The Real Effects of Liquidity Shocks in Sovereign Debt Markets: Evidence from Italy

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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.

JEL classification: E44

Keywords: Liquidity, Sovereign Debt, Proxy-SVAR, Financial Shocks

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1 Introduction

The sovereign debt crisis has dramatically affected European countries since 2010. Southern European countries (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.[1] 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 sovereign bonds' liquidity could impact banks' lending decisions.[2] Moreover, liquidity could mirror the uncertainty concerning the future financial-economic conditions.

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.[3] 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.[4] The *Bank Lending Survey* and the *ISTAT Business Confidence Survey* reveal that liquidity shocks impact on banks

[1] Notice that we refer to market liquidity, opposed to funding liquidity.

[2] 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.

[3] 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.

[4] 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).

lending behavior 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.

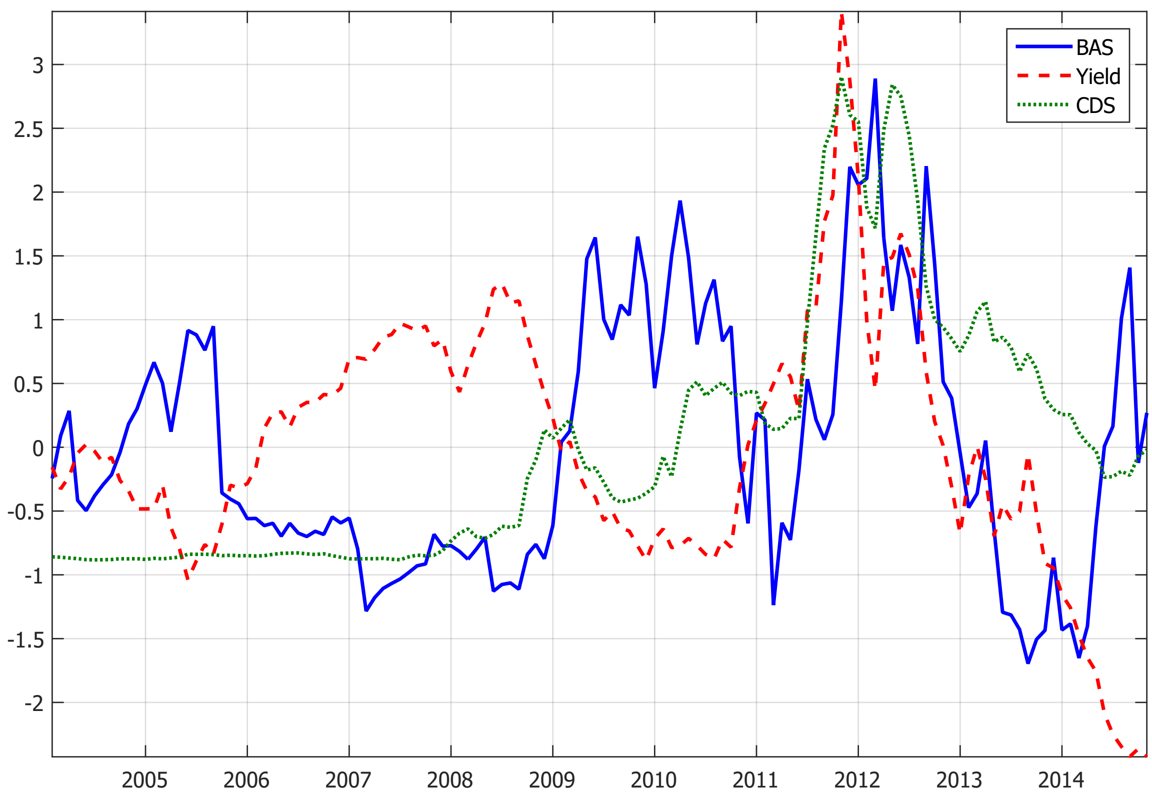

FIGURE 1: *Italian (standardized) BAS, CDS and Yield (monthly average). Each variable corresponds to the first principal components of 2, 5, 10 years bond maturities.*

Although we are the first to provide empirical evidence on the macroeconomic effects of liquidity shocks, some works have already studied liquidity in a theoretical framework. Del Negro, Eggertsson, Ferrero, and Kiyotaki (2011) and Benigno and Nistico (2014) study the effects of these shocks, where liquidity properties are determined exogenously, in a theoretical framework. They find that abrupt changes in liquidity generate strong effects on economic activity and prices. By introducing liquidity risk, Passadore and Xu (2014) improve how their model matches the raise of Argentinian sovereign spread during the crisis of 2001. Using search models to endogenize liquidty dynamics, Cui and Radde (2015) and Cui (2016) show that asset illiquidity affects macroeconomic dynamics by limiting the amount of funding that can be channeled to constrained firms. We contribute to this literature by characterizing the empirical effects of liquidity shocks and by identifying its transmission through the banking sector. We devote Section 5 to the comparison between their theoretical results and our empirical findings.

This paper is also related to the strand of the literature that analyzes the macroeconomic effects of financial shocks. 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 banks' funding costs (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 presents the data, our empirical specification and empirical results employing two methodologies. Section 3 investigates the transmission channels by exploiting survey data. Section 4 compares the Italian results to France, Germany and Spain. Section 5 compares our results with the prediction of the outstanding theoretical models on the topic. Finally, Section 6 concludes.

2 Empirical Evidence: the Italian Case

As a first step, we analyze the effects of liquidity shocks in Italy. The Italian sovereign debt market is one of the most important in Europe, accounting for 26% of the European government debt.[5] Moreover, as we show in Section 2.1, financial variables related to sovereign debt markets display strong fluctuations. Section 2.1 describes the evolution of financial variables at daily frequency. Section 2.3 presents the macroeconomic effects of liquidity shocks at monthly frequency identified through recursive ordering. Section 2.4 shows macroeconomic effects using a Proxy SVAR.

2.1 Data

We devote this subsection to describe the main variables used in our empirical analysis. First, we present the high frequency variables, which are computed at daily frequency. Then we describe the macroeconomic variables, which are expressed at monthly frequency.

2.1.1 High Frequency Variables

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

[5] Source: European Central Bank Statistics.

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)).[6] These variables enable us to characterize the sovereign debt markets. Before proceeding to the analysis, we describe briefly the relationship between the three indicators. Table 1 displays the daily correlation between these variables, both in levels and growth rates.[7]

Levels	BAS	Spread	CDS
BAS	1	0.24***	0.36***
Spread	0.24***	1	0.91***
CDS	0.36***	0.91***	1

Growth Rates	BAS	Spread	CDS
BAS	1	-0.03	-0.03
Spread	-0.03	1	0.23
CDS	-0.03	0.23***	1

Table 1: *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.*

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).[8] 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.[9] 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 and 2012, related to problems in the European Sovereign Debt markets.[10] 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

[6] 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 C.4.

[7] The daily correlations correspond to trading (business) days only.

[8] Notice that there is still no consesus 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.

[9] 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.

[10] In fact, the decline in the implied volatility happens after the famous speech of Mario Draghi, president of the ECB, on July 26 2012.

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.[11] The dynamics of CDS and Spread are similar during 2012, in line with the correlations reported in Table 1, 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.

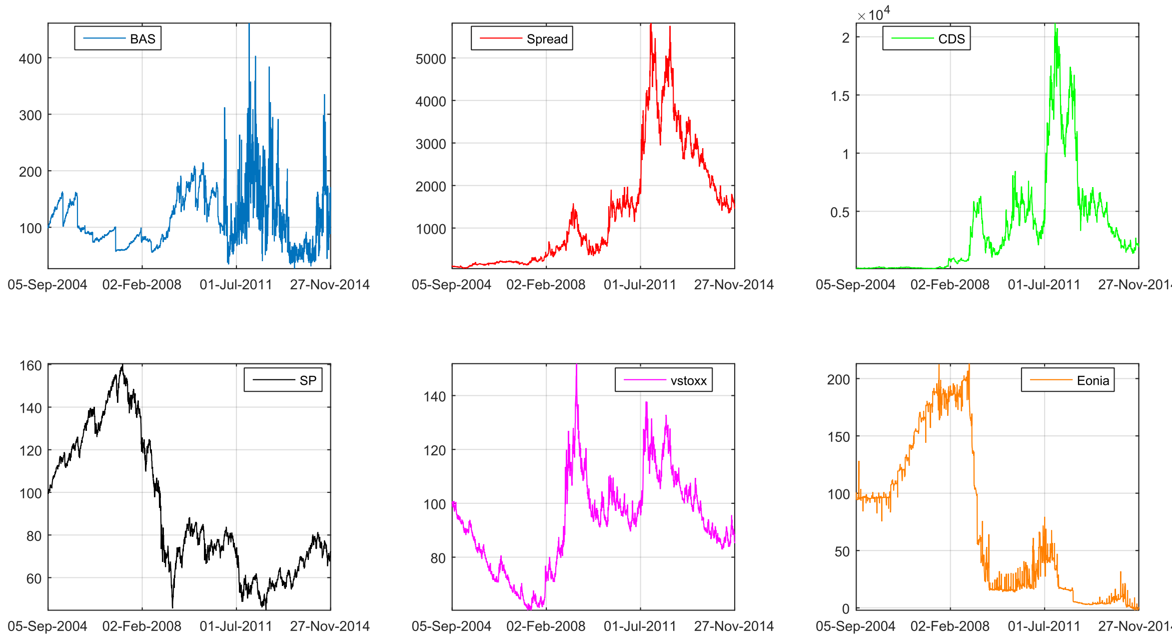

FIGURE 2: *Financial variables: BAS Italy, Spread Italy, CDS Italy, FTSE MIB (main Italian Stock Price index), Vstoxx (European Implied Volatiliy Index), Euro Overnight Index Average (Eonia). All variables are expressed in levels for all the business days since September 2004 to November 2014. All variables 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.*

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

[11] This fact holds for Spain only a few days later.

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.

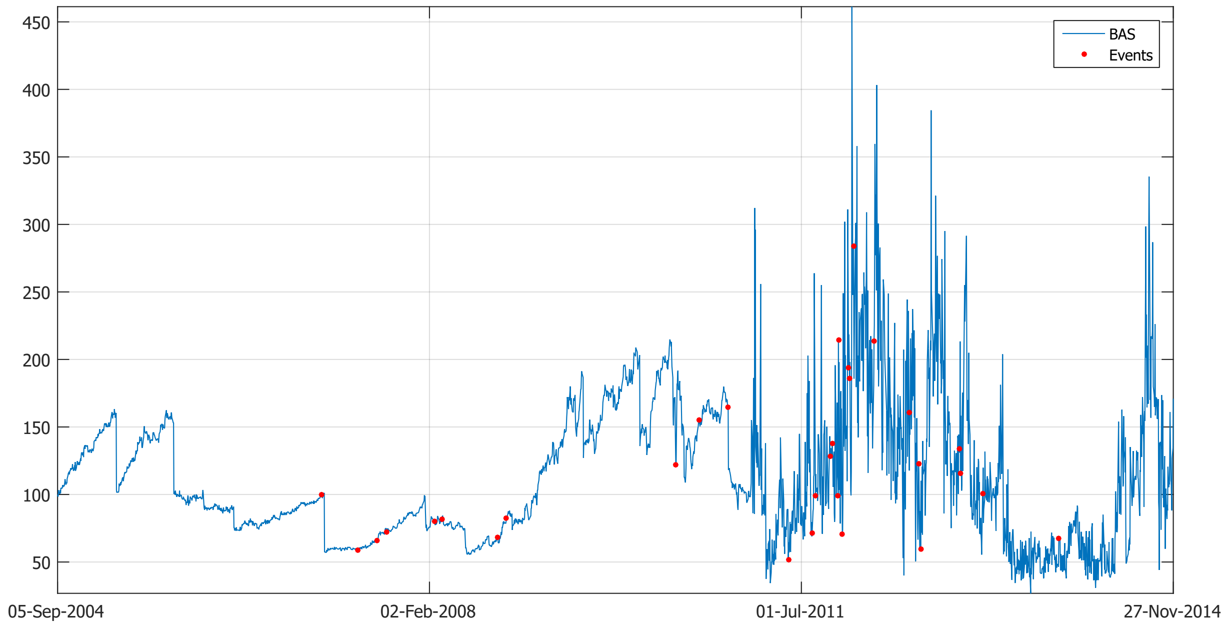

FIGURE 3: *Daily BAS Italy 2 Years (blue line) and key European events (red dots). Appendix A displays the list of all the events.*

2.1.2 Macroeconomic Variables

In order to measure macroeconomic conditions, we use the *Unemployment Rate* as a proxy for economic activity and the *Consumer Price Inflation*, expressed as an annual rate, to capture price dynamics.[12] We include fiscal and monetary indicators like the *Total Amount of Public Administration Debt*, the *ECB Repo Rate* and the *Italian contribution to M2.* These variables enable us to see how changes in liquidity affect the stock of these assets. Finally, we add forward-looking variables, which measure confidence, like the *Consumer Confidence* and *Business Confidence.* All the variables are either seasonally adjusted or we adjust them using the Census X-13.

2.2 Empirical 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 specify a large VAR system with

[12]In Appendix C, we report similar results obtained by using *Industrial Production* and the *Coincident Indicator of Economic Activity* (Ita-coin), a monthly indicator of economic activity computed by the Bank of Italy. See Itacoin for additional information on this series.

twelve variables: the six macroeconomic variables described in the previous subsection plus the five financial indicators (stock prices, Spread, CDS, BAS and VSTOXX). Our sample runs from February 2004 through November 2011. To deal with the different frequencies, we include the financial variables as monthly averages in order to capture all the dynamics during the period.[13] Following Sims, Stock, and Watson (1990), we estimate the model in (log-)levels by OLS, without explicitly modeling the possible cointegration relations among them.[14] 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.[15]

We employ two different methodologies to identify the liquidity shocks. First, we use the most standard VAR identification based on the recursive ordering (Section 2.3). In this case, we assume that macroeconomic variables cannot react contemporaneously to the financial shocks. Within the financial block, we consider all the possible orderings and we report the median and percentiles of the impulse responses and FEV. Even if results are comparable across different orderings within the financial block, we evaluate if they are robust following a more agnostic identification strategy (i.e. placing no restrictions on the timing or the sign of the response): the *Proxy-SVAR*. This methodology exploits information outside the VAR for partial identification (Section 2.4). In this case, we recover the exogenous variations in BAS from a high frequency VAR that includes six variables at daily frequency.

2.3 Recursive Ordering

The first identification strategy is the standard Cholesky decomposition, which is based on 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. Consequently, we order the macro variables available at monthly frequency in a first block (Macroeconomic block) with the following ordering [Unemployment, CPI, Public Debt, M2, Consumer Confidence, Business Confidence]. After the Macroeconomic block we include the financial variables. A severe problem arises from the five 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 720 rotations and, for each of those, we compute 5 bootstrap replications. Section 2.3.1 displays the results from this specification, where confidence bands incorporate both identification and statistical uncertainty. Different possible orderings across the financial block lead

[13] Results are robust if we compute the financial variables as the end of the month, date when the BAS reaches its maximum, release of Italian macroeconomic data. Results are displayed in the online appendix.

[14] 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.

[15] We check that the residuals are normally distributed and they do not exhibit autocorrelation.

to very similar results. Such a robustness means that the covariance matrix of the reduce form residuals is close to a diagonal matrix (so the order of financial variables is not affecting our results).

2.3.1 Empirical Results

Figure 4 displays the IRFs to a one standard deviation BAS shock (i.e. 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.

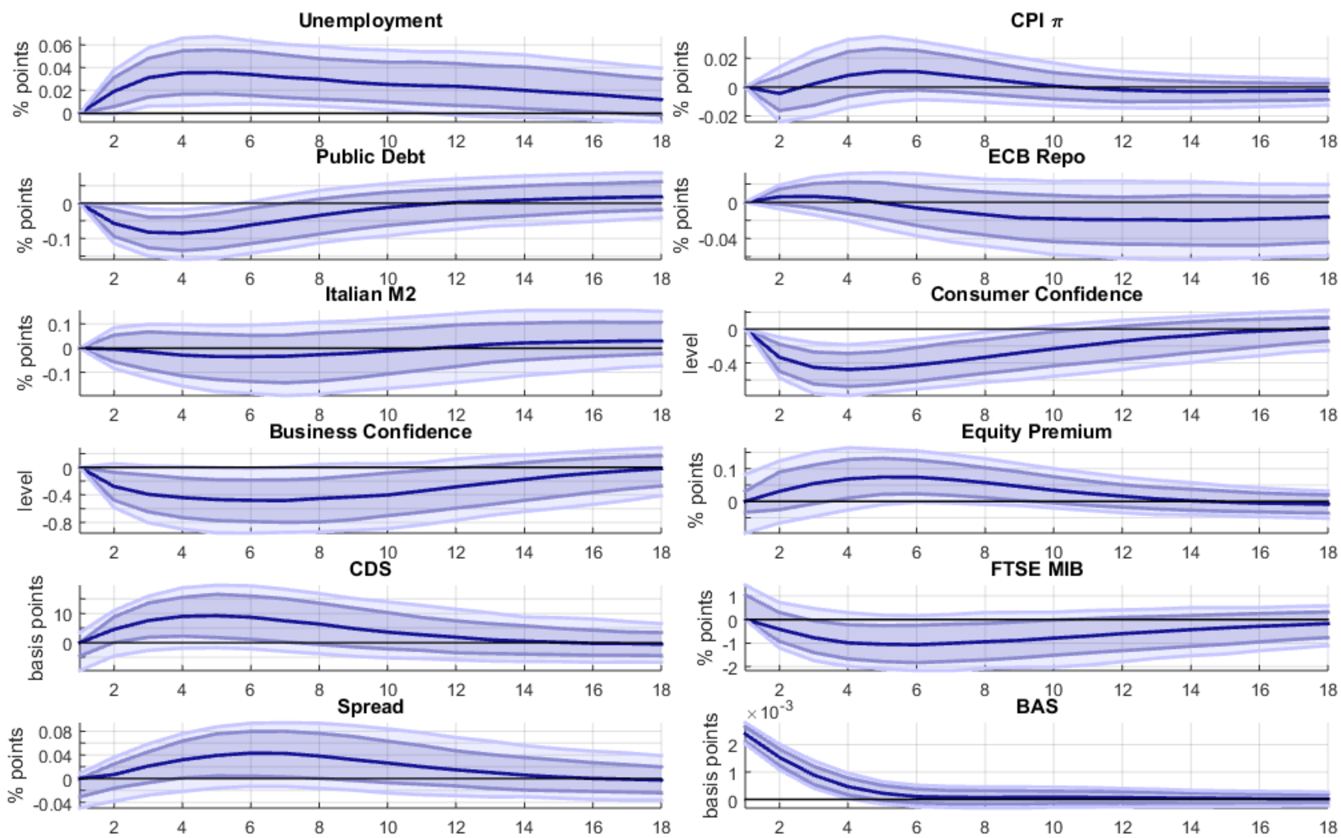

FIGURE 4. *IRFs to a 1 std BAS shock (liquidity deterioration) identified through the following ordering [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).*

The illiquidity shock induces an increase in unemployment that reaches its maximum after four months without a significant effect on inflation. 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 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 4) and Spread shocks (Figure 5).

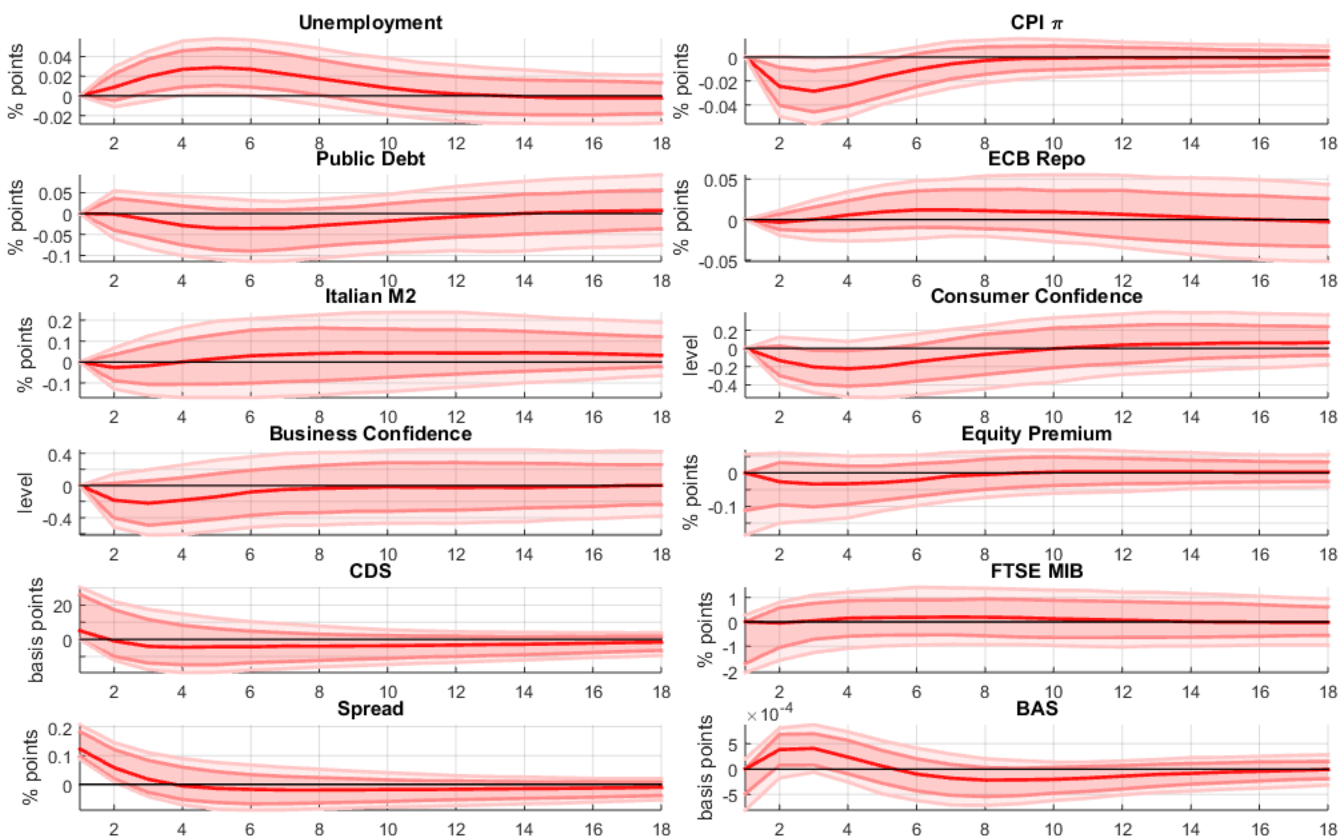

Figure 5. *IRFs to a 1 std Spread shock identified through the following ordering [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in red and light red, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).*

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 2.4 we show that, by using the Proxy-SVAR, the IRF of CPI to a BAS shock is also negative.[16] Notice that this difference comes from the years 2004-2009 as we display in Figure A2.[17] Unlike in the previous case, consumer confidence and business confidence do not display a significant reaction. Regarding the financial block, the response is 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. 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.

For a more comprehensive comparison among financial shocks, in Figure 6 we report the FEV decomposition of unemployment (i.e. how much each financial shock explains of unemployment's volatility).

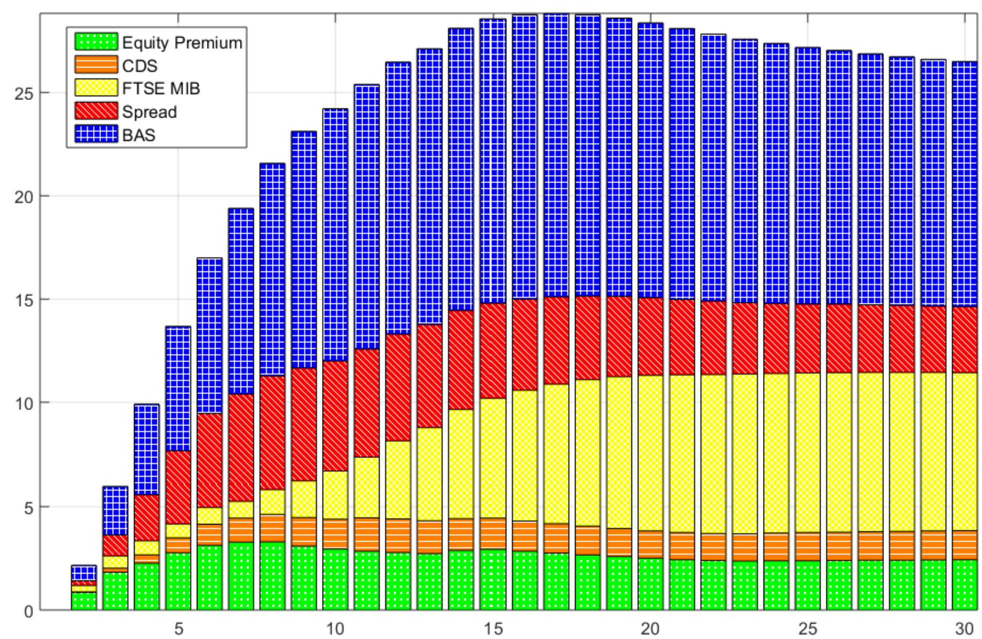

FIGURE 6. *FEV of Unemployment in the VAR [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block]. The bars denote the contribution of each financial shock in explaining the volatility of Unemployment at each horizon (expressed in months).*

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.[18]

[16] As we show later on, CPI is the only variable whose dynamics changes across the two methodologies.
[17] The response of Spread is robust for the sub-sample 2009-2014.
[18] The relative contribution of each financial shock changes if we consider the sub-sample 2009-2014 (Figure A3 in

2.3.2 Robustness

We perform a variety of robustness checks with the recursive ordering. First, we run the same analysis over the sub-sample 2009-2014 (Appendix C). Second, we use a different measure of liquidity that takes into account the quantity traded in the secondary markets (Appendix C).[19] Third, we compute the financial variables in different ways to check if the results are driven by the time aggregation of financial variables: as end of the month, as day in which the BAS displayed the maximum of the month, and, finally, as average of the week in which the ISTAT released macro data (results are reported in the online Appendix). Fourth, we include also BAS and CDS as spreads with respect to the corresponding German variables and we obtain the same results. Fourth, we include all the following variables in the VAR (one by one): Fiscal policy measures, LTRO, Expectation in Housing Market, Interbank Market Rate, Loans between MFI, CDS BAN dummies - Announcement and Implementation, Economic Uncertainty Index - Italy and European, CISS - European Financial Stress Index, Composite Index - Market Liquidity Index ECB, Intra-Monthly Volatility of Financial Variables. Results are comparable across all these specifications.

2.4 Proxy-SVAR

The results in previous section 2.3 are robust to the different recursive Cholesky rotations. 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.[20] 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.[21] We label this identification *"Bridge Proxy-SVAR"* because the Proxy-SVAR links two VAR systems that include data at different frequencies. Since we observe a structural break in the daily volatility of financial variables in 2009, we estimate a VAR at daily

Appendix C). In this case, the contribution of spread is similar to the one of BAS, which is quantitatively stable over the full sample.

[19] 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).

[20] The proxy is not assumed to be perfectly correlated with the structural shock, but only to be a component of it.

[21] We are currently formally testing this methodology using Monte Carlo simulations.

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. 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 2.2. 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 ε_{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.

3. Aggregate ε_{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 for the structural shock of interest in the LF-VAR ε_{LF}^{BAS}. Namely, the reduced form residual u_{LF}^{BAS} is instrumented with $\bar{\varepsilon}_{HF}^{BAS}$. Again, the underlying assumptions concern the relevance, $corr\left(\bar{\varepsilon}_{HF}^{BAS}\ ,\ \varepsilon_{LF}^{BAS}\right) \neq 0$, and the validity, $corr\left(\bar{\varepsilon}_{HF}^{BAS}\ ,\ \varepsilon_{LF}^{j}\right) = 0\ \forall j \neq BAS$, 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-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.[22] 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 2.3.1. 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.

[22]Figure 8 in Appendix D includes a figure with the first stage results.

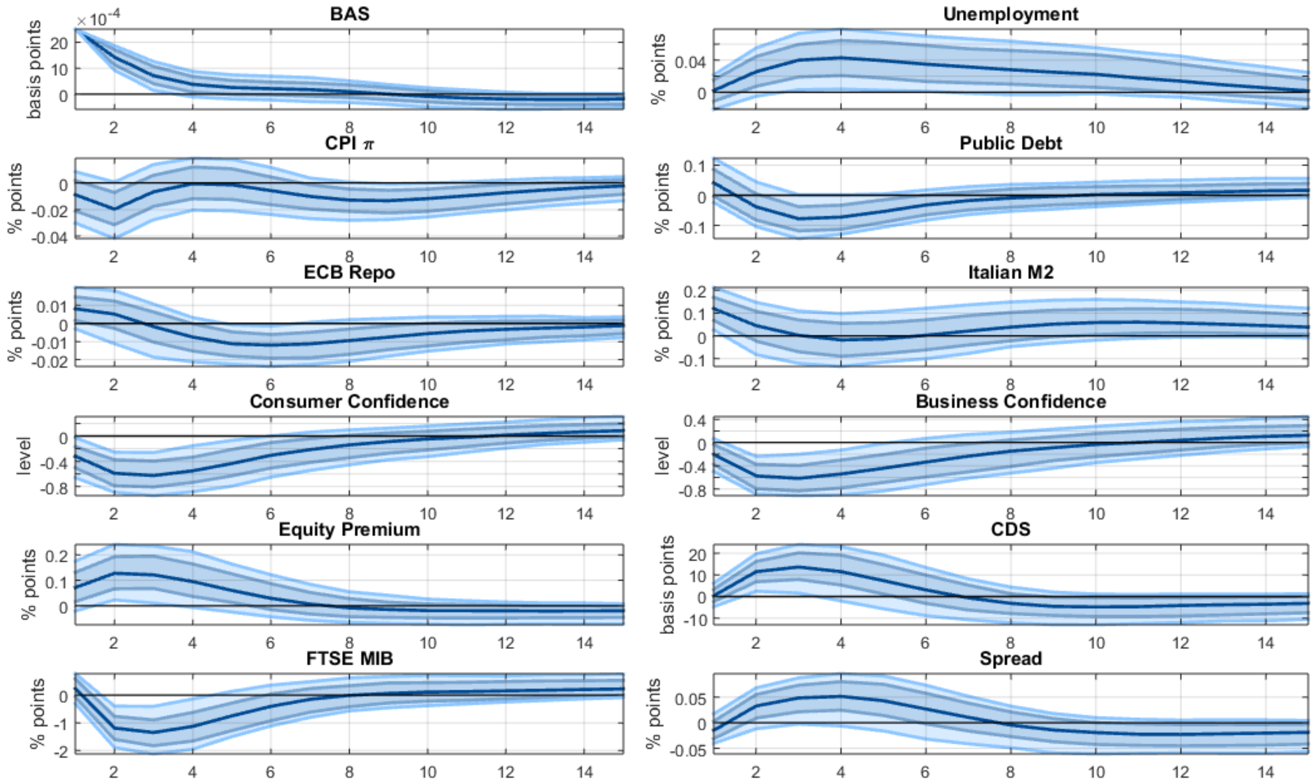

FIGURE 7. *IRFs to a 1 standard deviation BAS shock (liquidity deterioration) in the VAR [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block]. The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Jan:2009-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications.*

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 the FEV cannot be computed (without further assumptions) under this strategy and 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 8 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.

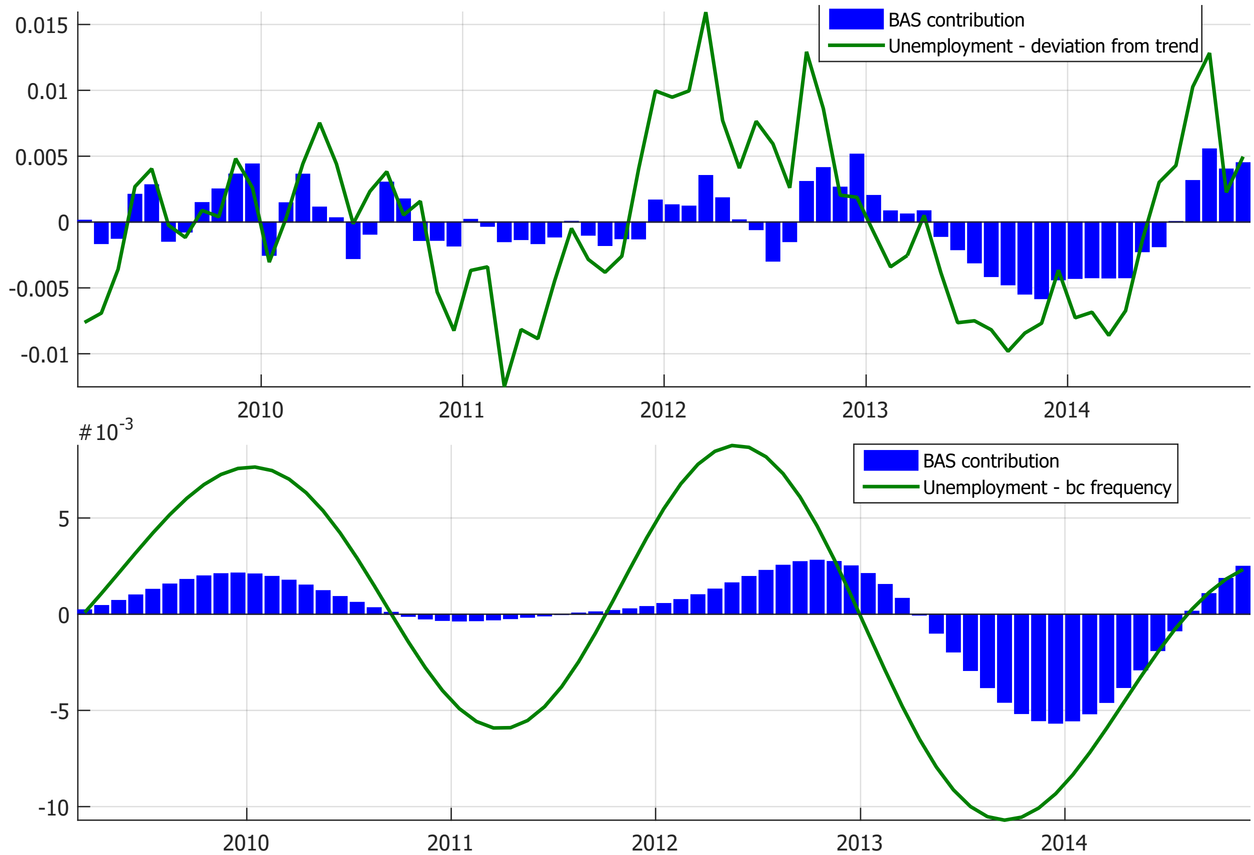

FIGURE 8. *Historical contribution of BAS to Unemployment. Identified in the VAR [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block] through the unpredictable variation of the BAS in a daily VAR system. Upper panel - Unemployment in deviation from trend. Lower panel - Unemployment at the business cycle frequency (18 to 96 months).*

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 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 *Indicatore Ciclico Coincidente (ITA-coin)*, a monthly indicator of economic activity published by the Bank of Italy.[23] Results with these two variables are reported in Appendix C (Figure A4 and A5, respectively). 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

[23] Appendix B displays the IRFs using each indicator. See https://www.bancaditalia.it/statistiche/tematiche/indicatori/indicatore-ciclico-coincidente/ for more information about ITA-coin.

economic activity (Ludvigson (2004)). Second, in the next section, we show that commercial banks change their lending conditions in response to liquidity shocks.

3 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 hold 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%.[24] 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.

3.1 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.[25] 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.[26] Given that the sample is shorter, we estimate the baseline VAR described in section 2.3 since August 2009, when all the variables are available, including one variable at the time to avoid loosing degrees of freedom. In particular, we assume that credit decisions cannot react on impact to a financial shocks and place these credit variables before the consumer confidence,

[24]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.

[25]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.

[26]The Data Appendix A contains the questions we consider from the ISTAT Business Confidence Survey.

business confidence and the financial block.[27] Figure 9 displays the IRF to a liquidity deterioration and a positive sovereign spread shocks.

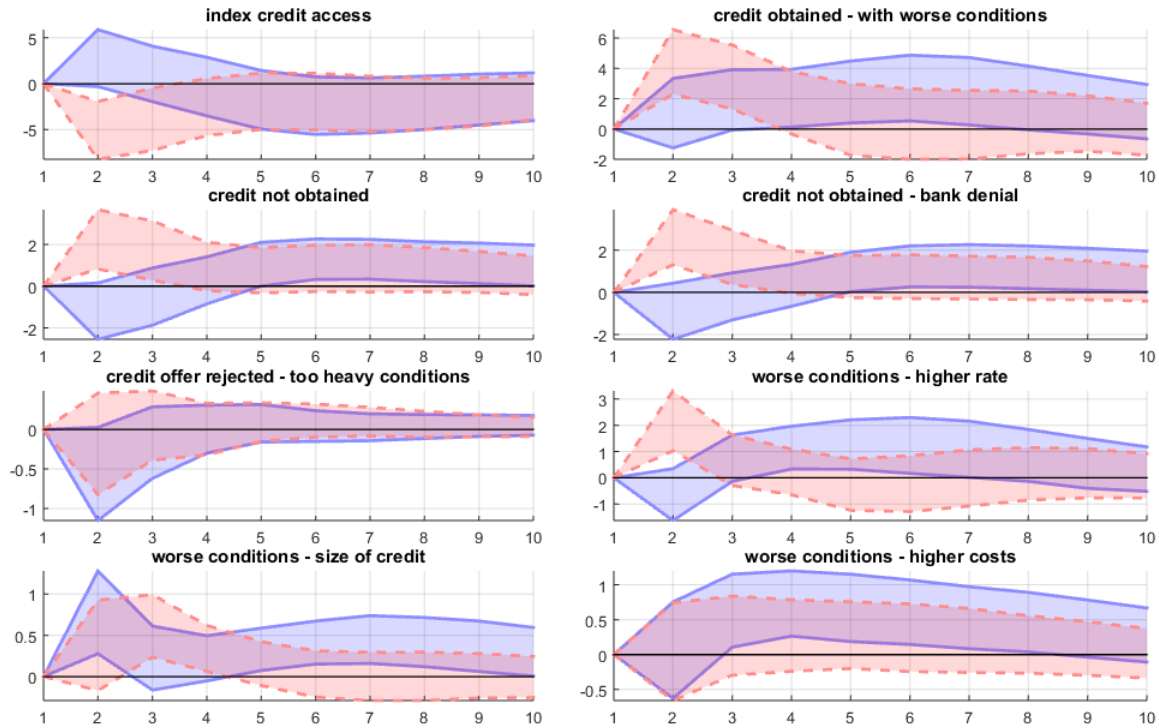

FIGURE 9. *Changes in the credit market for manufacturing firms in response to a one standard positive BAS (blue) and sovereign spread (red) shocks. All figures denote change in the corresponding index reported by ISTAT. Blue and red areas denote the 68% confidence intervals computed using bootstrap and include both identification and statistical uncertainty.*

Liquidity and sovereign spread shocks have different effects on the credit market. On the one 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. 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 2.3.1.

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.

[27] Results remain unchanged if we place this variable last in the VAR.

3.2 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.[28] 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 2.3 to quarterly frequency and estimate the following equation:

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

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 10).[29]

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 2 and 3, 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.

[28] More information about this survey can be found at BLS .

[29] The Data Appendix contains the detailed questions we consider from the Bank and Lending Survey.

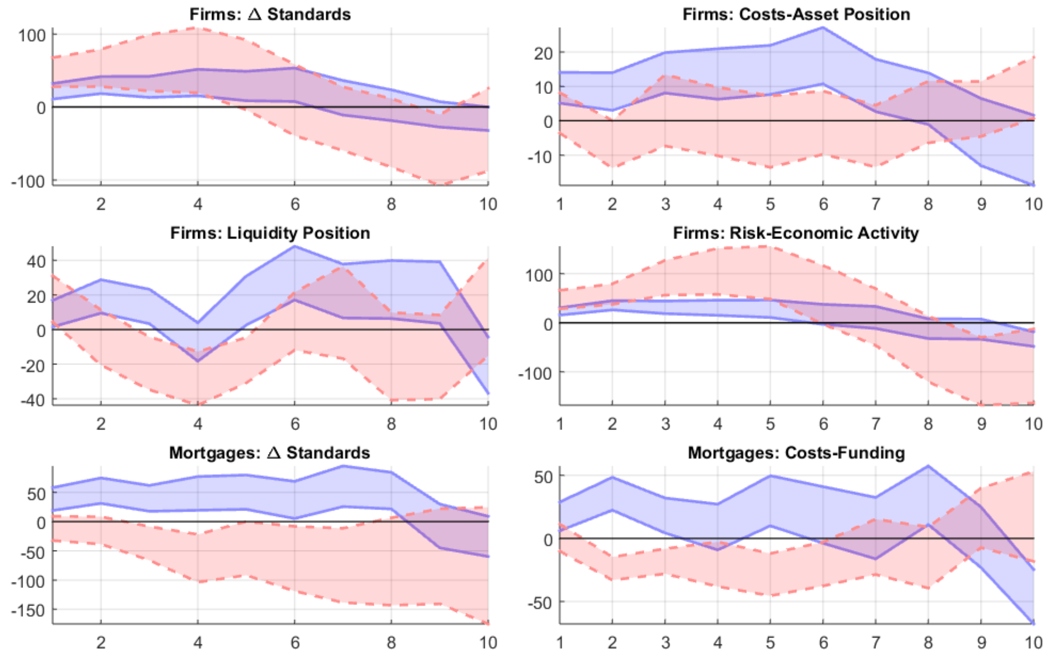

FIGURE 10. *Change in banks decisions in response to a positive shock in BAS and Spread. All the figures denote the change in the corresponding index as reported in the BLS. Blue and red areas denote the 90% confidence intervals computed using 500 bootstrap replications.*

4 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, in Table 2 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 correlations of 2 year sovereign BAS across countries (source: Bloomberg).*

Second, we estimate the baseline VAR described in Section 2.3 for each country to determine whether the macroeconomic results for Italy also hold for the other countries.[30] 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.[31] Both the correlation of the variables in levels and of the shocks indicate that liquidity in sovereign markets is driven by a relevant European component.

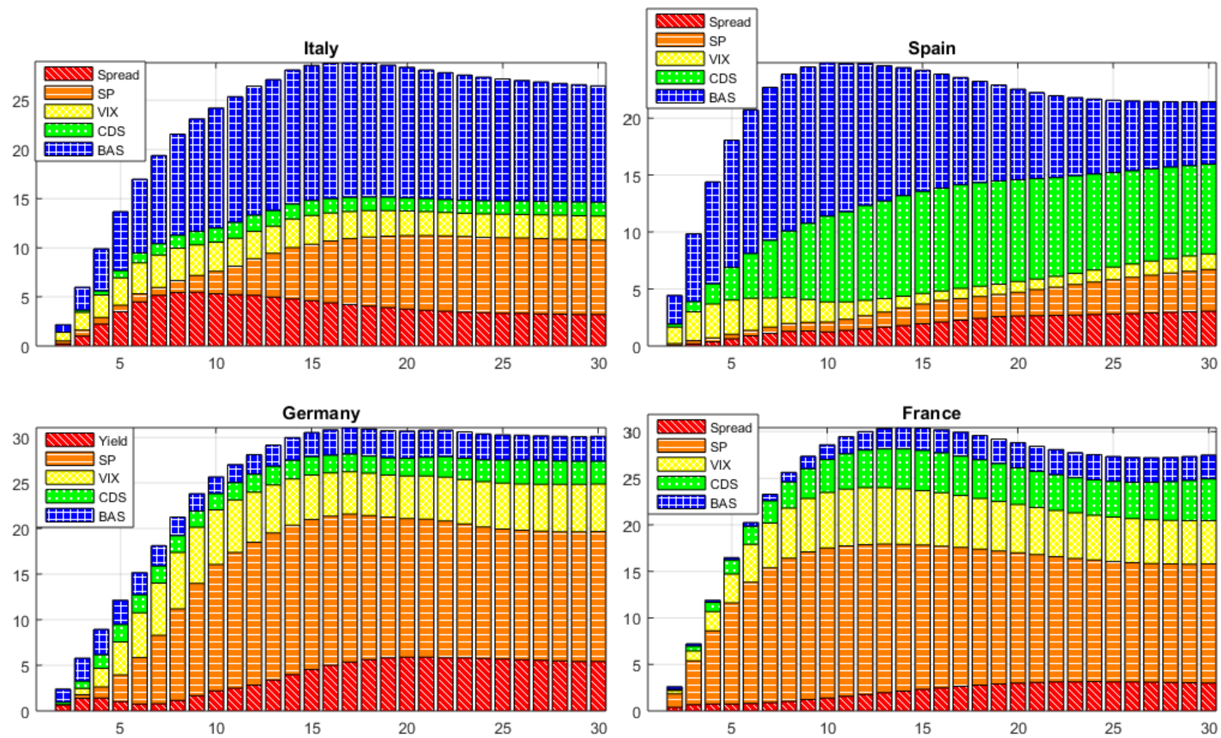

FIGURE 11. FEVD *of Unemployment for Italy, France, Germany, and Spain. The FEVD is computed estimating a VAR for each country that includes: [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block]. BAS shocks are identified from all the possible rotations across the financial variables.*

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.[32] 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

[30]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.

[31]In particular, the estimated cross-country correlations are statistically significant for all the cases but between France and Spain.

[32]Moreover, the IRF to a BAS shock has similar effects both in terms of magnitude and persistence.

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.

5 Comparison with Theoretical Models

This paper provides the first empirical characterization of the real effects of liquidity shocks and documents its transmission through the banking sector. However, as we mentioned before, previous papers have analyzed the macroeconomic effects of liquidity shocks in a theoretical framework. The comparison between the empirical results and the theoretical model on liquidity is crucial both to understand the possible mechanisms and to think appropriate policies to counteract the negative effects.

Del Negro, Eggertsson, Ferrero, and Kiyotaki (2011) and Benigno and Nistico (2014) develop theoretical models with an exogenous liquidity constraint, which restricts the fraction of an asset which can be used to purchase goods. The liquidity shock consists of exogenous changes in this fraction over time. 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. Both papers conclude that liquidity shocks (i.e a decrease in the release fraction of these assets) have strong negative effects on GDP and prices, which in both cases are partially explained by a fall in private consumption.[33] These conclusions differ from our empirical findings along some dimensions. First, while in our case unemployment increases with a lag and reaches its maximum six months after the shock, in the theoretical models the effect on output displays its maximum on impact. Second, CPI inflation decreases slightly on impact but only in the crisis sample is slightly significant, whereas it is a key quantitative result in the theoretical models. Third, in our analysis, liquidity shocks induce a fall a consumer confidence. Although a part of this indicator reflects current private consumption (Ludvigson (2004)), the empirical dynamics are more lagged compared to the theoretical counterpart. All in all, these models match the sign of the responses but not the dynamics presented in this paper. Considering that their objective is to compute the optimal policy response, we think that a better modeling of the financial sector could help to improve both their matching with our findings and their description of the transmission channels.

Some recent papers have considered aggregated conditions to determine liquidity through the

[33] Molteni (2016) employs a similar framework to Del Negro, Eggertsson, Ferrero, and Kiyotaki (2011), while focusing more specifically on the collateral role of government bonds in the Repo market. In his case, a raise in the haircuts (i.e. a decrease in liquidity) generates a contraction in output and consumption, comparable to the ones observed in Del Negro, Eggertsson, Ferrero, and Kiyotaki (2011), and also a lagged and persistent decrease in investment.

optimal decisions of buyers and sellers. Passadore and Xu (2014) investigates how liquidity risk and credit risk explain sovereign spread. 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. Cui and Radde (2015), employing also a search model, show that a negative intermediation shock makes investment into the liquid asset (money and sovereign bonds) as a hedge against future financial constraints. At the same time, the financial constraint of entrepreneurs tightens since other financial assets become less liquid and their prices fall. This situation induces a fall in investment and economic activity. Although the model induces a persistent contraction in economic activity, the reaction is stronger on impact, which differs from our empirical findings. The delayed response of consumption is consistent with the delayed identified response of consumer confidence. Unlike in Del Negro, Eggertsson, Ferrero, and Kiyotaki (2011) and Benigno and Nistico (2014), in Cui and Radde (2015) the fall in prices is not persistent, consistently with our findings. Finally, they find a strong and slightly persistent effect on asset prices, which is in line with the identified reaction of Stock Prices. All in all, endogenizing the dynamic of liquidity seems a relevant improvement. First, it is more consistent with our empirical analysis because we allow other financial and macroeconomic variables to affect liquidity. Second, the IRFs generated in Cui and Radde (2015) are more similar to the dynamics observed in our empirical results.

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.

Given 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. Frameworks of this kind, that 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. We regard Cui and Radde (2015) as a first step in this interesting direction for future research.

References

Bahaj, S. (2014): "Systemic Sovereign Risk: Macroeconomic Implications in the Euro Area," .

Beber, 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.

Garcia, J. A., and R. Gimeno (2014): "Flight-to-Liquidity Flows in the Euro Area Sovereign Debt Crisis," *Banco de Espana Working Paper*, 1429.

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. WRAMPELMEYER (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.

MOLTENI, F. (2016): "Liquidity, Government Bonds and Sovereign Debt Crises," .

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 Data Appendix

Table 1 displays the sources for each country.

Table 1: Data Sources

	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

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 3.2, we refer to the following questions from the Bank and Lending Survey:

1. *Firm Δ 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:* Δ *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 Events and Volume Traded

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 2: *List of European and Italian specific events.*

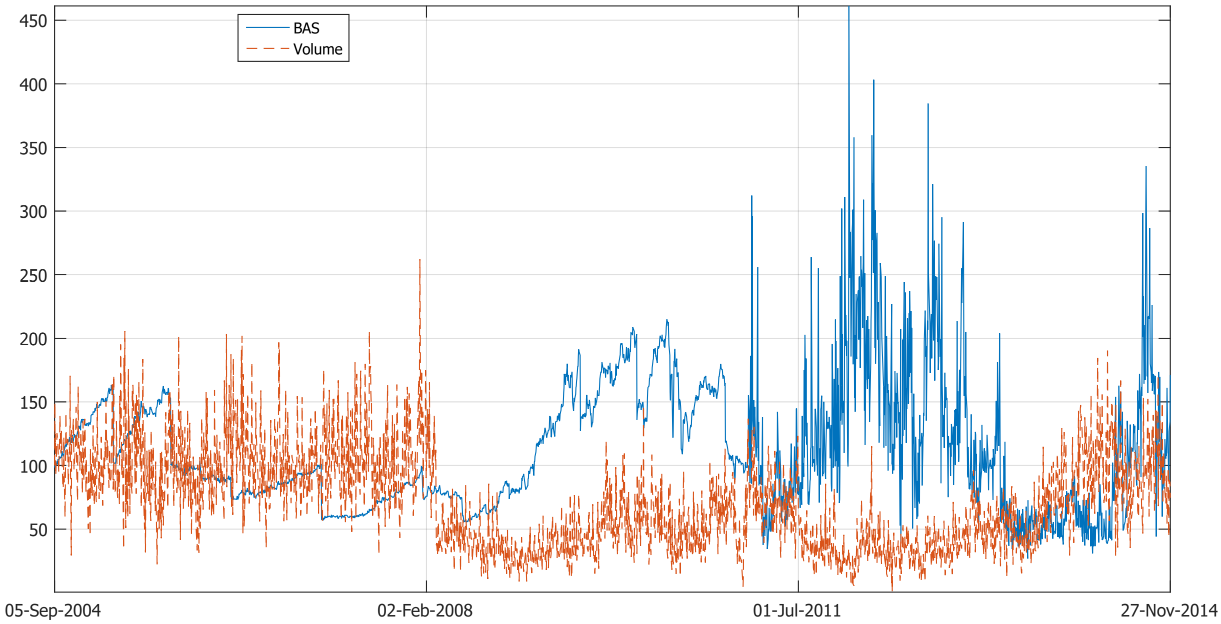

FIGURE A1: *Italian BAS and Turnover on the MTS platform.*

C Robustness

C.1 Baseline Sub-Sample 2009m1-2014m11

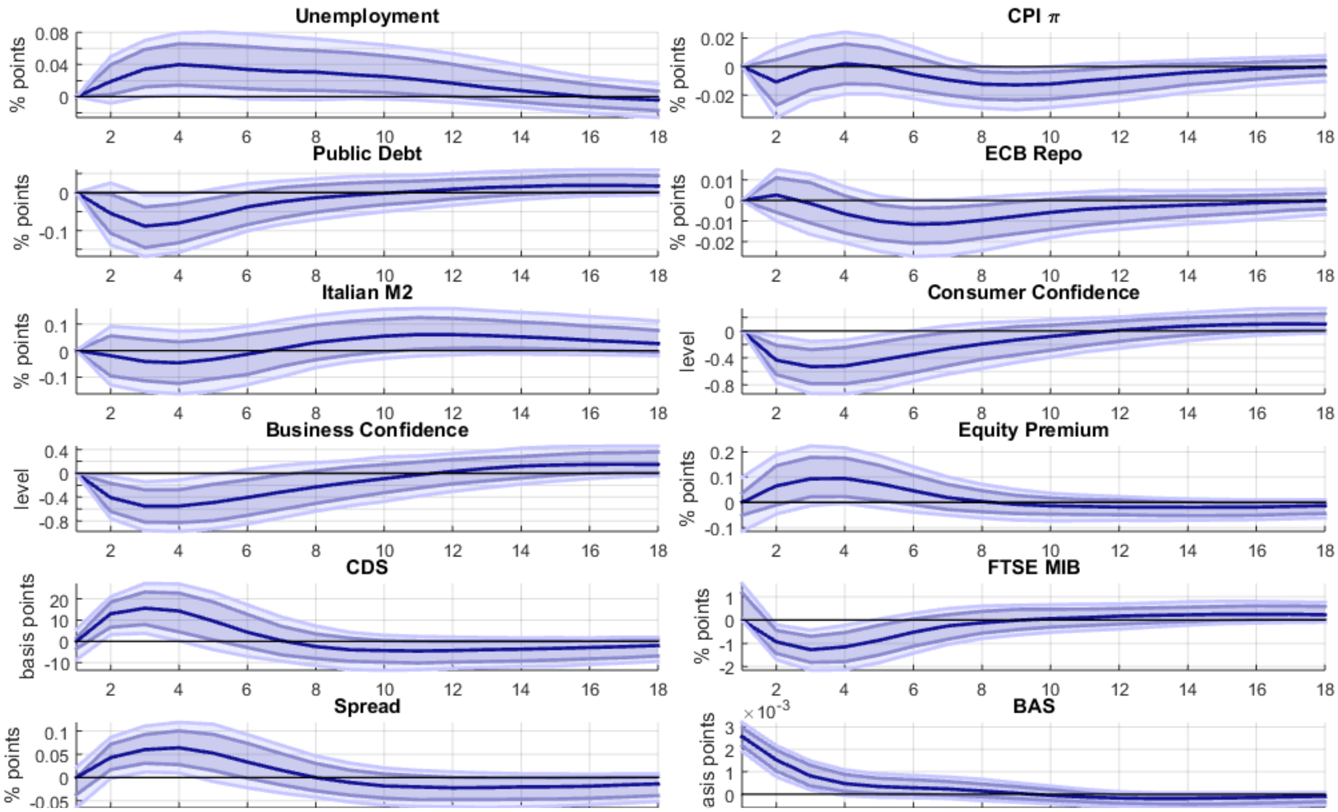

FIGURE A2. *IRFs to a 1 std Liquidity Index shock (liquidity improvement) identified through the following ordering [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% and 90% bands include statistical and identification uncertainty (from all the possible ordering within the financial block).*

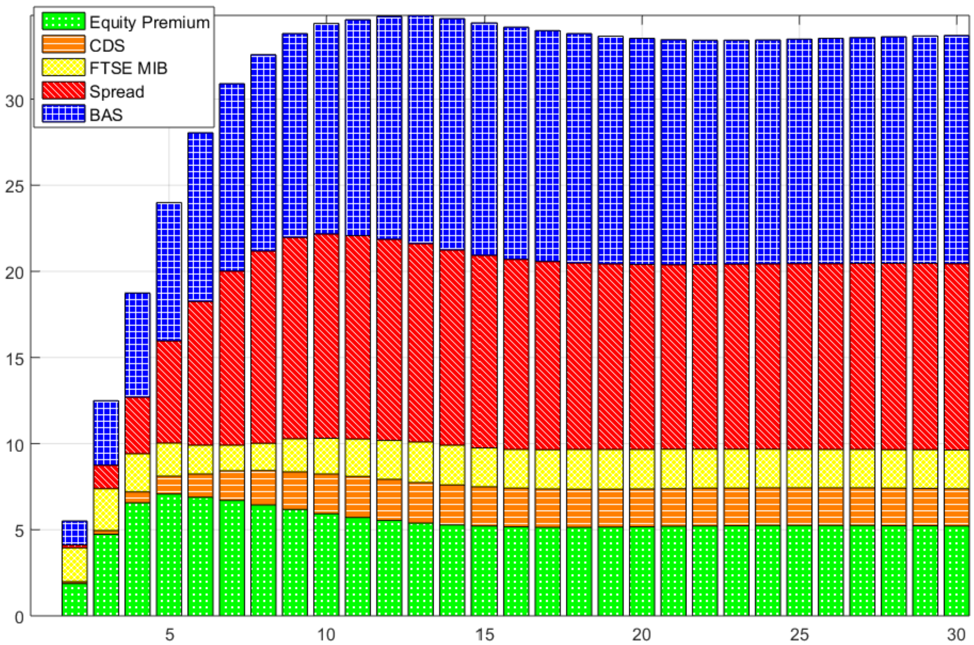

FIGURE A3. *FEV of Unemployment including the Liquidity Index identified through the following ordering [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block].*

C.2 Industrial Production Sub-Sample 2009m1-2014m11

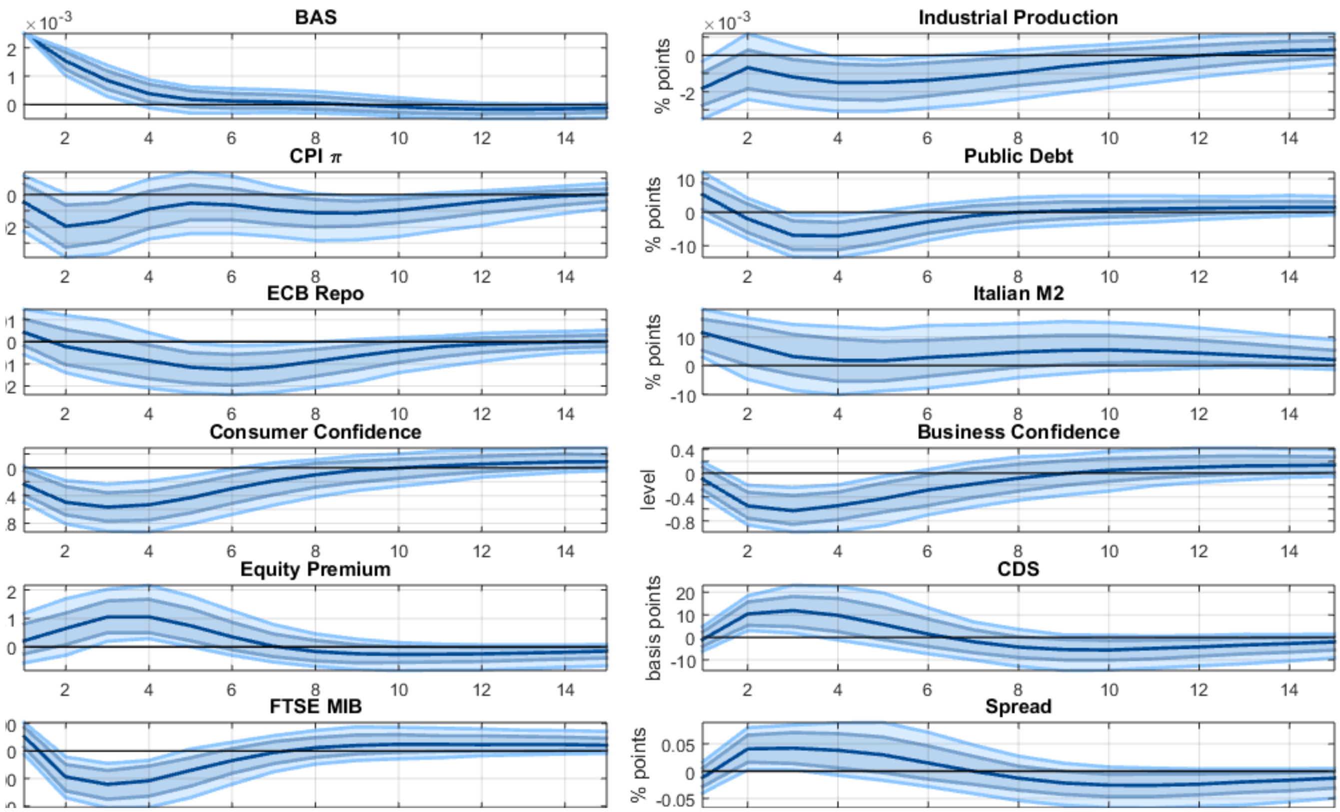

FIGURE A4. *IRFs to a 1 standard deviation BAS shock (liquidity deterioration) in the VAR [IP, π, Public Debt, R, M2, CC, BC, Financial Block]. The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Jan:2009-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications.*

C.3 Itacoin Sub-Sample 2009m1-2014m11

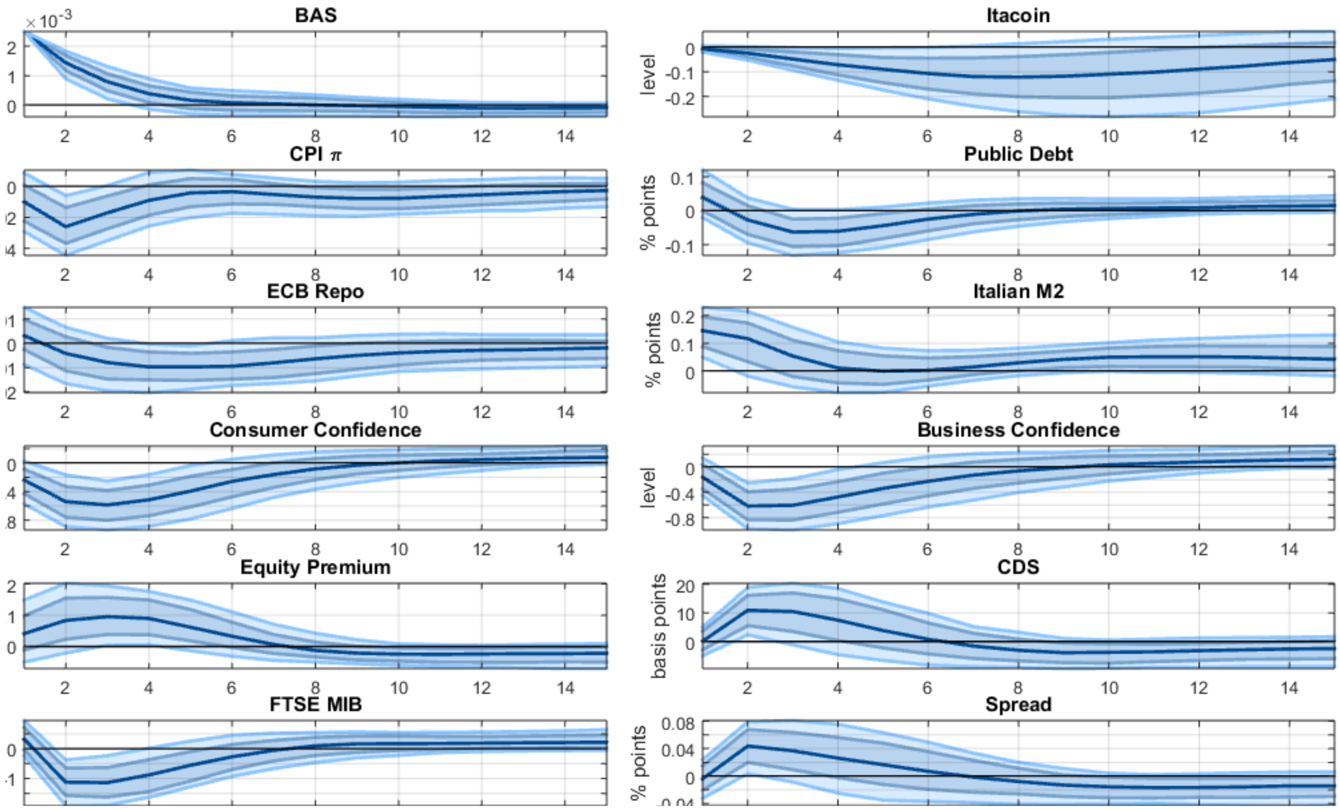

FIGURE A5. *IRFs to a 1 standard deviation BAS shock (liquidity deterioration) in the VAR [IP, π, Public Debt, R, M2, CC, BC, Financial Block]. The shock is identified through the unpredictable variation of the BAS in a daily VAR system. Sample: Jan:2009-Nov:2014. The median point estimate, 68% and 90% confidence bands are reported in blue and light blue, respectively. Confidence bands are computed using wild bootstrap with 1,000 replications.*

C.4 Liquidity Index

In this section, we estimate the same VAR including the Liquidity index in sovereign debt markets instead of BAS. Figure 6 displays the responses to an increase in the Liquidity index (comparable to a reduction in the BAS).

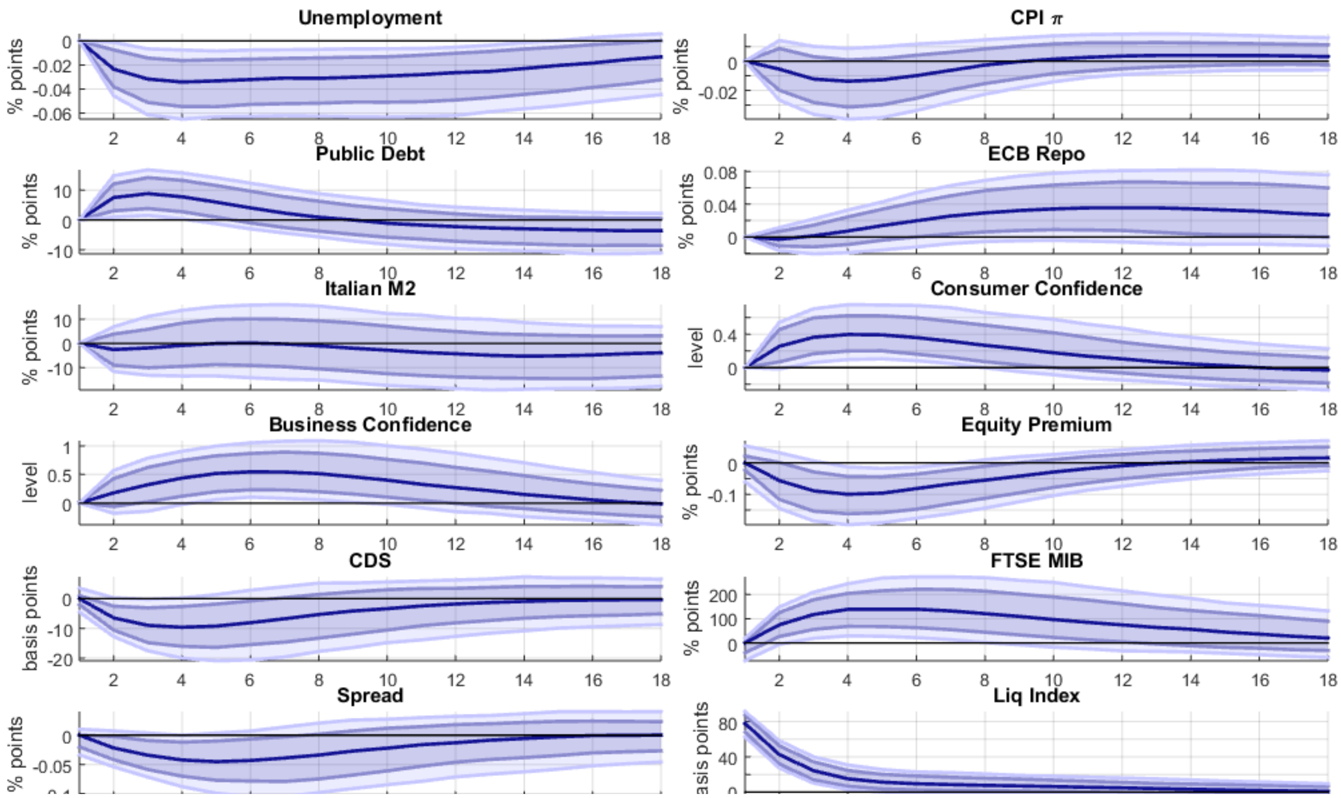

FIGURE A6. *IRFs to a 1 std Liquidity Index shock (liquidity improvement) identified through the following ordering [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block]. The median point estimate, 68% and 90% confidence bands are reported in cyan, blue, and light blue, respectively. 50%, 68% 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 2 of the paper. Figure 7 displays the Forecast Error Variance of Unemployment.

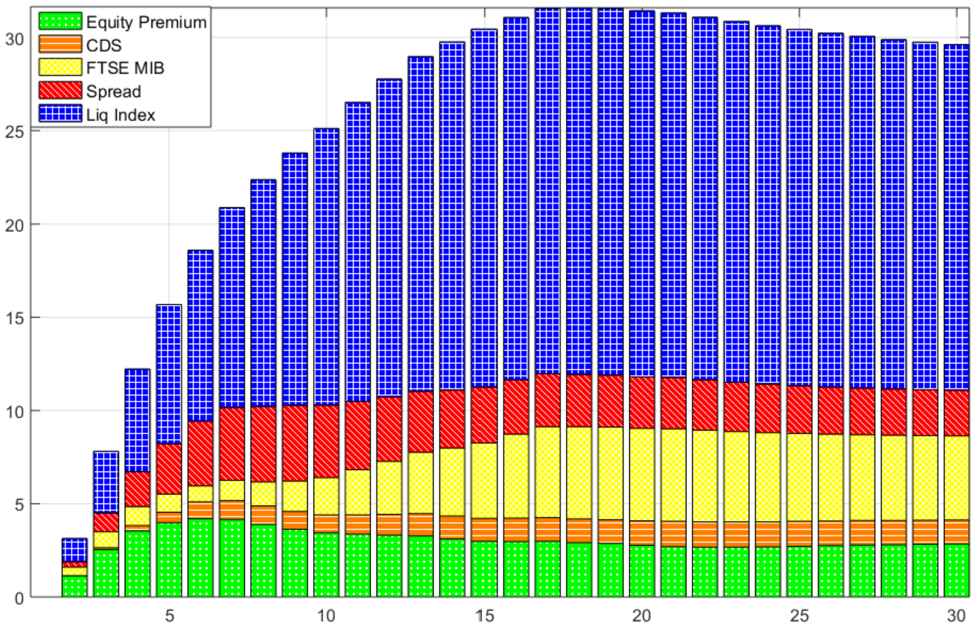

FIGURE A7. *FEV of Unemployment including the Liquidity Index identified through the following ordering [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block].*

Liquidity accounts for around 20% of Unemployment fluctuations in the period under analysis, in line with results presented in Section 2.

D Proxy-SVAR

D.1 Theoretical Reference

Consider the following VAR:

$$Y_t = AY_{t-1} + u_t \tag{2}$$

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

$$Y_t = AY_{t-1} + B\varepsilon_t \tag{3}$$

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

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

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 ε_t^{bas}. z_t is assumed to be a proxy for (a component of) the true ε_t^{bas} with the following (instrumental variable) properties:

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

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

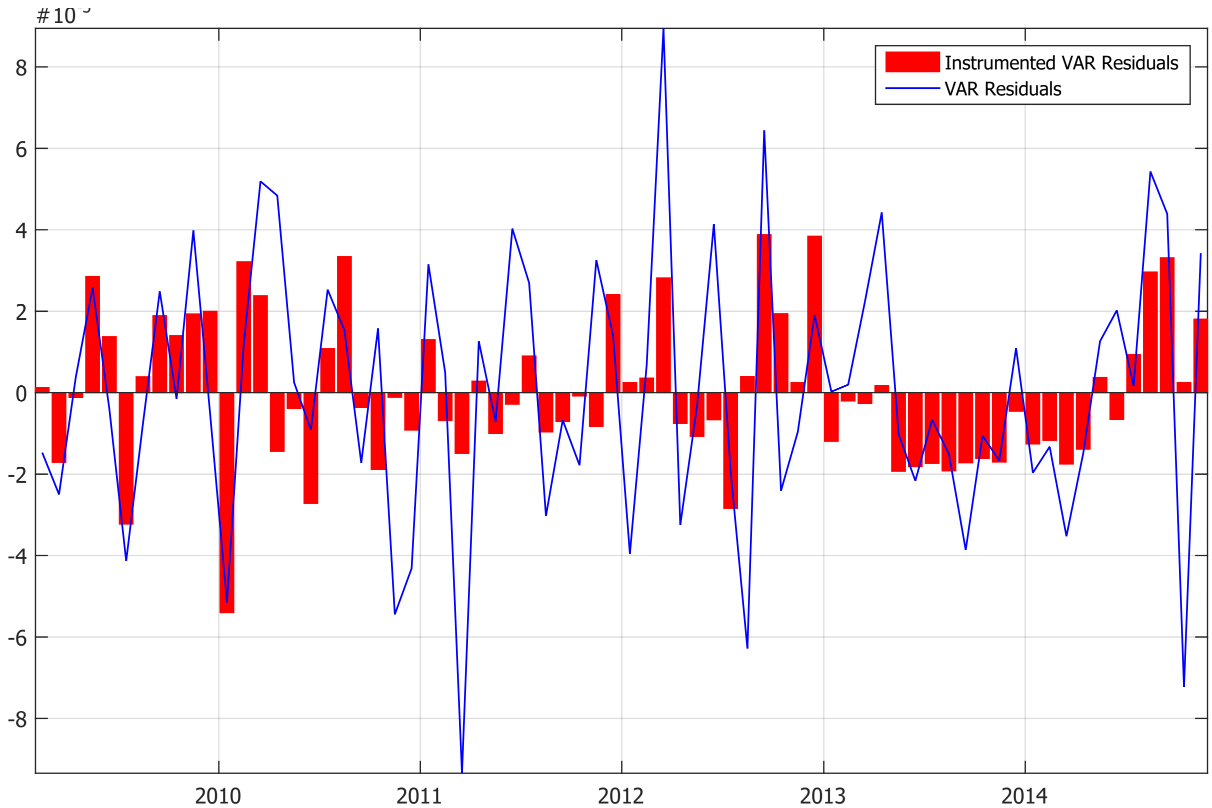

FIGURE A8. *First stage result: the blue line represents the RF residuals of the BAS from the VAR featuring [Unemployment, π, Public Debt, R, M2, CC, BC, Financial Block]; the red bar is the RF residuals predicted by the Proxy (BAS shocks identified in a daily VAR including $[BAS, CDS, Yield, FTSE, Eonia, VIX]$)*