collateralized loans and, in case of no repayment and liquidity problems, banks may not find it easy to release the house and that may explain why they increase their standards. Finally, both shocks are associated with an increase of similar magnitude in the perception of risk about economic activity.

With the evidence presented in Sections 3 and 4, we conclude that liquidity shocks have relevant real effects on the Italian economy and we document that transmission is through changes in the credit supply. In the next section, we analyze whether liquidity shocks are also relevant for the other three major Eurozone economies: Germany, France, and Spain.

## 5 Comparison with other European Countries

In order to assess whether liquidity shocks are also relevant drivers of the business cycle in other European economies, we perform the previous analysis also for Germany, France, and Spain. First,

---

<sup>33</sup>More information about this survey can be found at [BLS](#).

<sup>34</sup>The Data Appendix contains the detailed questions we consider from the Bank and Lending Survey.

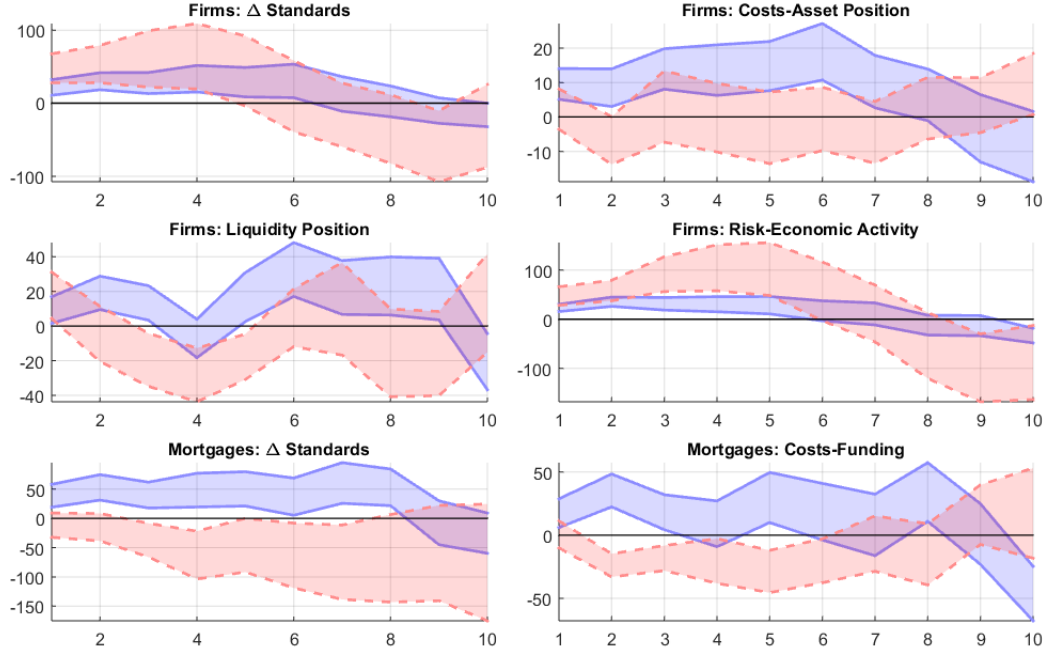


Figure 11: Change in banks lending decisions  
*Change in banks decisions in response to a positive shock in BAS and Spread. All the figures denote the change in the corresponding index as reported in the BLS. Blue and red areas denote the 90% confidence intervals computed using 500 bootstrap replications.*

in Table 5 we analyze if sovereign BAS are correlated across countries, which would indicate to what extent they are explained by common shocks. We observe that BASs are positively correlated across the biggest four Eurozone economies. While BAS for Germany seems to be less correlated with the rest of the countries, the correlation is stronger between France, Italy and Spain.

	Italy	Spain	France	Germany
Italy	1	0.49***	0.56***	0.24***
Spain	0.49***	1	0.69***	0.32***
France	0.56***	0.69***	1	0.42***
Germany	0.24***	0.32***	0.42***	1

Table 2: Daily correlation of European BAS  
*Daily correlations of 2 year sovereign BAS across countries (source: Bloomberg).*

Second, we estimate the baseline VAR described in Section 3.2 for each country to determine whether the macroeconomic results for Italy also hold for the other countries.<sup>35</sup> A first relevant finding is that the identified BAS shocks are positively correlated across countries: the correlation ranges from 0.3, France-Germany, to 0.21, France-Italy.<sup>36</sup> Both the correlation of the variables in

<sup>35</sup>The sample is February 2004-November 2014 for Germany, Italy and Spain. Due to the lack of CDS data before 2005, the sample for France starts in August 2005. All financial variables are expressed as monthly averages.

<sup>36</sup>In particular, the estimated cross-country correlations are statistically significant for all the cases but between



levels and of the shocks indicate that liquidity in sovereign markets is driven by a relevant European component.

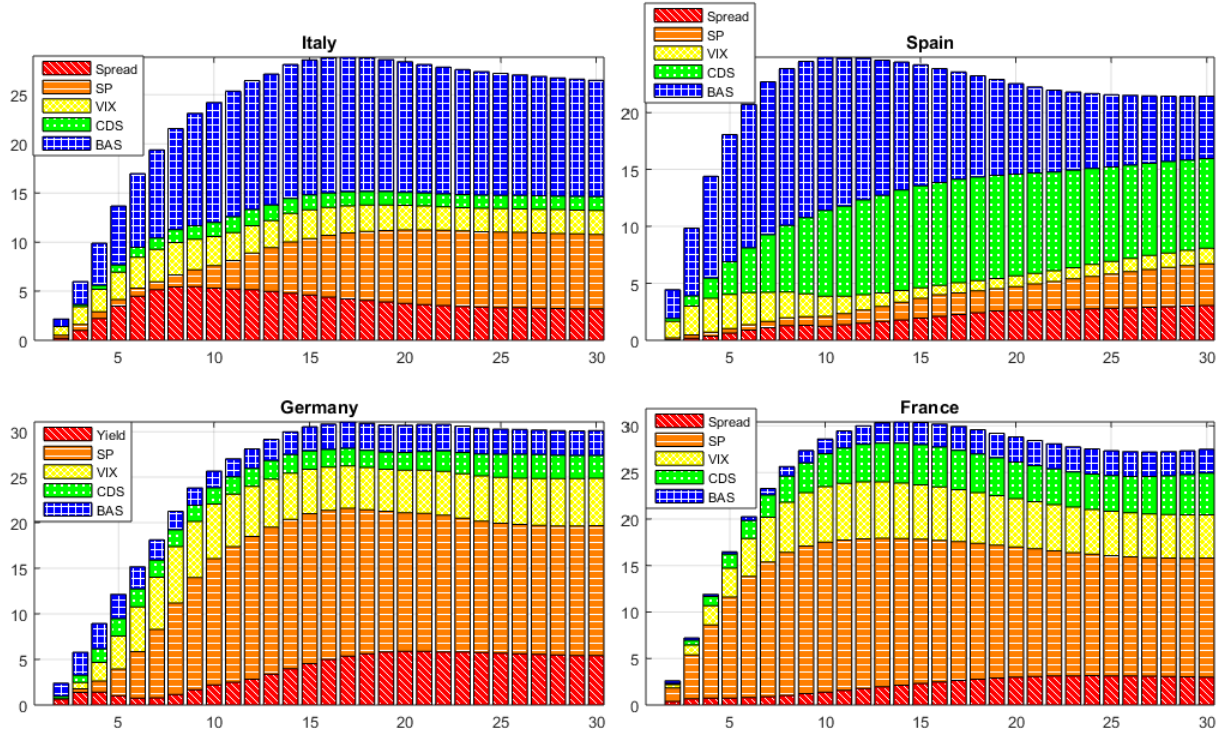


Figure 12: FEVD of Unemployment for European countries

FEVD of Unemployment for Italy, France, Germany, and Spain. The FEVD is computed estimating a VAR for each country that includes: [Unemployment,  $\pi$ , Public Debt,  $R$ , M2, CC, BC, Financial Block]. BAS shocks are identified from all the possible rotations across the financial variables.

We present the macroeconomic relevance of the financial shocks, across the four countries, in Figure 11 through the Forecast Error Decomposition of unemployment. There is clear heterogeneity between the Mediterranean countries and the central European ones. On the one hand, changes in BAS are an important driver of unemployment for Spain and Italy. For both cases, BAS shocks account for 15% of unemployment fluctuations.<sup>37</sup> A special feature of Spain is the relevance of CDS, which might be due to the perceived higher default risk. On the other hand, exogenous fluctuations in stock markets are the most relevant source of unemployment fluctuations for Germany and France. In fact, neither BAS nor sovereign spread seem to be relevant to explain unemployment fluctuations in these countries. Even if financial shocks explain a similar fraction of the total variability of unemployment (around 30%), the relevance of each financial shock differs across countries. Although the sources of this difference are beyond the scope of this paper, one possible reason could be the lower tensions in sovereign debt markets in France and Germany.

France and Spain.

<sup>37</sup>Moreover, the IRF to a BAS shock has similar effects both in terms of magnitude and persistence.



## 6 Conclusions

Economists have been focusing on sovereign debt markets due the European Sovereign Debt Crisis. Contrary to the growing number of theoretical models that analyze changes in liquidity in those markets, the empirical evidence on their real effects is still null. In this paper, we provide the first empirical evidence on the macroeconomic effects of changes in liquidity in secondary sovereign debt markets. We focus on the European economies that were hit both by credit risk and liquidity shocks during the recent crisis. In particular, we consider the Italian case by using monthly data from 2004 to 2014 in a VAR analysis. The two alternative identification strategy that we employ, recursive ordering and the Proxy-SVAR, yields consistent results. The former takes into account all the possible orderings among financial variables. The Proxy-SVAR exploits a daily financial VAR to control for all high-frequency changes in financial markets. Specifically, we use daily BAS structural shocks as proxy for the monthly BAS structural shocks. We find that, contrary to popular perceptions, liquidity is a major financial driver of economic activity. An exogenous raise in this variable generates a strong (15% of the Forecast Error Variance) and persistent (10 months) surge in unemployment. The other variables that are mostly affected are confidence indicators as Stock Prices, and Consumer and Business Sentiment. Banks and firms survey data reveal that liquidity shocks have significant effects on banks standard, in terms of loan's size and through ancillary costs, particularly due to the asset and liquidity position of Italian banks. Similar macroeconomic effects hold for Spain, whereas liquidity shocks are not a significant driver for France and Germany.

Our results differ from existing models, as [Del Negro, Eggertsson, Ferrero, and Kiyotaki \(2011\)](#) and [Benigno and Nistico \(2014\)](#), where liquidity shocks induce a pronounced deflation. Therefore, in particular in the light of our findings related to the banking channel, we believe that models that focus on the asset and liquidity position of financial intermediaries can enhance our understanding of these phenomena. We regard [Cui and Radde \(2015\)](#) as a first step towards this interesting direction for future research. Frameworks of this kind, which can generate macroeconomic effects consistent with the empirical evidence, can be used to assess whether and how policy makers should react to changes in liquidity ([Cui \(2016\)](#)). They mainly focus on the liquidity of corporate bonds as their reference is the US economy. Instead, by studying European economies we conclude that the liquidity of sovereign bonds is a key financial dimension for the macroeconomy. The liquidity of these two different assets may involve diverse policy implications.

## References

- BAHAJ, S. (2014): “Systemic Sovereign Risk: Macroeconomic Implications in the Euro Area,” .
- BEER, A., M. BRANDT, AND K. KAVAJECZ (2009): “Flight-to-Quality or Flight-to-Liquidity? Evidence from the Euro-Area Bond Market,” *Review of Financial Studies*, 22, 925–957.
- BENIGNO, P., AND S. NISTICO (2014): “Safe Assets, Liquidity and Monetary Policy,” .
- BOISSEL, C., F. DERRIEN, E. ORS, AND D. THESMAR (2014): “Sovereign Debt Crisis and Bank Financing: Evidence from the European Repo Market,” .
- CUI, W. (2016): “Monetary-Fiscal Interactions with Endogenous Liquidity Frictions,” Unpublished manuscript.
- CUI, W., AND S. RADDE (2015): “Search-based Endogenous Illiquidity and the Macroeconomy,” Unpublished manuscript.
- DE MARCO, F. (2016): “Bank Lending and the European Sovereign Debt Crisis,” .
- DEL NEGRO, M., G. EGGERTSSON, A. FERRERO, AND N. KIYOTAKI (2011): “The Great Escape? A Quantitative Evaluation of the Fed’s Liquidity Facilities,” *Federal Reserve Bank of New York Staff Reports*, 520.
- DICK-NIELSEN, J., P. FELDTHUTTER, AND D. LANDO (2012): “Corporate Bond Liquidity Before and After the Onset of the Subprime Crisis,” *Journal of Financial Economics*, 103(3), 471–492.
- GARCIA, J. A., AND R. GIMENO (2014): “Flight-to-Liquidity Flows in the Euro Area Sovereign Debt Crisis,” *Banco de Espana Working Paper*, 1429.
- GAZZANI, A., AND A. VICONDOA (2016b): “Proxy SVAR as a Bridge between Mixed Frequencies,” Unpublished manuscript.
- GENNAIOLI, N., A. MARTIN, AND S. ROSSI (2014): “Banks, Government Bonds, and Default: What do the Data Say?,” *IMF Working Paper*, 14/120.
- LUDVIGSON, S. (2004): “Consumer Confidence and Consumer Spending,” *Journal of Economic Perspectives*, 18(2), 29–50.
- MANCINI, L., A. RANALDO, AND J. WRAMPPELMAYER (2014): “The Euro Interbank Repo Market,” *Swiss Finance Institute Research Paper*.
- MERTENS, K., AND M. O. RAVN (2013): “The Dynamic Effects of Personal and Corporate Income Tax Changes in the United States,” *American Economic Review*, 103(4), 1212–47.

- NERI, S., AND T. ROPELE (2015): “The Macroeconomic Effects of the Sovereign Debt Crisis in the Euro Area,” *Bank of Italy Working Papers*, 1007.
- PASSADORE, J., AND Y. XU (2014): “Illiquidity in Sovereign Debt Markets,” .
- PELIZZON, L., M. SUBRAHMANYAM, D. TOMIO, AND J. UMO (2015): “Sovereign Credit Risk, Liquidity, and ECB Intervention: Deus Ex Machina?,” *SAFE Working Paper No. 95*.
- PERICOLI, M., AND M. TABOGA (2015): “Decomposing Euro Area Sovereign Spreads: Credit, Liquidity and Convenience,” *Bank of Italy Working Papers*, 1021.
- ROMER, C. D., AND D. H. ROMER (2004): “A New Measure of Monetary Shocks: Derivation and Implications,” *American Economic Review*, 94(4), 1055–1084.
- SCHWARZ, K. (2014): “Mind the Gap: Disentangling Credit and Liquidity in Risk Spreads,” .
- SIMS, C. A., J. H. STOCK, AND M. W. WATSON (1990): “Inference in Linear Time Series Models with Some Unit Roots,” *Econometrica*, 58(1), 113–44.
- STOCK, J., AND M. WATSON (2012): “Disentangling the Channels of the 2007-2009 Recession,” *Brookings Papers on Economic Activity*, Spring, 81–135.
- STOCK, J. H., AND M. YOGO (2002): “Testing for Weak Instruments in Linear IV Regressions,” *NBER Technical Working Papers*, 0284.

## A Appendix. Data

Table A1 displays the data sources for each country.

	Italy	Spain
Unemployment	ISTAT	Ministry of Economy
Industrial Production	ISTAT	INE
CPI Inflation	ISTAT	INE
Central Government Debt	Bank of Italy	Ministry of Economy
ECB Repo	ECB	ECB
M2	Bank of Italy	Banco de España
Consumer Confidence	ISTAT	Ministry of Economy
Business Confidence	ISTAT	Ministry of Industry
Volatility Index	ASR-Absolute Strategy	VSTOXX
CDS	Thomson Reuters CDS	Thomson Reuters CDS
Bid-Ask Spread	Bloomberg	Bloomberg
Yield Spread	ECB	ECB
Stock Prices	FTSE MIB	IBEX 35

	France	Germany
Unemployment	INSEE	OECD
Industrial Production	INSEE	Federal Statistical Office
CPI Inflation	Thomson Reuters	Thomson Reuters
Central Government Debt	Banque de France	Deutsche Bundesbank
ECB Repo	ECB	ECB
M2	Banque de France	Deutsche Bundesbank
Consumer Confidence	DG ECFIN	DG ECFIN
Business Confidence	DG ECFIN	DG ECFIN
Volatility Index	Euronext Paris	Deutsche Boerse
CDS	Thomson Reuters CDS	Thomson Reuters CDS
Bid-Ask Spread	Bloomberg	Bloomberg
Yield Spread	ECB	ECB
Stock Prices	CAC 40	MDAX Frankfurt

TABLE A1: *Data Sources*

All the variables are seasonally adjusted originally or by using the X-13ARIMA procedure. We deflate nominal variables by the corresponding CPI price index in order to estimate the VAR with real variables.

In Section 4.2, we refer to the following questions from the Bank and Lending Survey:

1. *Firm  $\Delta$  Standards:* Changes in bank's credit standards for approving loans or credit lines to enterprises, Overall (all firms and types of loans), Past three months.

2. *Firm: Costs-Asset Position:* Changes in the contribution of cost of funds and balance sheet constraints (costs related to bank's capital position) affecting credit standards for approving loans or credit lines to enterprises.
3. *Firm: Liquidity Position:* Changes in the contribution of cost of funds and balance sheet constraints (bank's liquidity position) affecting credit standards for approving loans or credit lines to enterprises.
4. *Firm: Risk-Economic Activity:* Changes in the contribution of perception of risk about general economic situation and outlook affecting credit standards for approving loans or credit lines to enterprises.
5. *Mortgages:  $\Delta$  Standards:* Changes in credit standards for approving loans to households, loans for house purchase in the last three months.
6. *Mortgages: Costs-Funding:* Changes in the contribution of the following factors affecting credit standards for approving loans to households for house purchase, cost of funds and balance sheet constraints.

For what concerns the ISTAT survey, the questionnaire can be found at [ISTAT questionnaire](#) (only in Italian). We refer to the following questions/answers:

- 43 Today, in our opinion, are the credit conditions more or less favorable compared to three months ago? (Possible answers: *More; Constant; Less*)
- 45 Have you obtained the loan you requested to the bank or financial institution? (Possible answers: *Yes, at the same conditions; Yes, at worse conditions; No; Only asking information*)
- 46 In case answer to 43 was *No* - Has the bank reject your request or you have not accepted their offer due to the conditions they were setting? (Possible answers: *The bank has not offered a loan; We have not accepted the loan due to not favorable conditions*)
- 47 In case answer to 45 was *Yes, at worse conditions* - Why the conditions have become worse? (Possible answers: *Higher rate; More personal collateral requested; More real collateral requested; Limits on the amount of the loan; Additional costs*)

## B Appendix. High Frequency Variables

We report the main events plotted in Figure 2, the evolution of volume traded and BAS to characterize the dynamics of liquidity in sovereign debt markets, and the dynamic correlations between the BAS and the Spread in Yields.

Date	Events
2/7/07	HSBC issue with subprimes
6/7/07	Bearn Sterns first bad news
8/9/07	BNP Paribas
9/13/07	Northern Rock
2/18/08	Northern Rock Nationalized
3/14/08	Bearn Sterns bought by JP Morgan
9/15/08	Lehman
10/16/08	Greek Deficit Surprise
5/7/10	EFSF
7/23/10	Stress Test
10/28/10	ESM
5/17/11	Portugal asks help
8/5/11	Letter to Mr. Berlusconi from ECB
8/16/11	ECB buys after Ita take measures
10/4/11	Downgrade ITA-SPAIN
10/11/11	CDS-ban announced
10/31/11	Draghi takes over
11/1/11	CDS-ban in place
11/14/11	Mr. Monti takes over
12/5/11	Mr. Monti package
12/8/11	LTRO announced
12/21/11	1st LRTO
2/28/12	LTRO announced
6/26/12	Cyprus requests aid
7/26/12	Mr. Draghi whatever it takes
8/2/12	OMT announced
12/10/12	Monti resigns
12/13/12	SSM announced
11/7/13	ECB cuts Rate

TABLE A2: *List of European and Italian specific events.*

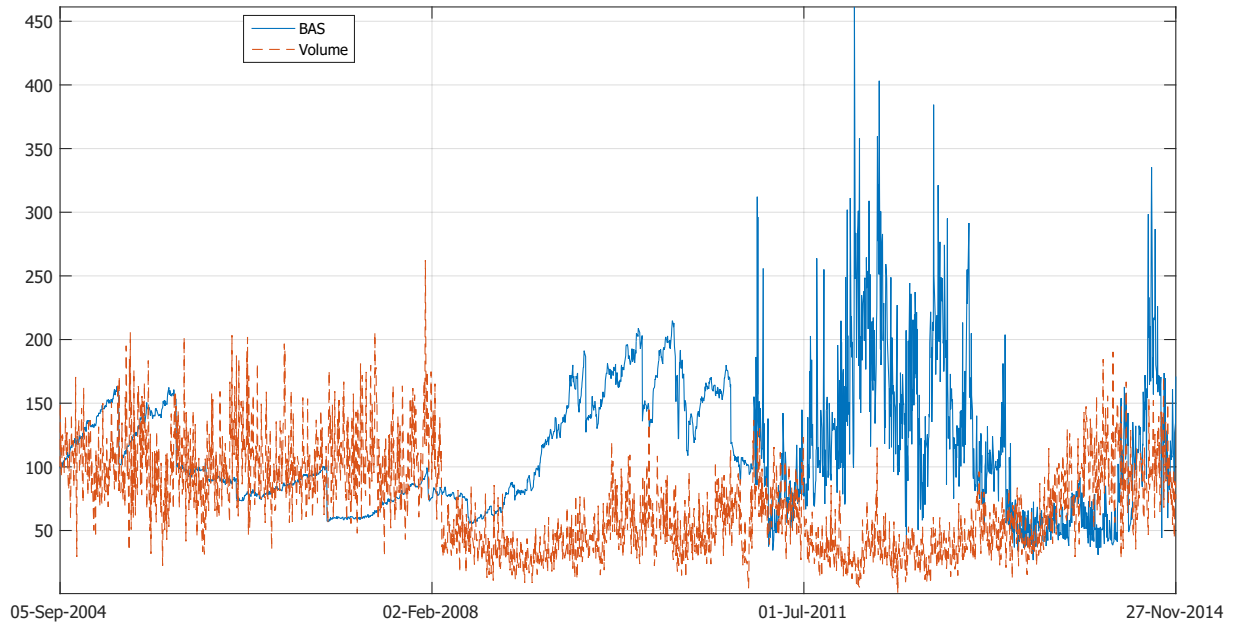


FIGURE A1: *Italian BAS and Turnover on the MTS platform.*

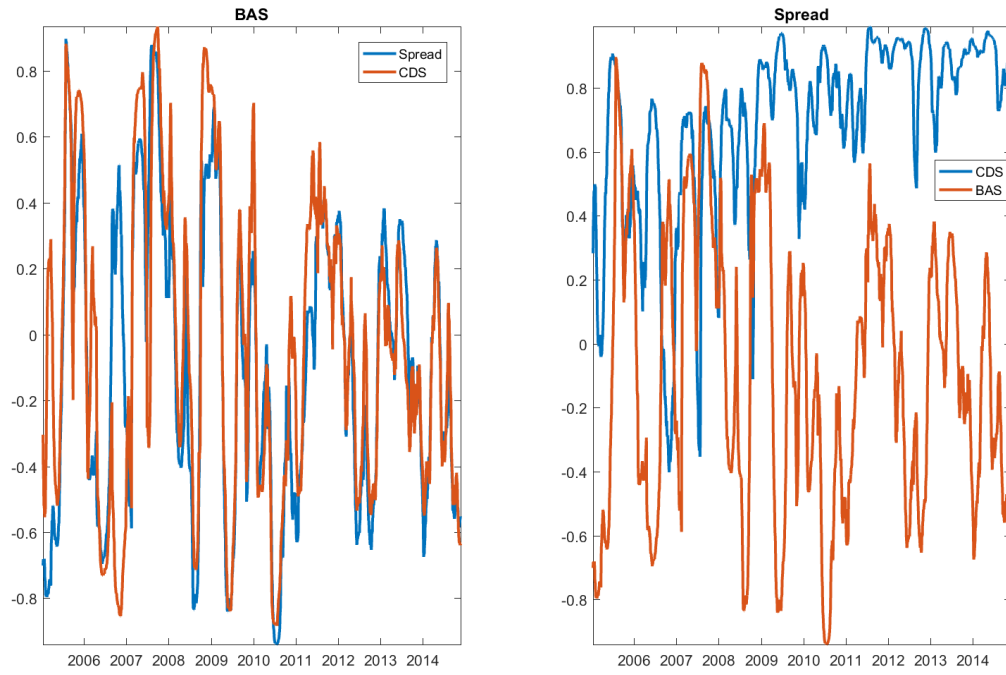


FIGURE A2: *Dynamic Correlations among Spread, CDS and BAS (2004-2014). Correlations are computed over a 90 days rolling window.*

## C Appendix. Financial Variables at Monthly Frequency

Table A3 summarizes statistics of the financial variables used in the empirical analysis at monthly frequency:

	Full Sample			2009-2014		
	BAS	Yield	CDS	BAS	Yield	CDS
Mean	0.017	4.318	98.278	0.020	4.41	169.58
Max	0.037	7.057	546.159	0.037	7.057	546.159
Min	0.007	1.990	2.343	0.007	1.990	36.352
St. Dev.	0.007	0.809	124.411	0.007	1.008	128.619
Auto Corr.	0.836	0.956	0.964	0.782	0.957	0.940

TABLE A3: *Descriptive statistics of sovereign debt financial variables at monthly frequency. Sources: Bloomberg, Datastream and Bank of Italy. Maturities: BAS and CDS 2Y and Yield 10Y.*

There is no significant change in volatility and standard deviation in the period of the sovereign debt crisis at monthly frequency.

## D Appendix. Proxy-SVAR

We describe the the Proxy SVAR methodology that we use to identify the effects of BAS shocks and the first stage results (i.e. the linear projection of the reduced form residuals on the exogenous variations of BAS identified at daily frequency).

### D.1 Theoretical Reference

Consider the following VAR:

$$Y_t = AY_{t-1} + u_t \quad (2)$$

with  $Y_t$  a vector of endogenous variables and  $u_t$  is a vector of reduced form residuals with variance-covariance matrix  $\Sigma_u$ . The objective is to recover the structural form of the VAR, characterized by the vector of structural shocks  $\varepsilon_t = B^{-1}u_t$ :

$$Y_t = AY_{t-1} + B\varepsilon_t \quad (3)$$

We can rewrite the VAR system as partitioned (or bivariate for a matter of interpretation):



$$\begin{bmatrix} Bas_t \\ X_t \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix} \begin{bmatrix} Bas_{t-1} \\ X_{t-1} \end{bmatrix} + \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix} \begin{bmatrix} \varepsilon_t^{bas} \\ \varepsilon_t^X \end{bmatrix} \quad (4)$$

The Proxy-SVAR is an identification strategy that (potentially) partially identifies the unknown  $B$  matrix. Namely, we aim at identifying only the block  $\begin{bmatrix} B_{11} \\ B_{21} \end{bmatrix}$ , which would allows us to compute the IRFs of the system to a structural innovation in the BAS. In order to reach the identification, we exploit information from outside the VAR system. We use the variable  $z_t$  as a proxy for the true structural shock  $\varepsilon_t^{bas}$ .  $z_t$  is assumed to be a proxy for (a component of) the true  $\varepsilon_t^{bas}$  with the following (instrumental variable) properties:

$$\begin{aligned} \mathbb{E}[\varepsilon_t^{bas} z_t] &\neq 0 \\ \mathbb{E}[\varepsilon_t^X z_t] &= 0 \end{aligned}$$

In fact, under those assumptions, we can obtain consistent estimates of  $\begin{bmatrix} B_{11} \\ B_{21} \end{bmatrix}$  by taking an instrumental variable approach:

**First Stage:** regress  $u_t^{bas} = \beta z_t + \xi_t$  obtaining  $\hat{u}_t^{bas}$

**Second Stage:**  $u_t^X = \frac{B_{21}}{B_{11}} \hat{u}_t^{bas} + \zeta_t$

Given that the BAS reacts one to one to its own structural shock (on impact), we can normalize  $\frac{B_{21}}{B_{11}} = B_{21}$ . The IRFs to a BAS shock can be then computed across different horizons as:

$$\mathcal{IRF}_0^X = B_{21}$$

$$\mathcal{IRF}_n^X = A^{n-1} \mathcal{IRF}_{n-1}^X \quad \forall n > 0$$

## D.2 First Stage

Figure A4 displays the RF residuals predicted by the proxy, compared to the original RF innovation series.

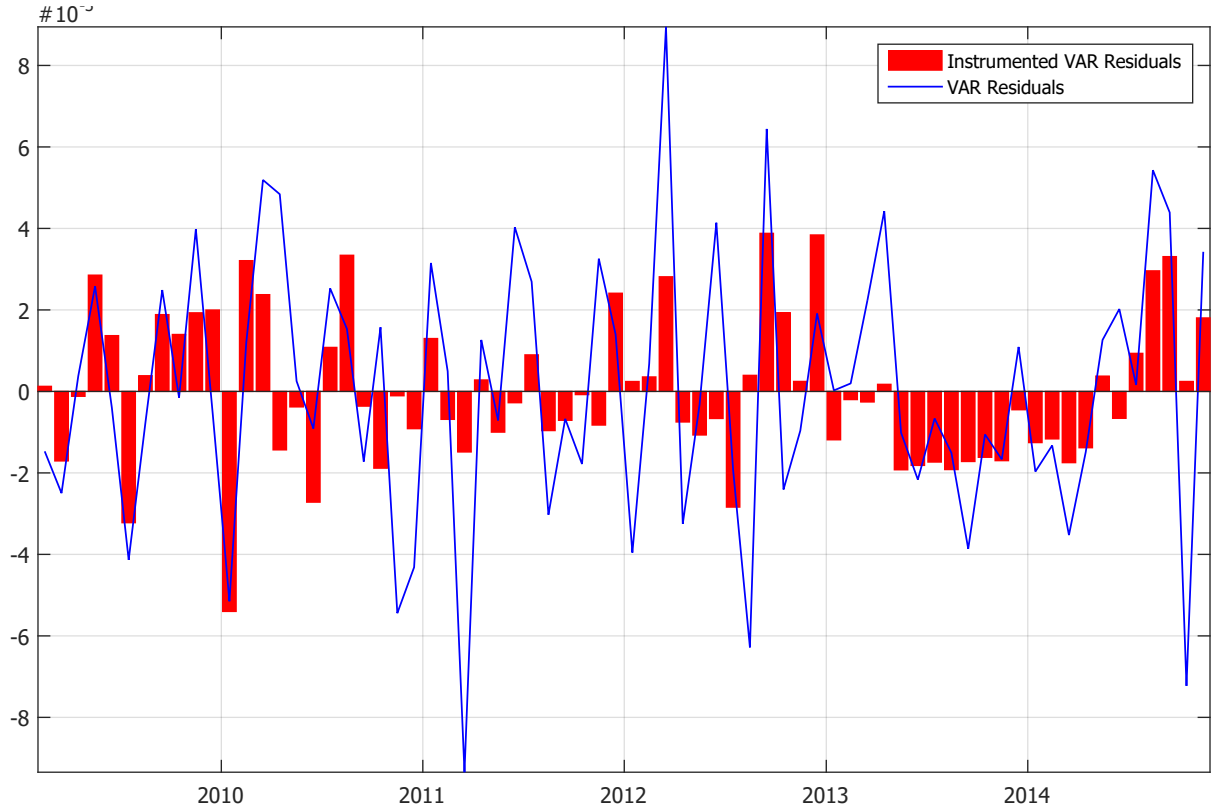


FIGURE A4: First stage result: the blue line represents the RF residuals of the BAS from the VAR featuring [Unemployment,  $\pi$ , Public Debt,  $R$ , M2, CC, BC, Financial Block]; the red bar is the RF residuals predicted by the Proxy (BAS shocks identified in a daily VAR including [BAS, CDS, Yield, FTSE, Eonia, VIX])

## E Appendix. Alternative VAR Specifications

We present the results from alternative VAR specifications described in Section 3.4. To keep the appendix short, we only report results using some particular identification schemes (Basic, Full or Proxy SVAR). Results are robust using the other identification schemes and are available from the authors upon request.

### E.1 Indicator of Liquidity

Figures A5-A6 report the IRFs to a BAS shock of the Full VAR and Proxy-SVAR specifications including the Turnover instead of the Equity Premium, respectively. Figure A7-A8 display the IRFs to a liquidity shock and the FEVD of Unemployment from the Full VAR including the Liquidity Index instead of the BAS. An increase (decrease) in the Liquidity Index is analogous to a decrease (increase) in the BAS.

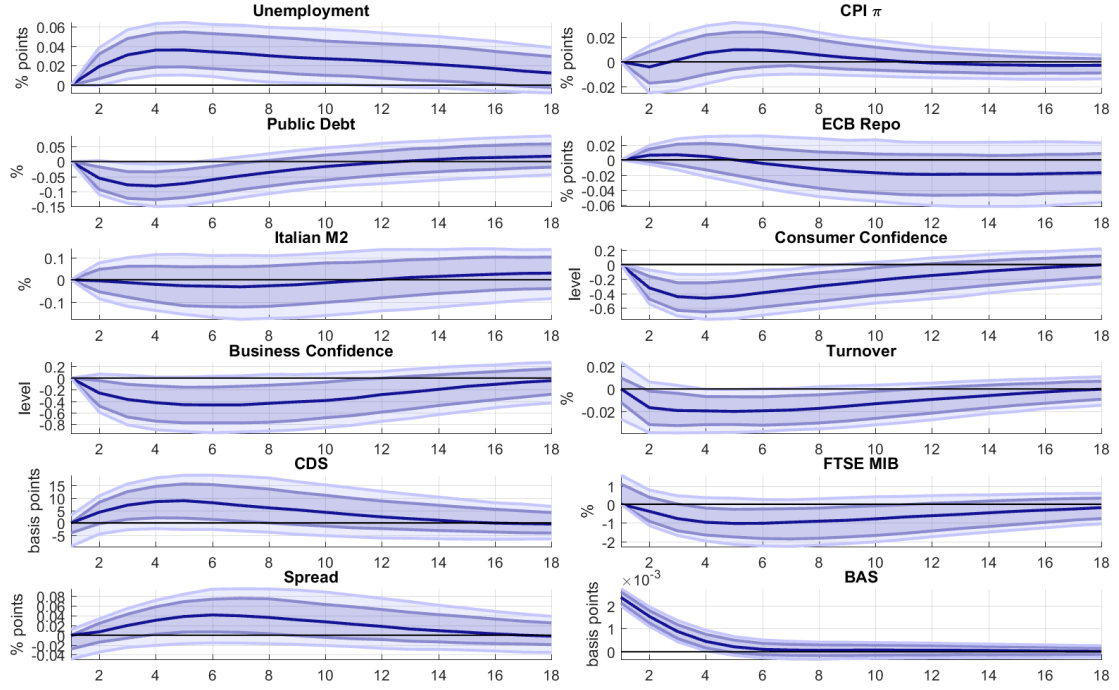


FIGURE A5: IRFs to a 1 std BAS shock identified through the following ordering [Unemployment,  $\pi$ , Public Debt,  $R$ , M2, CC, BC, Financial Block]. The turnover of Italian sovereign bonds is included in place of the equity premium. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

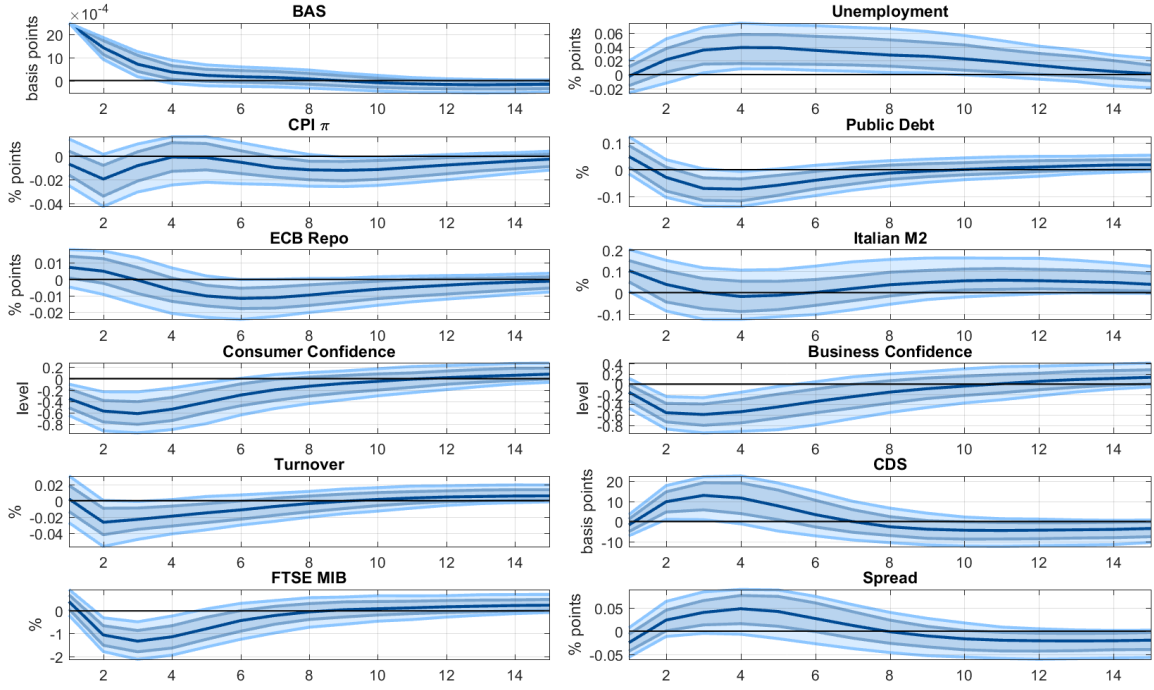


FIGURE A6: IRFs to a 1 standard deviation BAS shock (liquidity deterioration) in the VAR [ $IP$ ,  $\pi$ , Public Debt,  $R$ ,  $M2$ ,  $CC$ ,  $BC$ , Financial Block]. The turnover of Italian sovereign bonds is included in place of the equity premium.

The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Jan:2009-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications.

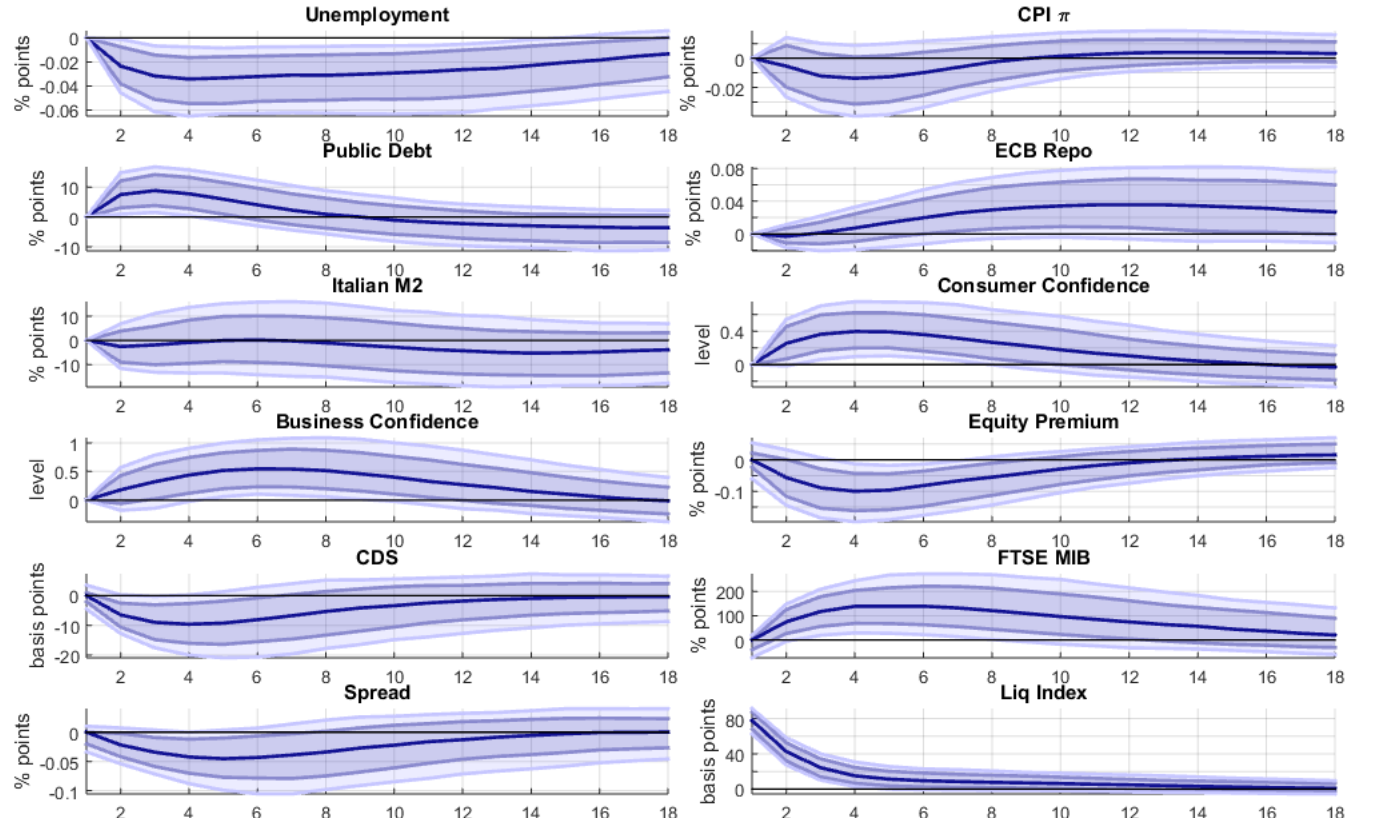


FIGURE A7: IRFs to a 1 std Liquidity Index shock (liquidity improvement) identified through the following ordering [Unemployment,  $\pi$ , Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

Responses are similar to the ones displayed in Section 3.2 of the paper. Figure A8 displays the Forecast Error Variance of Unemployment.

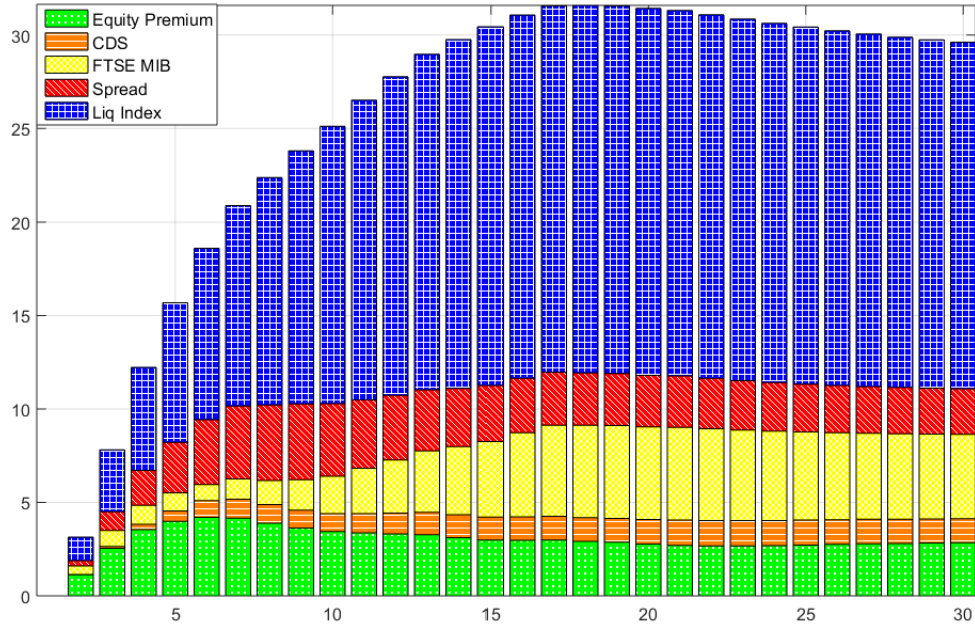


FIGURE A8: *FEV of Unemployment including the Liquidity Index identified through the following ordering [Unemployment,  $\pi$ , Public Debt,  $R$ , M2, CC, BC, Financial Block].*

Liquidity accounts for around 20% of Unemployment fluctuations in the period under analysis, in line with results presented in Section 3.2.

## E.2 Measures of Economic Activity

In this case, we use alternative measures of economic activity and present the corresponding IRFs. We include results both with our small VAR system and with the Proxy-SVAR. In Figure A9-A11, we employ Industrial Production while in Figure A10-A12 the ITA-Coin.

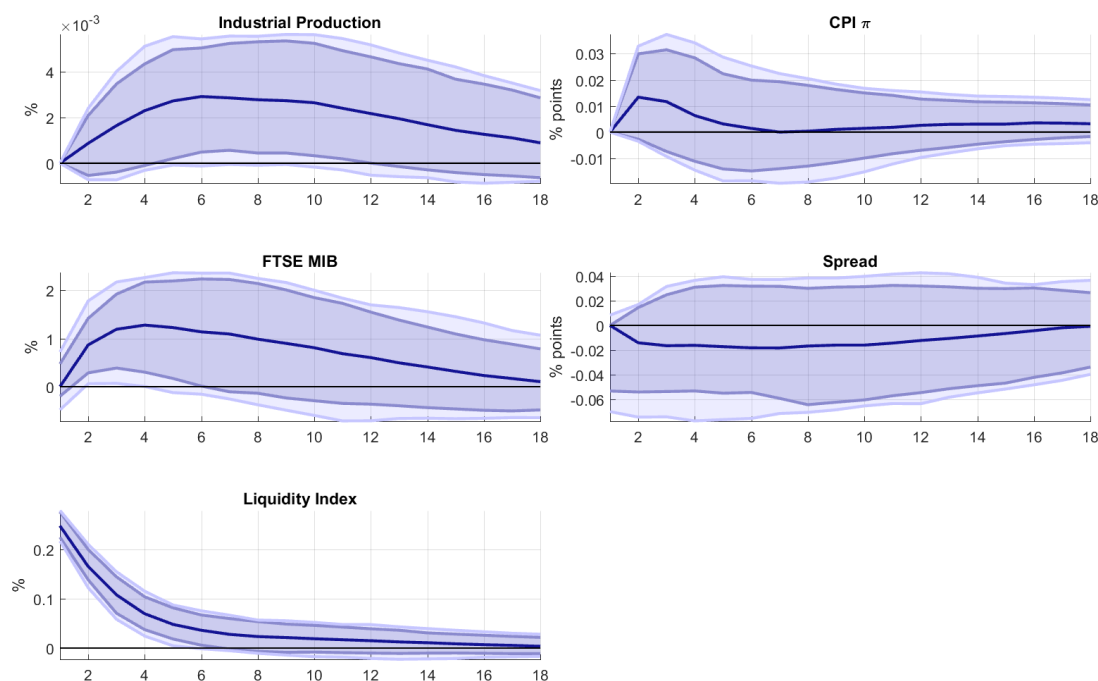


FIGURE A9: IRFs to a 1 std Liquidity Index shock (liquidity improvement) identified through the following ordering [Industrial Production,  $\pi$ , FTSE, Spread, BAS]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

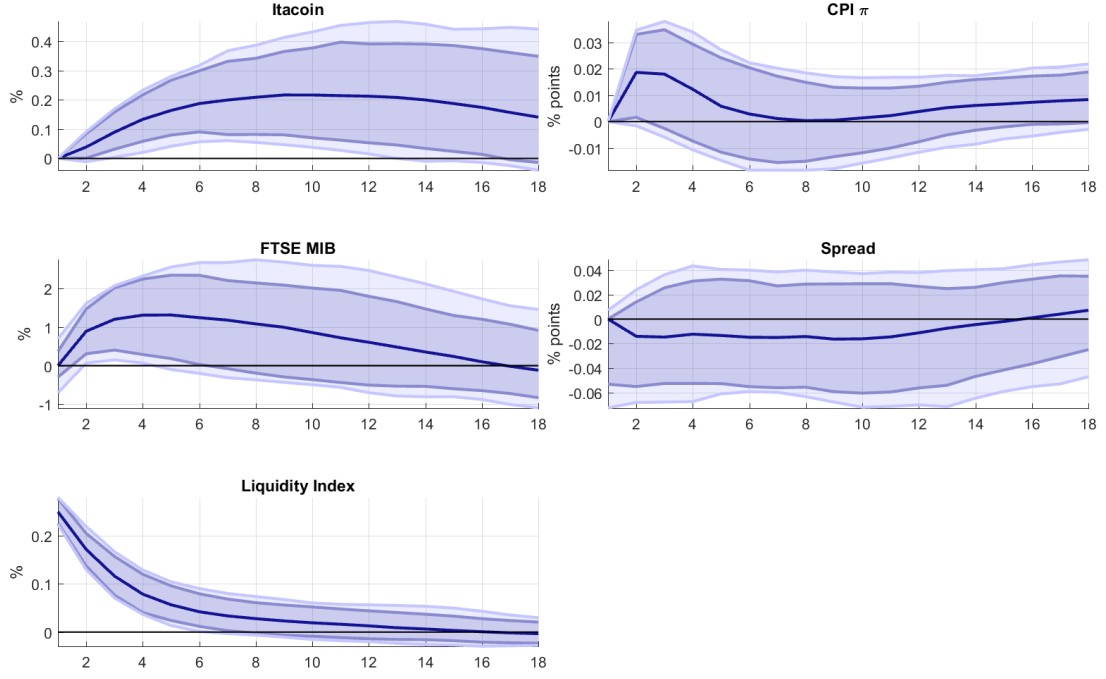


FIGURE A10: IRFs to a 1 std Liquidity Index shock (liquidity improvement) identified through the following ordering [Itacoin,  $\pi$ , FTSE, Spread, BAS]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).



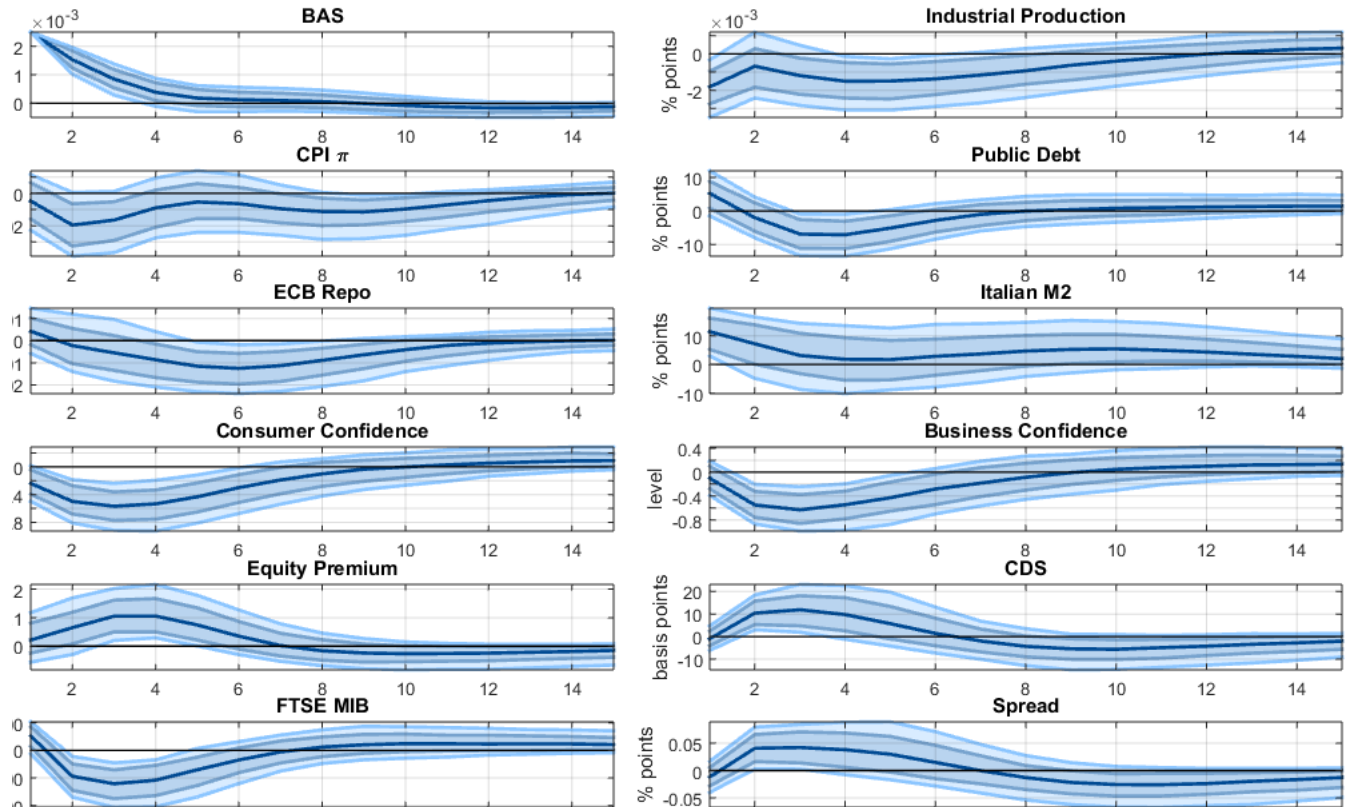


FIGURE A11: IRFs to a 1 standard deviation BAS shock (liquidity deterioration) in the VAR [ $IP$ ,  $\pi$ , Public Debt,  $R$ ,  $M2$ ,  $CC$ ,  $BC$ , Financial Block]. The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Jan:2009-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications.

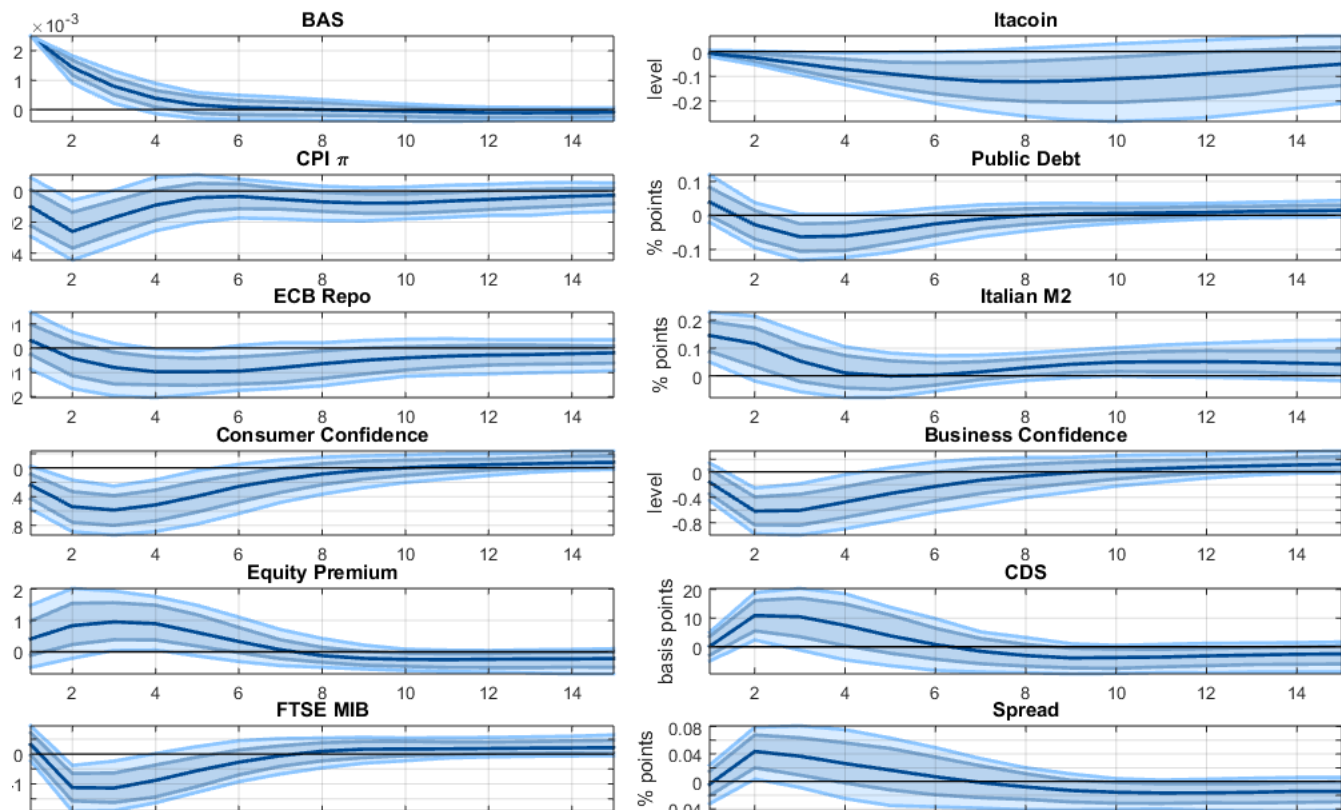


FIGURE A12: IRFs to a 1 standard deviation BAS shock (liquidity deterioration) in the VAR [ $IP$ ,  $\pi$ , Public Debt,  $R$ , M2, CC, BC, Financial Block]. The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Jan:2009-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications.

### E.3 Alternative Samples

We study the dependence of our findings on the sample used. Figures A13-A14 display the IRFs to a BAS shock and FEV of Unemployment using the sample January 2009-November 2014. Figure A15 displays the IRF of the Basic VAR using the pre-crisis sample (February 2004-December 2008). The main conclusions remain unchanged.

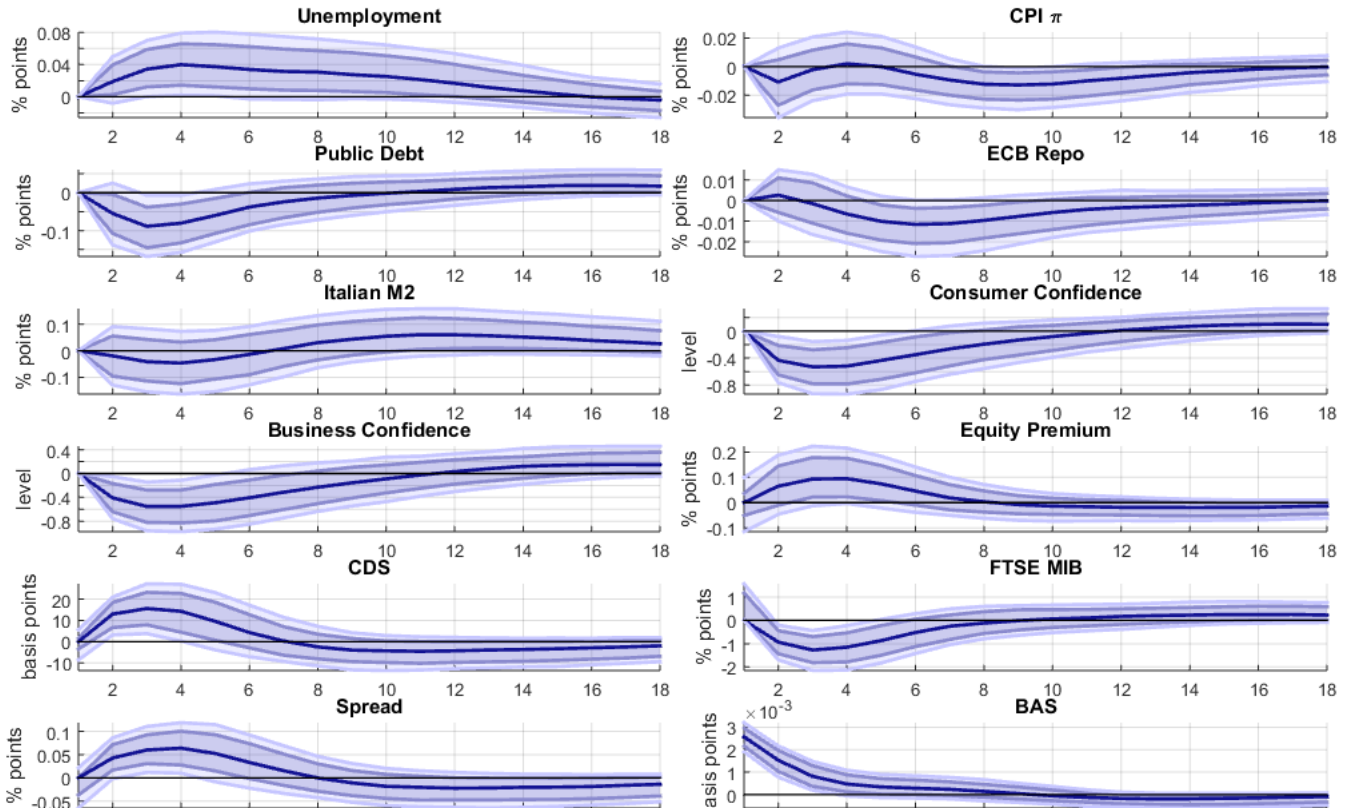


FIGURE A13: IRFs to a 1 std BAS shock identified through the following ordering [Unemployment,  $\pi$ , Public Debt,  $R$ , M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

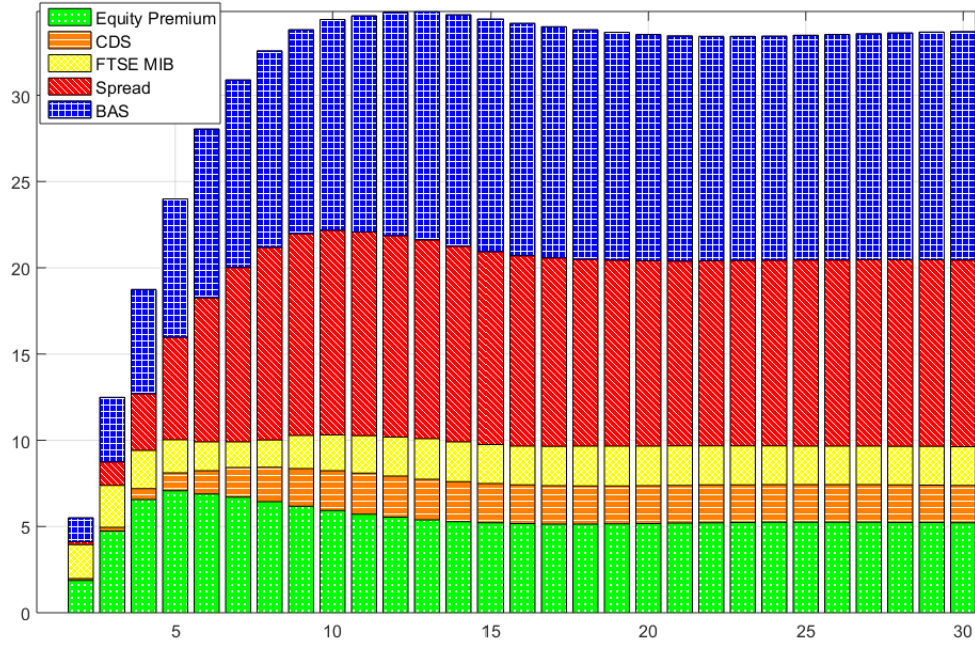


FIGURE A14: *FEV of Unemployment including the Liquidity Index identified through the following ordering [Unemployment,  $\pi$ , Public Debt, R, M2, CC, BC, Financial Block].*

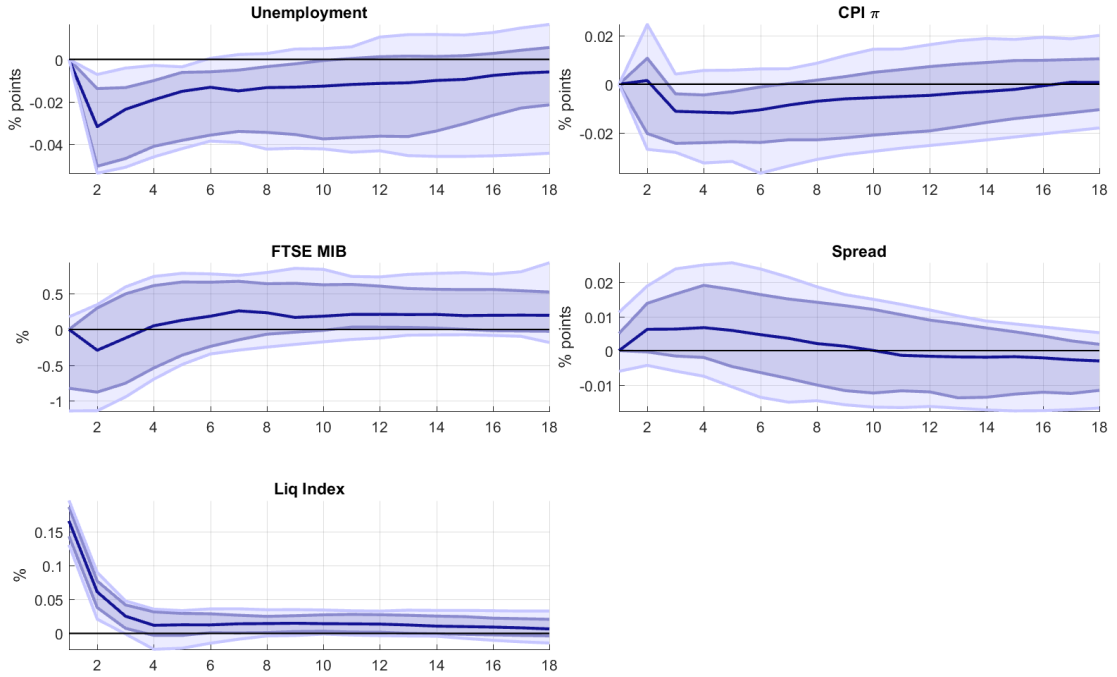


FIGURE A15: *IRFs to a 1 std Liquidity Index shock (liquidity improvement) identified through the following ordering [Unemployment,  $\pi$ , FTSE, Spread, BAS]. The median point estimate, 68% and 90% confidence bands are*

reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

## E.4 Corporate Liquidity

In this section, we consider the relationship between the Corporate and Sovereign liquidity. Figure A16 displays the evolution of the Corporate BAS together with sovereign variables aggregated at monthly frequency. Figure A17 displays the IRF to a shock to corporate BAS and compares it to the one to a sovereign BAS. Finally, Figure A18 shows the IRFs using as a variable the spread between Corporate and Sovereign BAS instead of the BAS.

Levels	BAS-S	Spread	CDS	BAS-C
BAS-S	1	-0.08	0.39*	0.31*
Spread	-0.08	1	0.35	0.5*
CDS	0.39*	0.35	1	0.9*
BAS-C	0.31*	0.5*	0.9*	1

Table 3: Sovereign and Corporate Liquidity

Correlation over the 2004-2014 among Sovereign and Corporate BAS, Spread and CDS (as monthly averages).

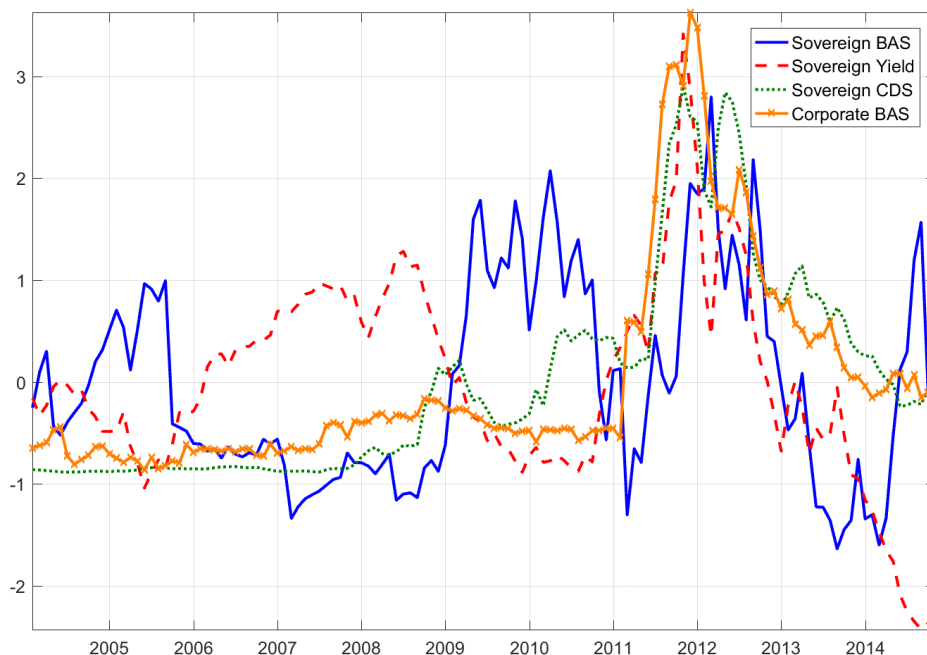


FIGURE A16: Comparison among Sovereign and Corporate BAS, Spread and CDS (as monthly averages). Source of Corporate BAS: Bloomberg.

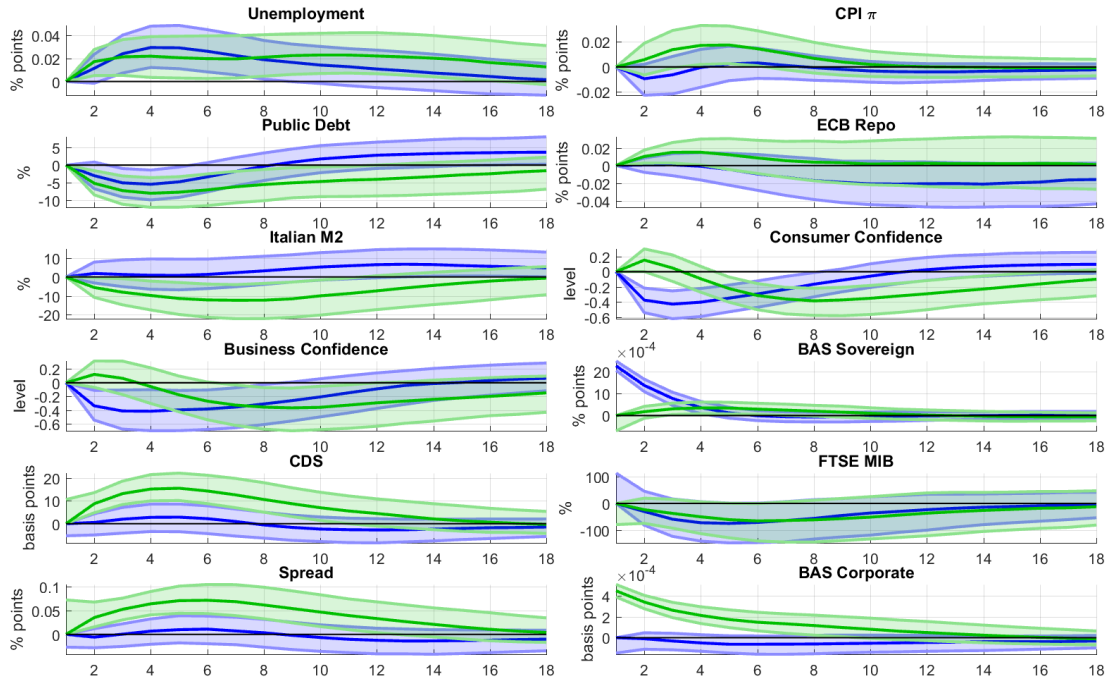


FIGURE A17: IRFs to a 1 std Corporate BAS shock (compared to a sovereign BAS shock in blue) identified through

the following ordering [Unemployment,  $\pi$ , Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

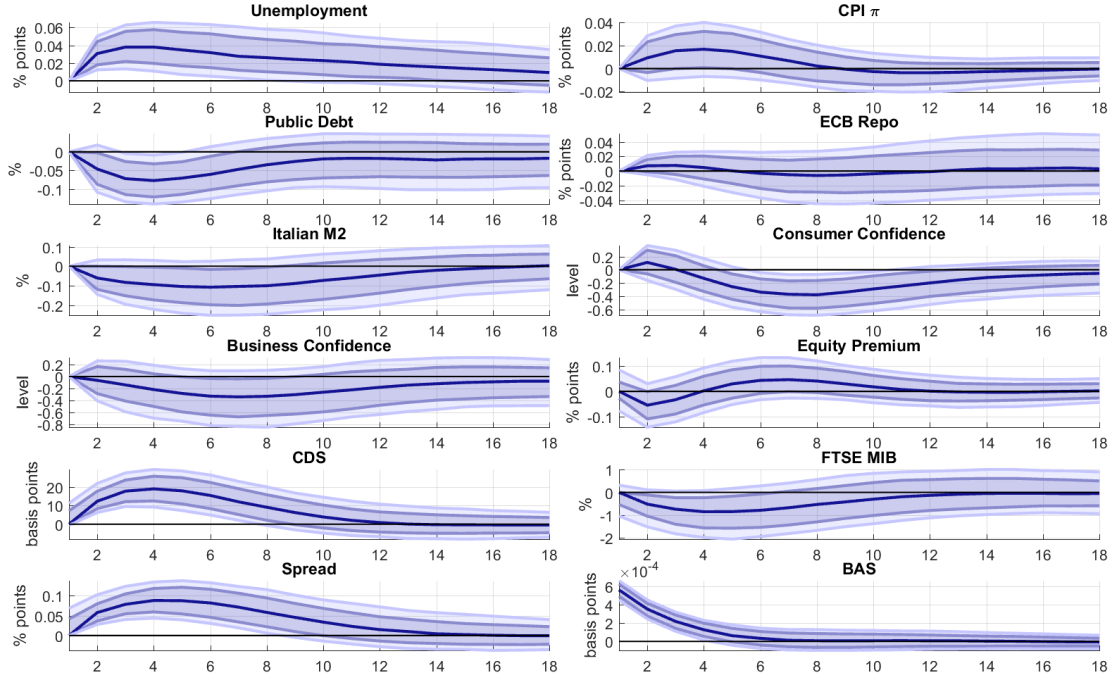


FIGURE A18: IRFs to a 1 std (Corporate-Sovereign) BAS shock identified through the following ordering [Unemployment,  $\pi$ , Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).

## E.5 Market Stress Index

Figure A19 displays the IRFs to a BAS shock of the enlarged VAR that includes the *Composite Indicator of Systemic Stress*, computed by the ECB.

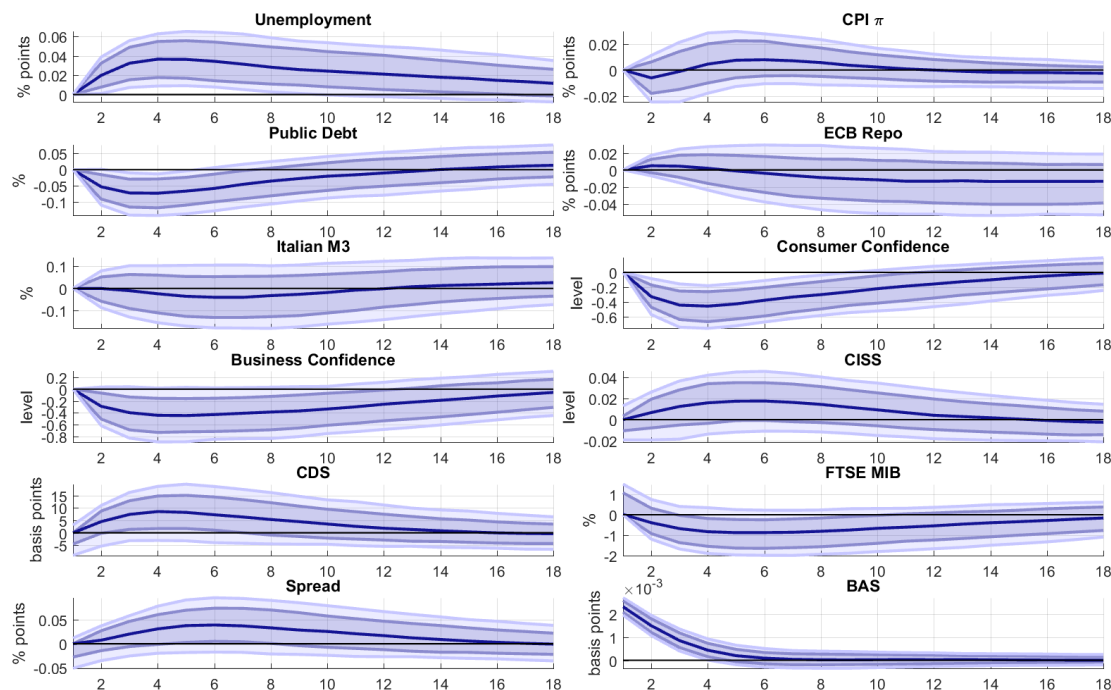


FIGURE A19: IRFs to a 1 std BAS shock identified through the following ordering [Unemployment,  $\pi$ , Public Debt,  $R$ , M2, CC, BC, Financial Block]. The CISS Index is included in place of the the equity premium. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).



## E.6 Financial Volatility

Figure A20 displays the IRFs to a BAS shock of the enlarged VAR that includes an indicator that account for volatility in sovereign debt markets. This indicator is defined as the first principal component of the realized montly volatility of sovereign BAS, Spread and CDS, computed using daily data.

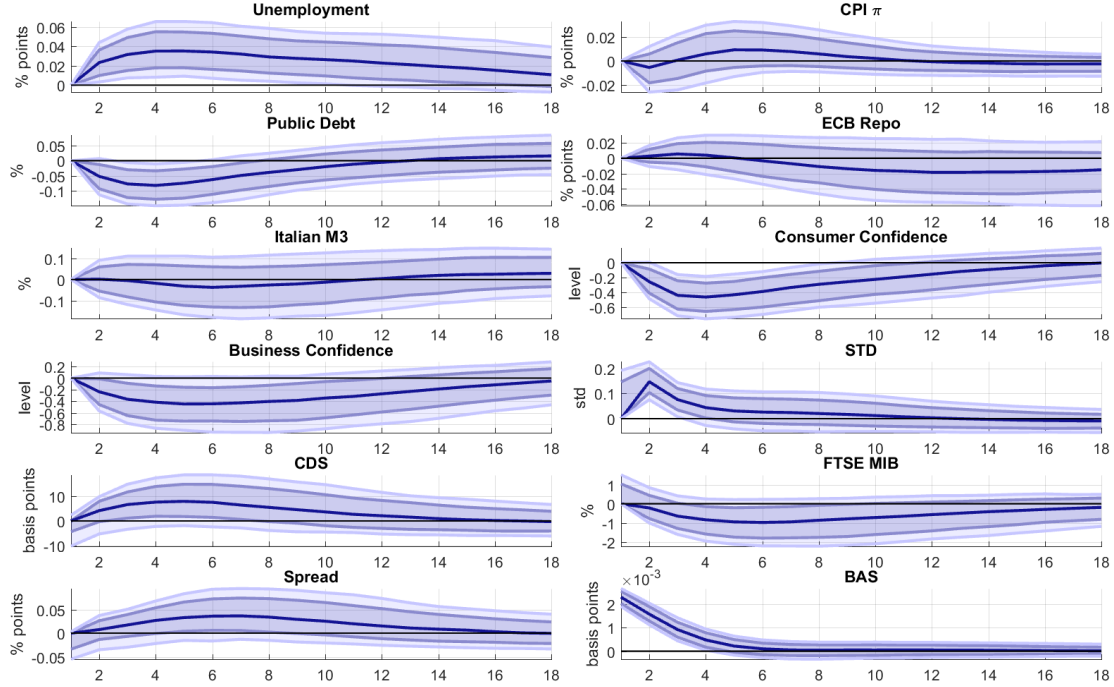


FIGURE A20: IRFs to a 1 std BAS shock identified through the following ordering [Unemployment,  $\pi$ , Public Debt,  $R$ , M2, CC, BC, Financial Block]. A principal component that summarizes the volatility of financial variables is included in place of the equity premium. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).