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The credit channel of the sovereign spread: A Bayesian SVAR analysis ☆

Gianluca Cafiso [a,*], Alessandro Missale [b], Giulia Rivolta [b]

[a] Università degli Studi di Catania, Dipartimento di Economia e Impresa and CESifo Research Network, Corso Italia 55, 95129 Catania, Italy
[b] Università degli Studi di Milano, Dipartimento di Economia, Management e Metodi Quantitativi, Via Conservatorio 7, 20122 Milano, Italy

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ABSTRACT

Sovereign bond spread shocks are thought to threaten debt sustainability mainly through their impact on refinancing costs. Our analysis sheds light on a less evident channel, we call it the spread-credit channel. It originates from the negative impact of spread shocks on bank loans, which can trigger a "diabolic loop" between slowing economic activity, high debt, increasing spreads and banks' vulnerability. Contrary to other studies in the literature, we identify the structural shocks to the Italian spread using a Proxy-SVAR model. The Bayesian estimation of the Proxy-SVAR shows that spread shocks negatively affect bank lending and economic activity making the debt-to-GDP ratio increase. Debt sustainability also depends on how investors react to shocks. We find evidence that foreigners disinvest, while domestic investors buy more debt when it becomes riskier.

1. Introduction

The interest rate differential between the Italian and German 10-year government bonds, i.e. the BTP-Bund spread, has long been in the news since the 2011–12 Euro debt crises and has become a point of focus to gauge the market's assessment of the risk of an Italian sovereign default. A large literature investigates the determinants of the BTP-Bund spread, and highlights the positive feedback loop between the spread and the debt-to-GDP ratio through its impact on the cost of debt service (Ghosh et al., 2013; Lorenzoni and Werning, 2019). This literature often points to the detrimental effect of an economic slowdown on the BTP-Bund spread.[1] In this paper, in line with other contributions (Bocola, 2016; Faia, 2017; Barbieri-Hermitte et al., 2023), we investigate the opposite direction of this relationship: from an increase in the spread to a contraction in economic activity. We explain the transmission mechanism of such an effect by the deterioration of banks' balance sheets, which leads to a contraction of credit supply, what we call the *spread-credit channel*.

Italy is characterized by a large public debt relative to GDP that carries a significant default premium, i.e. a sovereign risk premium, as measured by the BTP-Bund spread. Italian government bonds represent a disproportionate share of Italian banks' assets, which is the main ingredient of the "diabolic loop" in Brunnermeier et al. (2011, 2016), Acharya et al. (2014) and Farhi and Tirole (2018). We examine the impact of the BTP-Bund spread on the supply and cost of loans and, in turn, on the real economy and the debt-to-GDP ratio. We conduct our analysis through the Bayesian estimation of a vector autoregressive (VAR) model using Italian monthly data from January 2003 to December 2019.

To the best of our knowledge, the present study is the first VAR-based analysis showing the impact of a shock to the Italian sovereign spread on the unemployment rate and the debt-to-GDP ratio, and its transmission through an increase in the cost of credit and its contraction triggered by banks' losses on their holdings of government bonds.[2] More importantly, while most studies in the empirical literature bypass the endogeneity of the sovereign spread, which is germane to the

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* Corresponding author.
E-mail addresses: gianluca.cafiso@unict.it (G. Cafiso), alessandro.missale@unimi.it (A. Missale), giulia.rivolta@unimi.it (G. Rivolta).

[1] For empirical evidence see IMF (2023) and the references therein.
[2] Beqiraj et al. (2021) also examine the sovereign-bank risk pass-through but, as they focus on the fundamental determinants of sovereign and bank spreads, they do not consider bank loans, bond holdings and deposits in their VAR.

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sovereign-bank-risk nexus, we identify the structural shocks to the Italian spread by means of a structural VAR (SVAR). Specifically, we apply the Proxy-SVAR methodology of Caldara and Herbst (2019); we instrument the spread with the principal component of the spreads of other Euro area countries. This original solution exploits the independence of global pricing trends from domestic fundamentals and the role of such trends as the main drivers of the Italian spread (see Codogno et al. 2003). We also show that our results are robust to alternative identification methods.

The Bayesian estimation of a large VAR including macro and banking sector specific variables returns all the relevant interactions highlighted in the literature. It shows that structural shocks to the BTP-Bund spread reduce the market value of banks' holdings of Italian government bonds. As a result, banks have to adjust their balance sheets. This leads to a significant reduction in loans and a subsequent increase in bond holdings. The interest rate on loans increases relative to the interbank rate and remains higher over time. Then, spread shocks cause a contraction in economic activity, as shown by the significant and long lasting increase in the unemployment rate. Finally, the debt-to-GDP ratio rises possibly because of lower GDP growth and tax revenues besides higher debt servicing costs. Although the economic slowdown could also be explained by firms' disinvestment due to concerns for higher uncertainty and sovereign risk, the finding of a significant increase in the lending rate is evidence that the direction of causality runs from banks to the real economy. In fact, tighter borrowing conditions suggest that the credit contraction is supply driven, consistently with the results of Albertazzi et al. (2014) and Altavilla et al. (2017).

In a second part of our analysis, we investigate the effect of Italian spread shocks on the demand for government bonds by different investor groups. The analysis points to the different behavior of domestic and foreign investors, with the former, mainly banks, increasing their holdings of domestic debt while the latter flying away from Italian debt as sovereign risk and bond yields rise (Cafiso, 2016).

The results of our analysis are important for crisis prevention as they provide a better understanding of the relationship between the sovereign spread, economic activity and debt dynamics. A high debt largely held in domestic banks' portfolios exposes the government to the risk of a crisis and default by making debt sustainability particularly vulnerable to an increase in the yield spread. Even though the long maturity of the debt makes the cost of debt service little sensitive to changes in bond yields, sovereign spread shocks still threaten debt sustainability through the *spread-credit channel*.

The paper is structured as follows. Section 2 reviews the relevant literature. Section 3 presents the empirical model. Section 4 shows the results of the Proxy-SVAR regarding the effect of sovereign spread shocks on bank lending, the unemployment rate, and the debt-to-GDP ratio. Section 5 reports the results on debt holdings by different investor groups. Section 6 concludes.

2. Literature review

The objective of our analysis is to empirically investigate the spread-credit channel, i.e. how sovereign spread shocks affect economic activity through their negative impact on lending. We first review the main contributions in the literature and then outline the specific contribution of our study.

Regarding the origin of the spread-credit channel, Brunnermeier et al. (2011, 2016) first highlighted the "diabolic loop" between sovereign and bank solvency risks due to balance sheet effects arising from the large exposure of European banks to domestic government bonds. A *balance-sheet channel* for the effect of sovereign spreads on credit supply works through banks' losses on their holdings of government bonds which reduce banks' equity value. As the leverage constraint tightens and the cost of funding rises, banks have to reduce lending to firms and households, leading to an economic slowdown.[3] In turn, sovereign risk increases due to bailout expectations or the budgetary impact of lower growth (see, e.g., Acharya et al. 2014 and Farhi and Tirole 2018). In addition to the deterioration of bank capital, Bocola (2016) considers a precautionary motive, say a *risk channel*, for the effect of sovereign risk on credit supply. Banks demand higher returns on loans, not only because of tighter leverage constraints, but also because they perceive firms as riskier. Furthermore, Faia (2017) emphasizes the *asset-liquidity risk* and the *collateral channels*. As sovereign risk impinges on banks' asset risk, investors withdraw their deposits, thereby creating a liquidity shortage that cannot be met in the repo market because of the lower collateral capacity of sovereign bonds.

Our study is closely related to Bocola (2016), Faia (2017) and Barbieri-Hermitte et al. (2023) who examine the effects of sovereign risk on the aggregate supply of credit and economic activity. They simulate the effects of sovereign spread movements by using structural models, which are intrinsically different from VAR analysis. In Barbieri-Hermitte et al. (2023) a higher spread reduces economic growth through an increase in the interest rate on bank loans that leads to a contraction in lending and investment. Bocola (2016) examines the effects of sovereign risk in a business cycle model in which bank lending is impaired by balance-sheet losses on sovereign bond holdings. A significant contraction in investment and output is obtained from simulations that take sovereign risk as exogenous, i.e. proxied by the CDS probability of default. Faia (2017) develops a general equilibrium model in which banks act as delegated monitors of firms, and are subject to runs. Simulation results based on perturbation methods show that sovereign risk shocks (estimated using CDS premia) lead to a contraction in economic activity by raising banks' funding costs and reducing the supply of credit through the balance sheet, liquidity, and collateral channels discussed above.

We investigate the same effects by estimating a structural vector autoregression (SVAR) which, compared to the other models in the literature, imposes the least possible structure on the relationship between the key banking, financial and macroeconomic variables. Our study complements the analysis in Beqiraj et al. (2021). While they shed light on the state-dependent responses of sovereign and credit spreads to fiscal and macroeconomic shocks using a Markov-switching VAR model, we investigate the effects of sovereign spread shocks on the supply of bank credit by considering the response of the banking sector balance sheet along with the cost of credit. We further investigate the role of the investor base for debt sustainability by studying the effect of spread shocks on the demand of domestic bonds by different investor groups, in particular by foreign investors (see, e.g., Arslanalp and Tsuda 2012, Abbas et al. 2014, Cafiso 2016).[4]

Importantly, while Bocola (2016) and Faia (2017) assume that changes in sovereign risk are exogenous, and bypass the endogeneity problem that is germane to the sovereign-bank-risk nexus, we identify the structural shocks to the Italian spread by applying the Proxy-SVAR model. Furthermore, its Bayesian estimation returns all the relevant interactions highlighted in the literature, since we can include several macro and bank-sector specific variables. This is made possible by Bayesian methods that allow to estimate large VARs by reducing the parameter space, thereby overcoming the overparametrization problem (Bańbura et al., 2010). The Proxy SVAR method for structural

[3] Bocola (2016) refers to this channel as the liquidity channel because, in his model, the deterioration of banks' capital implies higher financing needs and costs.

[4] In doing so we extend the analysis of banks' demand to other debt holders, thus complementing the work of Battistini et al. (2013), Acharya and Steffen (2015), Ongena et al. (2019), Altavilla et al. (2017) who show that public and/or poorly capitalized banks in stressed countries respond to increases in sovereign yields by purchasing more domestic debt because of moral suasion and/or carry trade incentives, respectively.

identification, also known as external instruments method (Stock and Watson, 2012) has been widely used with financial variables to identify monetary policy shocks (Gertler and Karadi, 2015; Caldara and Herbst, 2019) and uncertainty shocks (Carriero et al., 2015; Piffer and Podstawski, 2018). We apply the most recent techniques developed by Arias et al. (2021) and Caldara and Herbst (2019) to estimate Proxy SVAR using Bayesian inference.

Our results are consistent with Zoli (2013), who estimates a sizable pass-through of the sovereign spread on lending rates during the Euro debt crisis, with Albertazzi et al. (2014), who show that the Italian sovereign spread has a significant negative effect on bank lending, and with Altavilla et al. (2017), who show that stressed-country banks with larger sovereign exposures cut lending more deeply than less exposed banks.[5] Importantly, the latter find that such a contraction is not driven by demand-side factors, as exposed banks also reduce lending to firms in non-stressed countries.[6] Evidence from our SVAR also supports the supply-side origin of the credit contraction by showing a significant negative co-movement of bank loans and lending rates.

3. Empirical model

This section describes the econometric model and the methodology used to identify the structural shocks to the Italian sovereign bond yield spread; for simplicity, spread shock*s* hereinafter. We are interested in the effect of spread shocks primarily on the amount and cost of loans extended by Italian banks to Italian firms and households, as well as on economic activity that we measure with the unemployment rate. The quantification of such effects is by means of Impulse-Response Functions (IRFs) derived from the Bayesian estimation of a VAR. Identification of the spread shocks is based on the Proxy-SVAR methodology of Caldara and Herbst (2019) for which we use the variation of the principal component of the sovereign spreads of Euro area countries (Italy excluded) as the instrument for Italy's sovereign spread. A visual inspection of the variables under analysis is in Fig. 1.

Using the same analytical method (Proxy-SVAR), we also investigate how spread shocks affect the demand for government bonds by different debt holders in the second part of our analysis. Details on the estimation and the identification of the structural shocks, the data and the proxy used are in the following subsections.

3.1. The SVAR model

The empirical analysis is based on the following reduced-form VAR:

$$Y_t = \alpha + \sum_{l=1}^{P} B_l Y_{t-l} + u_t \quad u_t \sim N(0, \Sigma), \tag{1}$$

where Y_t is a 10-variable vector and α, B and u_t are conformable vectors and matrix of coefficients and residuals, respectively. The VAR includes 13 lags for each variable to cover one year of data as common in this strand of literature. The model is estimated with Bayesian techniques.

In order to evaluate the effect of a spread shock, we need to consider the VAR in structural form:

$$A_0 Y_t = c + \sum_{l=1}^{p} A_l Y_{t-l} + e_t \ ,$$

where e_t is the vector of structural shocks. The matrix A_0 includes the coefficients for the contemporaneous relationships between the endogenous variables. Such coefficients allow to retrieve the structural shocks as:

$$e_t = A_0^{-1} u_t.$$

The identification problem consists in placing enough restrictions on the matrix A_0 so that it is possible to recover the structural shocks from the reduced-form residuals. Many strategies have been developed to identify structural relations in VAR models.[7] Given the large number of endogenous variables in our system, and the fact that we are just interested in exploring the effects of an exogenous change in the spread, we identify only partially the model relying on the Bayesian Proxy-SVAR approach of Caldara and Herbst (2019).

In the structural VAR literature, financial shocks are typically identified using sign restrictions (see e.g. Furlanetto et al. 2019, Brianti 2021). Sign restrictions are more reliable when the model is fully identified. Partial identification of financial shocks based on sign restrictions is also feasible, especially in models with many endogenous variables (Caldara et al. 2016, Brianti 2021 and Caggiano et al. 2021). However, those models are based on US data and, either employ sign restrictions on ratios of quarterly variables relative to GDP, or rely on some indicators to distinguish uncertainty from financial shocks. Similar variables are not available in our study based on monthly data for the Italian economy, whose aim is to study just the effect of spread shocks through the credit sector.[8] In contrast, the Proxy SVAR method for structural identification, also known as external instruments method (Stock and Watson, 2012), does not require full identification and it has been widely used with financial variables to identify monetary policy shocks (Gertler and Karadi, 2015; Caldara and Herbst, 2019) and uncertainty shocks (Carriero et al., 2015; Piffer and Podstawski, 2018). This method is based on an external instrument (i.e. the proxy) that is correlated to the shock of interest but orthogonal to the other structural shocks so that it can be used to identify the relevant shock following the instrumental variable approach (Stock and Watson 2012 and Mertens and Ravn 2013). More recently, Arias et al. (2021) and Caldara and Herbst (2019) developed algorithms to estimate proxy SVAR using Bayesian inference.

Caldara and Herbst (2019)'s approach has the following main advantages. First, it does not work in sequential steps as in Stock and Watson (2012), Mertens and Ravn (2013) or Piffer and Podstawski (2018) but it allows to model simultaneously the interaction between the SVAR and the proxy as they augment the likelihood of the model with an equation that relates the proxy to the structural shock of interest. This is achieved by writing the model in state-space form. Second, inference is valid even if the information content of the proxy is weak and the information contained in the proxy is used to produce inference both on reduced-form and structural-form parameters as all sources of uncertainty are taken into account in the estimation process. Third, the Bayesian framework allows the estimation of large models since it deals with the overparametrization problem by restricting the parameters space (Bańbura et al., 2010).

[5] Gennaioli et al. (2018) also find a strong negative correlation between banks' holdings of sovereign bonds and their loans during sovereign default episodes in a large panel of banks of different countries.

[6] Specular evidence of the supply-side nature of the credit contraction is provided by Bofondi et al. (2018) for the case of Italy during the Euro debt crisis.

[7] A model is said to be *fully identified* when are identified as many shocks as the number of equations in the VAR. On the other hand, it is also possible to identify only a subset of shocks so that the model is said to be *partially identified*.

[8] Furthermore, sign restrictions are not an option in our analysis because, first, we would need to specify the sign of the responses of the several financial, credit and balance-sheet variables included for the objective of our analysis and, second, be able to distinguish the shocks to the different credit variables from those to the financial variables; this is unrealistic in our application. Overall, the sign restriction approach is appropriate when backed by solid theory about the effects of the shocks to identify, solid theory would also allow to distinguish the relevant shocks without imposing too much structure on the impulse response functions as the risk is to obtain results that are weakly supported by the data. Here we do not want to impose any predetermined structure to the impulse responses and we rather favor a more data-driven approach.

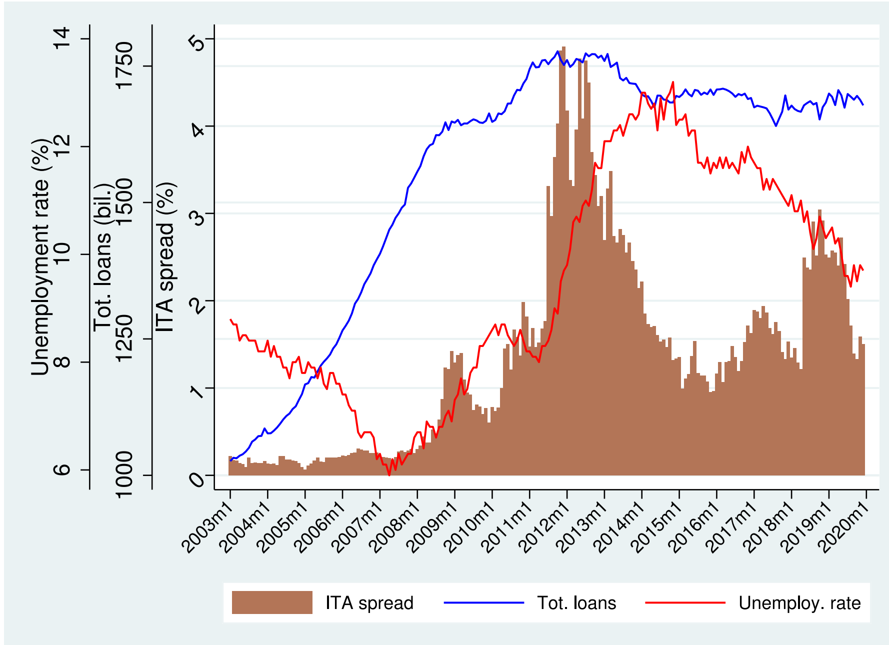

Fig. 1. Italy's spread, loans, unemployment. Plot of Italy's spread, total loans and unmployment rate. For the source of these variables, see Table 1.

The structural VAR model can be written in compact form as:

$$A_0 Y_t = A_+ X_t + e_t$$

where $A_+ = \left[A_1, \ldots, A_p, c\right]$ and $X_t = \left[Y'_{t-1}, \ldots, Y'_{t-p}, 1\right]'$. The reduced-form parameters and the structural parameters are linked as follows:

$$\Sigma = (A'_0 A_0)^{-1} \quad B = A_0^{-1} A_+.$$

As mentioned before, to identify the spread shocks, we only need to retrieve the structural coefficients of the spread equation. For sake of simplicity, we place the spread in the first position so that we only need to identify the coefficients of the first equation, i.e.:

$$A_{0,1} y_t = A_{+,1} x_t + e_{SP,t}.$$

Identification of this subset of structural coefficients is achieved specifying a measurement equation that links the proxy m_t with the spread shock $e_{SP,t}$:

$$m_t = \beta e_{SP,t} + \sigma_\upsilon \upsilon_t, \tag{2}$$

where υ_t is an i.i.d. measurement error distributed as a standard normal and orthogonal to e_t. Relevance and exogeneity of the proxy are crucial to the method (Stock and Watson, 2012). The relevance of the proxy for the structural shock of interest is measured by the squared correlation between m_t and $e_{SP,t}$, and it is directly related to the signal-to-noise ratio β/σ_υ:

$$corr\left(m_t, e_{SP,t}\right)^2 = \frac{\beta^2}{\beta^2 + \sigma_\upsilon^2}.$$

These quantities determine how much information the proxy brings in to identify the shocks and therefore the strength of the relationship between the two. It is possible to impose a higher relevance for the proxy by changing the prior on the parameters of Eq. (2), as discussed in greater detail in Appendix B. We use the standard prior in our baseline model, i.e. we do not impose any restriction on the role of the measurement error,[9] but our results are still robust to the use of the high-relevance prior (Appendix B).

Furthermore, the proxy is exogenous to the other structural shocks of the VAR model $e_{NSP,t}$, so that:

$$E[m_t, e'_{NSP,t}] = 0.$$

It is important to notice that the specification of the model, that is used to generate the unobserved structural shocks $e_{SP,t}$, affects the relevance and the exogeneity of the proxy.[10]

This model is estimated following the Bayesian approach and using the BEAR toolbox that applies the Metropolis-within-Gibbs algorithm described in Caldara and Herbst (2019). The technical details of the Bayesian estimation of the model are in Appendix B. In order to check the robustness of the IRFs obtained with the Proxy-SVAR methodology, we also apply the Cholesky decomposition and the narrative sign restrictions approach of Antolín-Díaz and Rubio-Ramírez (2018) as robustness checks in Section 4.4.

3.2. Data

Our analysis is based on a monthly dataset consisting of Italian and European variables that are listed with their respective sources in Table 1.

For our SVAR analysis we use 10 time series to describe the banking, financial and real sectors of the Italian economy. The sovereign spread is computed as the difference between the Italian and the German 10-year government bond yields. We measure economic activity with the unemployment rate, and inflation with the consumer price index. The unemployment rate has the advantage, compared to other monthly indexes such as industrial production, to include the service sector and to respond more rapidly to an investment disruption caused by a credit contraction. The debt-to-GDP ratio is taken as the indicator of fiscal fundamentals; it is originally at a quarterly frequency and transformed to a monthly frequency by linear interpolation. Several

[9] By doing so, we find that the relevance of the proxy at its posterior median is 0.23, which translates into a correlation between the proxy and the shock of 0.48.

[10] As mentioned before, and as illustrated by Caldara and Herbst (2019), the likelihood function of the model depends on the likelihood of the VAR data that contains information about the reduced-form parameters, and on the conditional likelihood of the proxy given the VAR data.

Table 1
List of variables.

#	Variable	Source
1	debt to GDP ratio	Bank of Italy
2	consumer price index[a]	ISTAT
3	unemployment rate	ISTAT
4	banks' deposits[a]	ECB
5	banks' loans to Italian households & non-monetary institutions excluding government[a]	ECB
6	banks' holdings of Italian government bonds[a]	ECB
7	lending rate spread	Bank of Italy
8	policy shadow rate	ECB, Wu, Xia (2017, 2020)
9	Stock price index	Datastream
10	Italy's sovereign bond spread	Datastream
11	Principal component of the sovereign bond spreads of the EA countries (Italy excluded)	Datastream
12	A. Non-residents' holdings of government bonds[a]	Bank of Italy
13	B. Residents' holdings of government bonds (Total)[a]	Bank of Italy
14	B1. Residents: Monetary financial institutions' holdings of government bonds (banking institutions)[a]	Bank of Italy
15	B2. Residents: Other financial institutions' holdings of government bonds (non-banking institutions)[a]	Bank of Italy
16	B3. Residents: Households and other non-financial residents' holdings of government bonds[a]	Bank of Italy
17	B4. Residents: Bank of Italy's holdings of government bonds[a]	Bank of Italy

ECB stands for the European Central Bank, Istat for Italy's national statistics institute.
[a] Marks a variable entering the model in logarithm.

variables are specific to the credit sector. Credit supply is captured by the outstanding amount of loans extended by Italian banks to Italian households and non-monetary institutions, excluding government; i.e. mainly loans to firms and households. Banks' aggregate holdings of Italian government bonds (recorded at market value) are included to measure the exposure of Italian banks to domestic sovereign debt. Finally, the aggregate amount of bank deposits accounts for banks' main source of funding. These series are extracted from the European Central Bank's database "Aggregated Balance Sheet of Monetary Financial Institutions". The lending rate spread is the difference between the average interest rate on loans to non-financial corporations and the 3-month interbank offered rate (Euribor). An increase (decrease) in this spread signals a tightening (easing) of lending conditions relative to money market rates.[11] As the indicator of the monetary policy stance, we use the shadow rate for the Euro Area computed using the method of Wu and Xia (2017, 2020). The negative shadow rate accounts for the unconventional monetary policies implemented by the ECB after the global financial crisis; its impact on the economy would be identical to such policies as shown by Wu and Zhang (2019).[12] We also include the FTSE MIB index, that is, the main Italian stock market index.

To sum up, we use variables 1–11 in Table 1 in the main Proxy-SVAR analysis, and variables 12,14–17 in the second part of our analysis. Monetary variables are deflated using the CPI, and enter the model in logarithms like indices. All the other variables are in levels. The model is estimated over the period 2003–2019, as we intentionally exclude the Covid-19 period that would severely affect our estimates and results.[13]

We conclude this section by plotting in Fig. 2 the ratios of domestic government bonds and loans over total assets for Germany, France and Italy. Clearly, the exposure of Italy's banking sector towards domestic government bonds is by far higher than Germany's and France's; it has been around 10 percent of total assets during the last decade. The same applies to loans. Indeed, the chart shows that Italian banks run a more traditional type of business with regard to the incidence of loans over total assets, and that they are over exposed to sovereign risk.

[11] Computing the spread relative to the policy rate, i.e. EONIA, would not change the qualitative results of the analysis.

[12] As the policy shadow rate is available only from September 2004 (at J.C.Wu's webpage), we merge it with the EONIA rate from the ECB for the previous months.

[13] Our data set starts in 2003 as the series on banks' loans and banks' bond holdings are not available before.

3.3. The proxy variable

Our identification strategy relies on an external series used as a proxy to identify shocks to the Italian sovereign spread. We exploit the strong co-movement of bond yield spreads that is determined by the influence of global trends in asset pricing, particularly in the pricing of sovereign risk. We use as proxy the first principal component of the 10-year sovereign yield spreads over Germany for the following Euro area countries: Austria, Belgium, Finland, France, Greece, Ireland, Netherlands, Portugal, Spain.[14] Following Piffer and Podstawski (2018) we use the first difference of the principal component as the instrument for the spread to ensure that the instrument series is covariance stationary.

The rationale for using the first principal component of Euro area sovereign spreads (excluding Italy) is that it is strongly correlated with the Italian spread as it results from global pricing of risk, while it should not be related to contemporaneous shocks to Italian fundamentals and bank variables because of its external origin.

Proxies are judged with respect to their relevance and exogeneity. As for the relevance there is no doubt; the correlation of our proxy with Italy's spread is high. As for exogeneity, it is thorny since simultaneity is pervasive in macroeconomics. Nonetheless, we believe that the other countries' spreads can be driven only marginally by country-specific shocks to the Italian spread, and very unlikely, within a month, by Italian fundamentals. Our view is that the high correlation between the proxy and the Italian spread is more due to cross-country factors: worldwide financial uncertainty, global pricing of sovereign risk. Differently, when the evolution of the Italian spread depends only on domestic factors, the correlation is low because the other countries' spreads do not respond. For instance, consider the increase in the Italian spread in 2018, when it doubled, from 122 to 249 basis points between the end of April and the end of May, such an increase was due to unsuccessful attempts to form a new government after elections in which there was no clear majority. Then, the correlation with the proxy, which was as high as 0.866 before May 2018, dropped to 0.054 between May 2018 and May 2019 when Italian political instability became the main driver of the Italian spread.

Finally, consider the Sovereign CISS (SovCISS), a measure of stress in the sovereign bond market developed by Garcia-de Andoain and Kremer (2017). The SovCISS is built for eleven Euro area countries starting from yield spreads, a measure of yield volatility, bid–ask spreads and

[14] The principal component analysis is a statistical method that reduces the dimensions of a data set by concentrating most of the information into few series. Accordingly, the first principal component is a linear combination of the series in the original data set that captures the highest share of variability.

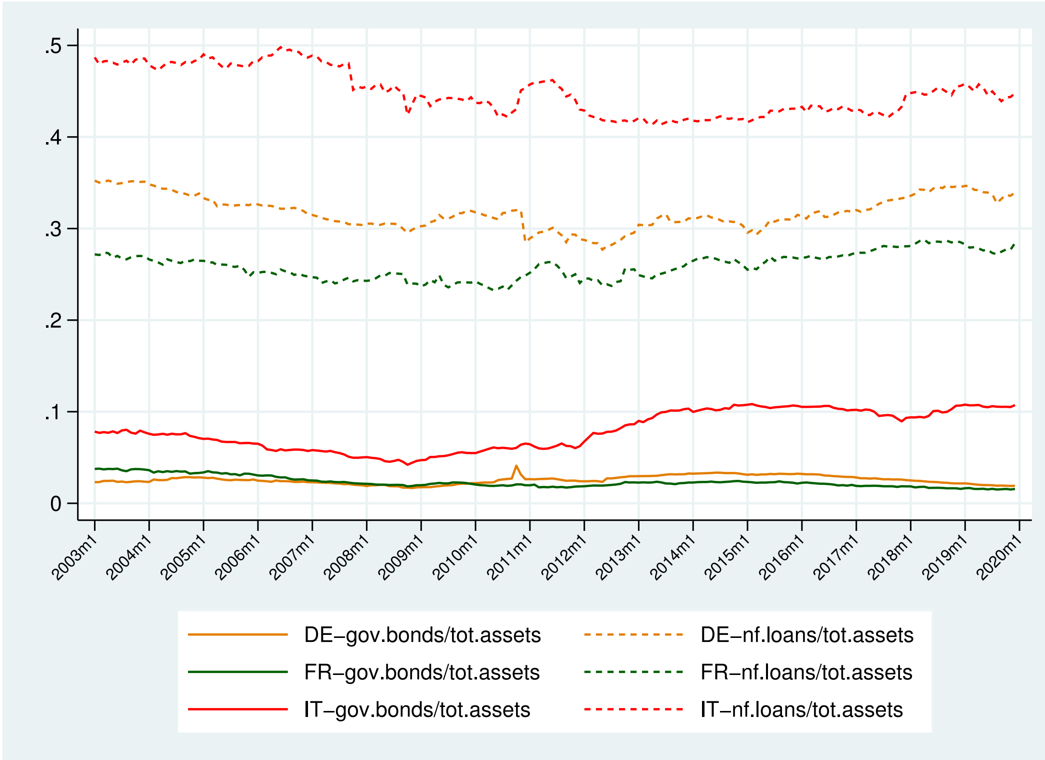

Fig. 2. Domestic government bonds and loans over total assets.
The figure reports the ratio of government bonds and loans over total assets for the banking sectors of Germany, France and Italy.

information coming from the short and long end of the yield curve. From the point of view of our analysis, this index is largely endogenous as it directly and contemporaneously depends on developments originating in the Italian economy. Then, we compared our proxy (i.e. the first principal component of European spreads) with this index, as well as with some other related composite indicators of systemic stress - CISS- for the Euro Area and Italy, to evaluate whether the information content is similar. While our proxy is positively correlated with all these measures, the correlation is low, ranging from 0.18 to 0.36, which suggests that the information content is different. Indeed, our proxy may be only marginally affected by financial stress originating in sectors of the Italian economy and by Italian fundamentals, which instead determine the CISS measures.

4. Results on the spread-credit channel

This section presents the results of the Bayesian estimation of the Proxy-SVAR. The discussion is based on IRFs, which quantify the response of the VAR variables to the sovereign spread shocks identified through the procedure described in Section 3.1. In addition, we discuss the historical decomposition that reports the portion of each variable's change explained by the cumulative spread shocks at each point in time and conditional forecasts of the variable of interest. We also present the robustness checks regarding the identification method and the setting of some parameters intrinsic to the Bayesian estimation.

4.1. Structural shocks and historical decomposition

Fig. 3 shows the times series of the identified structural shocks to the Italian sovereign spread. The visual inspection confirms a pattern coherent with the narrative of the last decades. Namely, shocks of larger magnitude are concentrated mostly during the second phase of the Euro area debt crisis (2011–2012), which hit Italy and Spain.

VAR models allow to establish the contribution of shocks to the historical dynamics of each series included in the model (Kilian, 2009), the so-called Historical Decomposition (HD). What is usually done is to decompose the actual time series into an exogenous *predictable* part and a part driven by shocks (Cafiso, 2022).[15] The idea is that structural shocks drive the time series away from its trend value. The HD plots are in Fig. 4. The black line in the background represents the difference, y_i^*, between the variable of interest, y_i, and the cumulative contribution of its deterministic components – i.e. its trend and initial conditions, τ_i – that is left to be explained by the cumulative effect of the identified structural shocks (Fig. 3). In fact, the deviation y_i^*, at each time t, can be decomposed as

$$\underbrace{y_{i,t} - \tau_{i,t}}_{y^*_{i,t}} = \underbrace{\sum_{j=0}^{t-1} \eta_{1,t-j}}_{\text{shock 1}} + \underbrace{\sum_{j=0}^{t-1} \eta_{2,t-j}}_{\text{shock 2}} + \cdots + \underbrace{\sum_{j=0}^{t-1} \eta_{n,t-j}}_{\text{shock n}},$$

where the first term is the historical contribution of the first structural shock (η_1), the second term of the second shock (η_2), etc. Since we identify only one shock, the spread shock, then $n = 1$. The red bars in Fig. 4 show the amount of y_i^* that is explained at each point in time by the cumulative spread shocks.

The HD decomposition shows that the evolution of the Italian sovereign spread is largely explained by its structural shocks, as illustrated in Fig. 4. While prior to 2010 the prevalence of negative shocks contributed to maintaining the spread below its trend, their cumulative effect subsequently reversed with the onset of the Euro debt crisis. Indeed, shocks pushed the spread upwards, which led to the sharp increase observed between 2011 and 2012, and then, to a lesser extent,

[15] The historical decomposition is made of two components : a determinist component which can be indeed interpreted as a steady-state, and a fluctuation component represented by the shocks. The exogenous part represents the first component, but it also includes the impact of the initial conditions at the beginning of the sample. The impact of these initial conditions normally fades away relatively quickly as the sample gets further away from its starting point.

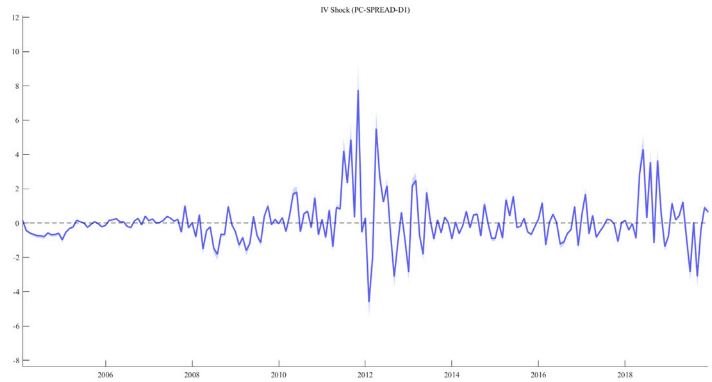

Fig. 3. Structural shocks. Structural shocks identified via the Proxy-SVAR approach.

in 2018. This is broadly consistent with the narrative of events.

Importantly, spread shocks significantly contributed to the deviations of the lending rate spread, as their cumulative effect closely tracks its up-and-down movements since 2009. Indeed, the deviations of the lending rate are accounted by the spread shocks far beyond the end of the crisis. The contribution of spread shocks to banks' loans also appears to be substantial between 2010 and 2015. Initially, loans expanded, also favored by a sequence of negative spread shocks but in mid-2011 they begun to decline due to the cumulative effect of positive shocks, which ultimately drove loans below their trend in 2012 with the Italian crisis reaching its apex. The substantial contribution of spread shocks to the evolution of both the lending rate and banks' loans, coupled with their negative co-movement, points to an important role of sovereign risk in the contraction of credit supply. Deleveraging is consistent with banks facing tighter leverage constraints, and higher financing costs, following losses on their holdings of government bonds, i.e. with the effect of a balance-sheet channel, but also with banks reducing their exposure to the productive sector in anticipation of higher riskiness of firms, i.e. with the operation of a risk channel. While both channels may have played a role, as shown by Bocola (2016), our evidence on banks' deposits provides little support for an *asset-liquidity risk channel* operating through a contraction in banks deposits, as proposed by Faia (2017). In particular, the sharp decline in deposits observed in 2011 appears to be unrelated to the impact of spread shocks, which only contributed to the decline in deposits from 2012 onwards. On the other hand, spread shocks account for a significant part of the deviation of banks' holdings of government bonds since 2011. In particular, a substitution of government bonds for loans in banks' portfolios seems to emerge from the accumulation of shocks that drove the sovereign spread above its trend since 2011. This finding is consistent with *carry trade* and *moral suasion* affecting banks' bond demand, as reported in studies using micro banking data.[16]

Notably, spread shocks contributed substantially to the unemployment rate deviations between 2010 and 2018. While a series of predominantly negative shocks helped to maintain the unemployment rate below its trend until 2011, the onset of the crisis saw a sharp rise in unemployment, with a large part of this variation accounted by positive spread shocks. Similar evidence is observed regarding the role of sovereign risk with respect to the debt-to-GDP ratio. The shocks to the Italian spread that characterized the crisis period were associated with a severe deterioration in fiscal fundamentals.

In light of these findings, the HD decomposition provides preliminary support for the hypothesis that sovereign risk significantly affects economic activity and debt sustainability through a spread-credit channel. However, a full assessment requires the analysis of the dynamic responses of the model variables to a spread shock using impulse response functions. IRFs reveal causal relationships and are discussed in the following section.

4.2. Impulse-response functions

The IRFs obtained from the estimation of the Proxy-SVAR are in Fig. 5. They show the responses to a shock to the instrumented variable, the sovereign spread. IRFs report the effect of a one standard-deviation shock, which is roughly the value that we visualize in Italy's spread chart at the impact: 0.16, i.e. 16 basis points. Except for consumer prices, the IRFs are all significant and consistent with the hypothesis of a credit channel for the negative effect of sovereign risk on the Italian economy and its fiscal fundamentals.

Bank loans fall slightly on impact and then decrease steadily, showing a decline of 0.6 percent after two years that translates into a 3.7 percent reduction in case of a larger shock of 100 basis-points in line with the result by Albertazzi et al. (2014).[17] The IRFs suggest that the credit contraction is possibly triggered by the market value losses that banks experience on their sovereign bond portfolios, as evidenced by the impact response of the value of banks' bond holdings (see below).[18]

The tightening of credit conditions manifests itself with the increase in the interest rate that banks charge on loans to non-financial corporations relative to the interbank offered rate.[19] As displayed by the IRF, the lending rate spread rises slightly on impact, and then sharply in the following months, reaching a peak after one year, to then decline overtime along with the sovereign spread. The effect is sizeable; the lending rate increases by 5 basis points over the interbank rate in the first quarter and, then, up to 9 points after a year. Thus, the pass-through of the sovereign spread on the lending rate is in the order of 30 percent within a quarter (around 50 percent within a year), which is in line with Barbieri-Hermitte et al. (2023) but lower than what estimated by Zoli (2013) for the Euro debt-crisis period.

[16] See Battistini et al. (2013), Acharya and Steffen (2015), Ongena et al. (2019), Altavilla et al. (2017).

[17] To assess all the responses in terms of a spread shock of 100 basis points we can multiply such responses by 6.2 (=100/16). For instance, in case of a spread shock equal to 100 basis points, the long-term reduction in the amount of loans would be equal to 3.7% (=0.6%*6.2).

[18] As bonds are recorded at market value in our dataset, we are able to capture the banks' losses on their bond holdings by the corresponding IRF showing a negative impact effect of the spread shock.

[19] The increase in the cost of credit may either reflect deleveraging or higher funding costs due to liquidity shortages and reduced collateral capacity of sovereign bonds (Faia 2017). Funding costs for banks also increase because sovereign risk spills over into bank credit risk and the interest rates on banks' financing instruments rise with those on government bonds. Finally, the lending rate may rise in anticipation of the economic slowdown because of the perception of an increased riskiness of firms' investment projects (Bocola 2016).

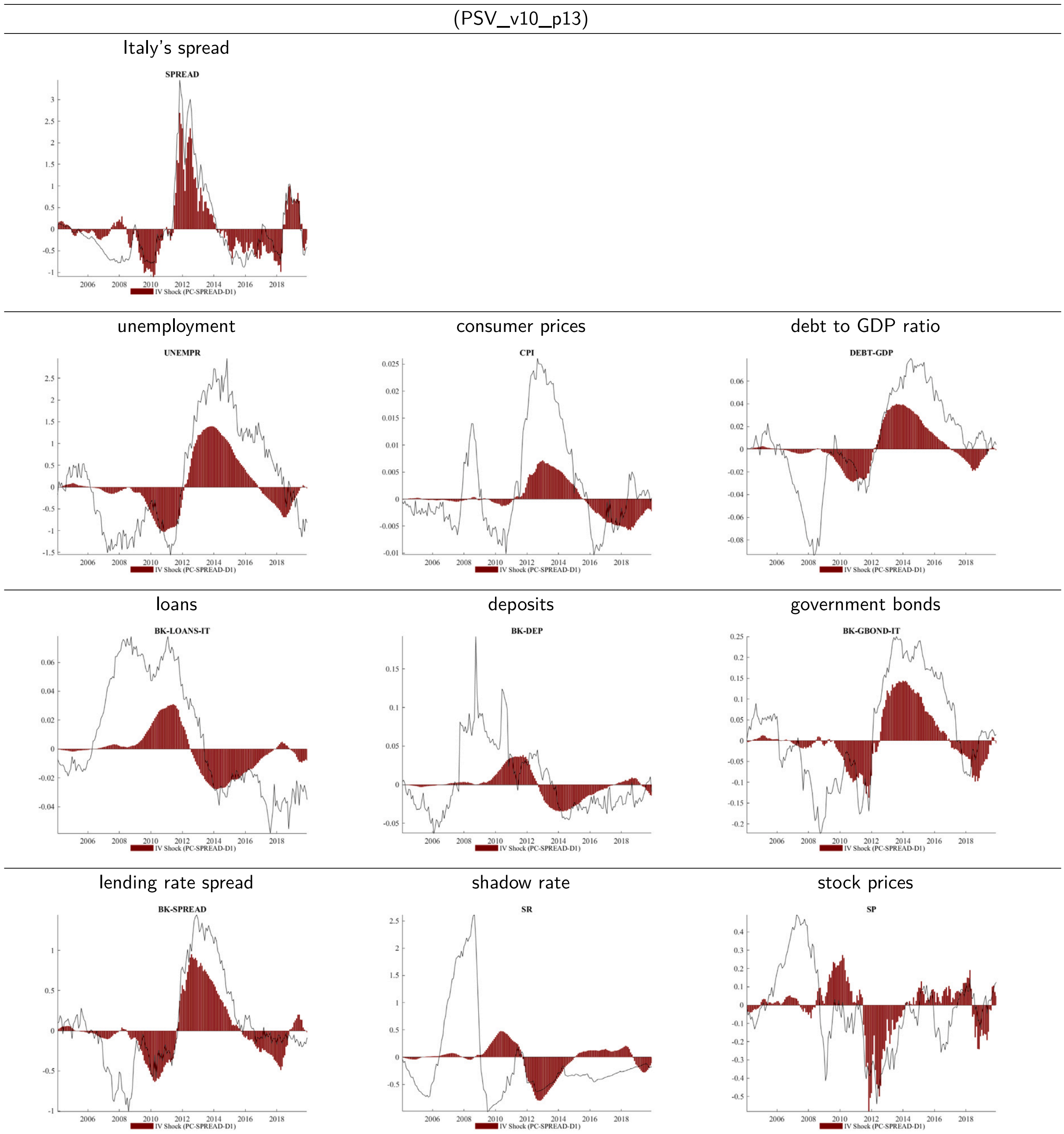

Fig. 4. Historical Decomposition, Proxy SVAR.
Historical decomposition plots. The black line in the background represents the amount of the variable that is left to be explained by the structural shocks after accounting for exogenous, constant and initial conditions. The red bars are the amount explained at each point in time by the accumulation of the sovereign shocks under consideration.

Evidence of a sharp increase in the cost of credit supports the hypothesis that the reduction in bank loans is supply driven. The impact of sovereign risk materializes first in a credit contraction and then in a slowdown in economic activity. Indeed, higher lending rates are inconsistent with lower credit demand, suggesting that the direction of causality runs from banks to the economy. This is consistent with the results by Altavilla et al. (2017) and Bofondi et al. (2018) who use granular data, and with those by Bocola (2016), Faia (2017) and Barbieri-Hermitte et al. (2023) that are derived from structural macroeconomic models.

The contraction in the supply of credit can be due either to the erosion of bank capital following losses on banks' bond holdings or to banks' perceptions of increased riskiness of firms and households. Both motivations for deleveraging may be at work, as formalized by Bocola (2016), and it is not possible to assess their relative importance using macro data. Higher lending rates might also reflect a liquidity shortage to the extent that investors withdraw their deposits in response to the higher risk of bonds and thus bank assets, as argued by Faia (2017). However, the IRF of deposits shows no significant impact response. Contrary to the hypothesis of a run, the initial fall of deposits is negligible, while their steady decline in the medium-long run seems to be the endogenous response to the contraction in credit and economic activity.

Another important finding is the impact drop shown by the IRF of the banks' holdings of Italian government bonds. Since bond holdings are recorded at market value, their initial reduction reflects the repricing induced by the spread shock, which negatively affects the value of bank capital, and forces banks to deleverage. The initial fall

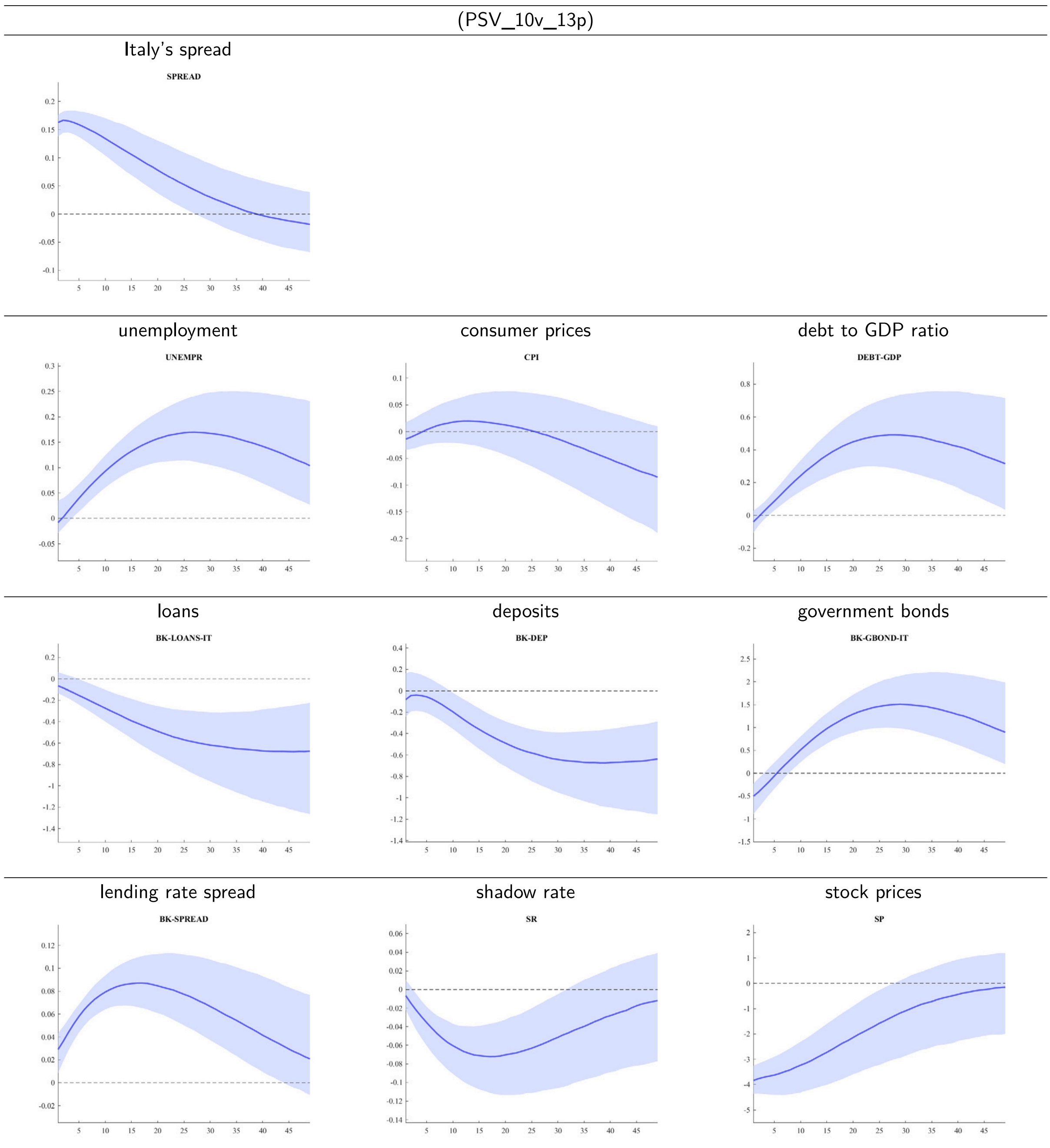

Fig. 5. IRFs, Proxy-SVAR. Response to the identified sovereign shocks. The blueish area is for the 16–84 interquartile confidence range.

is however short lived; the IRF shows that bond holdings return to their pre-shock value after five months despite the higher sovereign spread. In fact, banks' purchases of government bonds increase substantially in the two years following the shock. This result is in line with findings from previous studies that, in stressed-countries, domestic banks bought more sovereign debt than foreign banks when yields and financing needs increased, possibly because of moral suasion and/or yield seeking behavior (Battistini et al., 2013; Acharya and Steffen, 2015; Altavilla et al., 2017). The same result is obtained in the next Section 5; while foreign investors shade away from the risky Italian debt, residents increase their holdings of bonds when the sovereign spread increases. Larger holdings of government bonds partly make up for fewer loans in banks' portfolios in the medium- and long-run. This reallocation of banks' portfolios implies a greater exposure to sovereign risk. Substitution of bonds for loans is, however, only partial, as total bank assets decrease.[20]

Italian sovereign risk also hits financial markets strongly. Investors' perception of greater default risk comes with increased risk aversion and market uncertainty that are mirrored in the response of stock prices. The IRF shows a stock market falling sharply on impact and, then, recovering to its pre-shock level after three years. Indeed, stock prices appear to anticipate banking sector distress and lower growth ahead. Interestingly, the rise in the sovereign spread prompts monetary easing; the policy rate exhibits a significant, though temporary, reduction, which is consistent with a loosening of the ECB's monetary

[20] The percentage increase of bond holdings exceeds the percentage reduction in loans, but bonds are four times lower than loans in banks' portfolios (see Fig. 2).

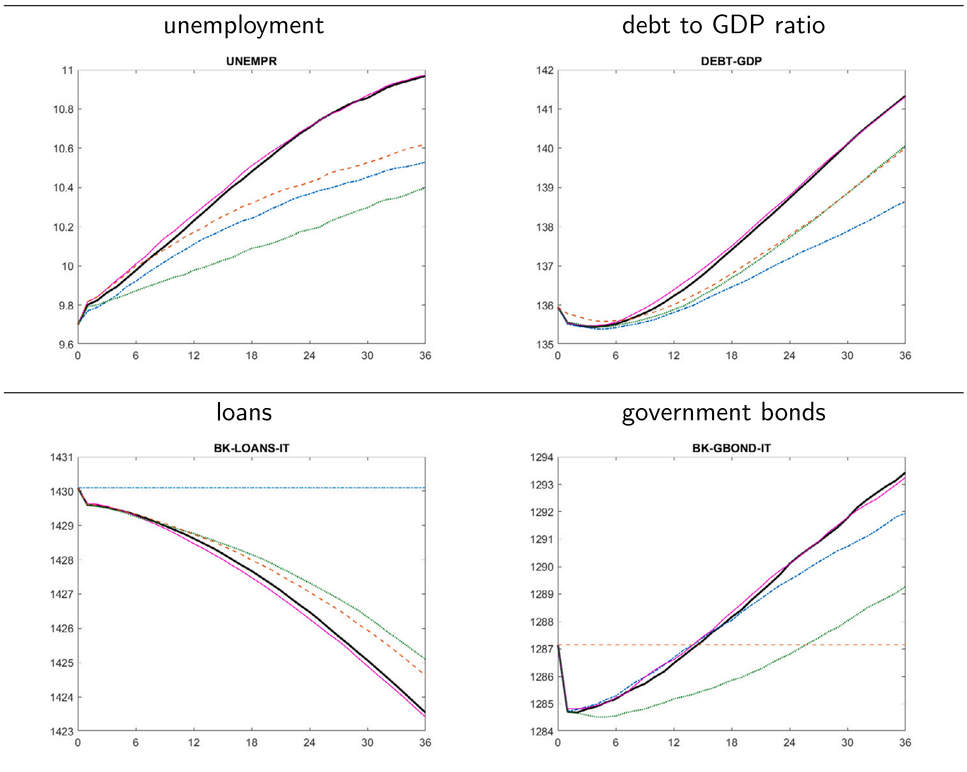

Fig. 6. Conditional forecasts.
The thick black line is for the baseline scenario where the spread is set at 3 percent, this condition is also in all the other scenarios. The solid-violet line is for the scenario in which deposits are kept constant. The dash-dot-blue line is for the scenario in which loans remain constant. The dot-green line is for the scenario in which the lending rate spread remains constant. The dash-orange line is for the scenario in which government bonds remain constant. When conditioned, the variables are held constant at their value in December 2019.

stance to cope with a rise in sovereign risk that is correlated across EA countries.

Consistent with its impact on credit, the spread shock causes a significant contraction in economic activity as shown by the steady and long-lasting increase in the unemployment rate. A one standard deviation shock leads to an increase in the unemployment rate of around 0.17 percent two years later that translates into a variation of 1 percent in case of a larger shock of 100 basis-points. We link such an increase in unemployment to lower economic activity resulting from fewer loans to firms and households. Evidence of the negative effect of the sovereign spread on the Italian economy has been previously reported by Bocola (2016), Faia (2017) and Barbieri-Hermitte et al. (2023) from simulations of structural econometric models.

Finally, the IRF of the debt-to-GDP ratio displays a gradual increase that lasts over more than two years.[21] Net borrowing rises both because of reduced tax revenues due to lower GDP growth and because of increased interest payments on the refinanced debt. Although the analysis cannot detect which factor is more important, the long maturity of the Italian debt suggests that the lower GDP and the revenue shortfall are probably the main determinants of the debt accumulation. The negative feedback loop between the sovereign spread and economic activity opens up the possibility of a self-reinforcing debt crisis. As the spread increases and banks' balance sheets deteriorate, banks stop lending, investment falls and the economy slows down worsening fiscal fundamentals. The higher debt-to-GDP ratio raises concerns about government solvency that makes the spread increase even more with a further contraction in credit supply.

4.3. Conditional forecasts

To gain further insight into the spread-credit channel, in this section we develop a scenario analysis based on a conditional forecasting exercise. The conditional expectation of a subset of variables is computed, given a specific path for the other variables in the model applying the Bańbura et al. (2015)'s algorithm.[22] This approach is a reduced-form exercise in the sense that the forecast of the variables is based on all possible structural shocks that are consistent with the information in the conditioning set, and the results will show the most likely situation in which the conditions materialize. This can be thought of as a counterfactual analysis in which we compare different scenarios

[21] The rise in the debt ratio reaches a maximum of 0.5 percentage points, which converts to a 3.1 percentage points in case of a spread shock of 100 basis points. Although fiscal fundamentals do not deteriorate permanently, four years after the shock the debt ratio is still 0.3 percentage points higher despite the narrowing of the spread and the economic recovery.

[22] Bańbura et al. (2015) prove their algorithm to be more efficient than traditional algorithms based on Waggoner and Zha (1999) or Jarociński (2010), especially for large models. Moreover, these algorithms require the use of the matrix of structural relationships, so it is necessary for this matrix to be full rank. In contrast, Bańbura et al. (2015)'s algorithm requires only the reduced-form coefficients and the variance–covariance matrix. This allows us to apply this methodology to the results of our Proxy SVAR estimation, where only the first row of the matrix of structural relationships is identified and therefore classical algorithms would not work.

that are compatible with some constraints on the observables.

We apply this methodology to the results from the estimation of the main Proxy SVAR (Fig. 5), i.e. we use the same reduced-form coefficients and variance–covariance matrix that are used to identify the spread shocks. The forecasting horizon is 36 months, starting from the end of the sample (December 2019). In our baseline scenario, the spread increases to 3 percent and remains constant for the entire forecasting horizon; this figure corresponds approximately to the spread value in December 2019 (1.76) plus two standard deviations (0.73 ·2).

Fig. 6 reports the mean forecast for the main variables of our model under five scenarios. All scenarios are characterized by the increase in the sovereign spread mentioned above. The first scenario does not add any other condition, as it generates the forecast of the variables against which to compare the effects of conditioning the banking variables in the model (thick black line). The other scenarios condition, one at a time, the banking variables in order to assess the relevance of each one of them in transmitting the impact of the spread increase to the economy. The second scenario requires that bank loans remain constant at the December 2019 level throughout the forecasting horizon, i.e., it prevents a contraction in bank lending despite the rise in the sovereign spread (dash-dotted blue line). The third scenario conditions the lending rate spread to remain constant at its December 2019 value, thus preventing an increase in the cost of credit (dotted green line). The fourth scenario prevents a decline in deposits (thin solid violet line). The fifth assumes that banks' holdings of government bonds remain constant (dashed orange line).

The top-left panel in Fig. 6 shows the evolution of the unemployment rate under the five scenarios. In the benchmark scenario (thick black line), when banking variables are unconstrained, the widening of the sovereign spread is associated with the highest increase in the unemployment rate. Unemployment rises less in the second scenario where loans are held constant (dash-dotted blue line) and even less in the third scenario where the lending rate spread is not allowed to widen (dotted green line). These results confirm the crucial role played by a contraction in the supply of credit, i.e., the credit channel, in the transmission of sovereign spread shocks to economic activity. In particular, the positive relationship of the unemployment rate with the cost of credit provides further evidence on the supply-side origin of the credit contraction.

Interestingly, when a contraction in bank deposits is prevented, as in the fourth scenario (thin solid violet line), the path of the unemployment rate is the same as in the benchmark scenario, which assumes only an increase in the sovereign spread. This suggests that deposit withdrawals played little or no role in the transmission of spread shocks, which is consistent with the findings in the previous sections. Indeed, the observation of Italian events also points to the fact that deposits did not decrease significantly during the Euro debt crisis.

In the fifth scenario (dashed orange line), where the value of banks' bond holdings is held constant, despite no condition on bank credit, unemployment is lower than in the benchmark scenario and only slightly higher than in the case of constant loans. This result, together with the large losses in the value of banks' bond holdings shown in the bottom-right panel, suggests that balance sheet losses were an important factor in banks' deleveraging, in addition to a possible response to the increased riskiness of firms. Indeed, the bottom-left panel shows that the contraction in lending associated with constant bond holdings is similar to that associated with a constant lending rate, and lower than in the benchmark scenario.

The top-right panel in Fig. 6 shows the path of the debt-to-GDP ratio. The increase in the debt ratio is largest in the benchmark and in the constant deposits scenarios, which are associated with the sharpest declines in economic activity. This confirms that the economic slowdown plays a predominant role in the deterioration of fiscal fundamentals. Since the debt ratio is lower in the scenarios where the supply and cost of credit are held constant, this evidence highlights the negative impact of the spread-credit channel on debt sustainability. However, the evolution of the debt ratio appears to be related also to banks' holdings of government bonds. Indeed, the bottom-right panel shows that banks' purchases of government bonds are higher, and the debt ratio lower, in the constant loans scenario than in the constant lending rate scenario. This finding suggests a potential stabilizing role of bank purchases of government bonds, which will be further examined in the next section.

4.4. Robustness checks

The analysis has undergone several checks to ensure its robustness. These concerned both the identification method and other aspects of our analysis. As for the identification, two other methods were examined. First, we used the Cholesky decomposition to identify the structural sovereign spread shocks, combined with the Giannone et al. (2015)'s procedure for the selection of the prior hyperparameters. Robustness was therefore tested with respect to the identification approach and the prior selection in this case.[23] We ordered the variables as in Table 1 and studied how shocks to the Italian spread impact on the other variables. It is worth noting that the sovereign spread is ordered last; i.e. it is assumed to respond to all the other variables contemporaneously, so that the shocks we identify do not depend on the other variables in the system by construction. Thus, this ordering sets up the worst possible scenario for detecting sizable effects but represents the safest check to evaluate the robustness of our results. The IRFs from this estimation are reported in Fig. 8 of Appendix A. Because of the ordering assumption the impact responses of all variables are zero but the estimated medium/long run effects are comparable to those obtained from the Proxy-SVAR.[24]

As an alternative identification approach, we also experimented with narrative sign restrictions (Antolín-Díaz and Rubio-Ramírez, 2018) on the sign of the structural shock and the historical decomposition.[25] The results show that narrative restrictions are not functional to identify spread shocks in our case because the responses of all the variables except the spread are non-significant.[26] As a last check, we verified that the restrictions defined on the sign of the shock correspond to

[23] In fact, the approach by Caldara & Herbst (2019) uses a Normal-Wishart prior distribution with user-selected values of the hyperparameters. On the contrary, Giannone et al. (2015) select the appropriate degree of shrinkage by treating priors' hyperparameters as additional unknown parameters, formulating a prior over them and maximizing the marginal likelihood to derive their posterior values. The innovation in Giannone et al. (2015)'s approach is that they treat these hyperparameters as unknown so that the model has a hierarchical structure.

[24] As an alternative to Cholesky, we have also computed generalized impulse-response functions (Pesaran and Shin, 1998) when using the same prior-selection method of Giannone et al. (2015). These impulse responses are very similar to the IRFs based on the Cholesky's decomposition.

[25] We identified eight dates on which we imposed a sign for the structural shock, two dates on which we imposed that the spread shock is the major contributor to the spread variable, and we set a positive effect on the spread variable on impact. The dates are: July 2011, positive sign because of rating downgrade of Ireland and Portugal; August 2011, negative sign related to ECB' purchase of Italian bonds; February 2012, negative sign because of the approval of Fiscal Compact and ESM; April 2012, positive sign related to contagion from Spain's banking sector; August 2012, negative sign for ECB's OMT announcement and delayed effect of "whatever it takes" speech by ECB President Mario Draghi; January 2013, negative sign related to resolution of the potential US fiscal cliff; February 2013, positive sign because of political instability after elections; May 2018, positive sign because of political instability after elections.

[26] Comparing the spread shocks of this model with those derived from our baseline estimation (Proxy-SVAR), we observe that the two series are highly correlated (0.95) but the shocks identified with the Proxy-SVAR approach have much higher variation. The estimation output is not reported, but the IRFs are available upon request.

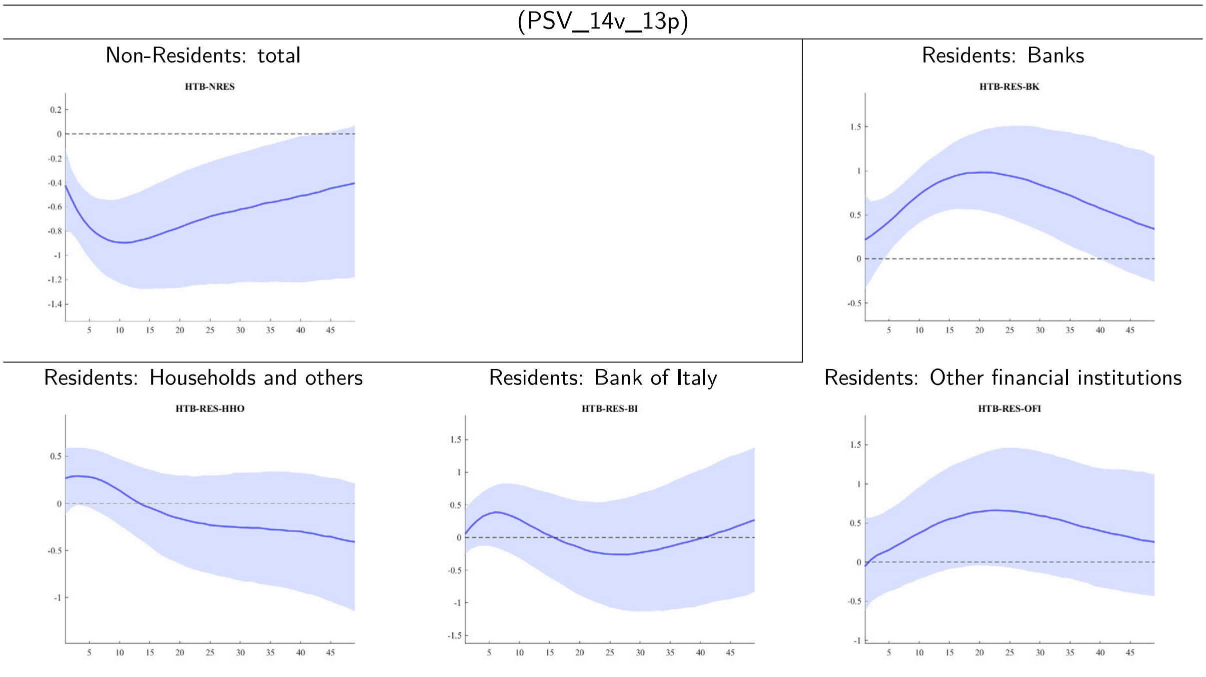

Fig. 7. IRFs, VAR, debt holdings.
Response to the identified sovereign shocks. 'Households and others' includes individuals and non-financial entities. The darker gray area is for the 16–84 interquartile confidence range.

the shocks identified through the Proxy-SVAR. Therefore, the proxy identification yields shocks that are consistent with the main narrative about spread shocks, without imposing any restriction on the impulse responses. On the other hand, the narrative identification retrieves shocks that, although highly and positively correlated with the former, are not able to generate a significant dynamics in the economy. Overall, we believe that these results confirm the appropriateness of our identification strategy based on the Proxy-SVAR.

As for the other robustness checks, we estimated smaller and larger versions of the Proxy-SVAR discussed in the previous subsection by considering 8 and 13 variables, as well as by including 7 instead of 13 lags.[27] Furthermore, we also tested the use of the high relevance prior option in the method of Caldara and Herbst (2019); this is more deeply discussed in Appendix B. Overall, the IRFs of the variables under investigation were very similar to those presented in the previous subsection in all these alternatives.

A final check consisted in verifying whether the conclusion on the effect of spread shocks on economic activity, which we base on the monthly unemployment rate, remains valid when we use the GDP. Since GDP is available only at a quarterly frequency, we interpolated quarterly GDP to monthly values by applying the Chow and Lin (1971)'s method, using the monthly index of industrial production as an instrument. Then, this GDP monthly series was used in place of the unemployment rate in the estimation of the Proxy-SVAR. The IRFs from this estimation are shown in Fig. 9 in Appendix A. It emerges that the results are very similar and lead to the same conclusions.

[27] Specifically, the larger VAR included these three additional variables: government bonds of other EA countries held by Italian banks; Italy's deficit to GDP ratio; commodity prices.

5. Spread shocks and debt holders

Since a high debt largely held in domestic banks' portfolios makes debt sustainability particularly vulnerable to changes in sovereign risk, it is important to understand how the distribution of debt by type of holders changes in response to spread shocks (see, e.g., Cafiso 2016). In fact, evidence on the response of bond demand by different investor groups has important implications for debt sustainability.

To investigate how the demand of government bonds by different investor groups respond to spread shocks, we estimate an extension of the VAR model presented in Section 4. We now include the holdings of Italian government bonds by each investor group (variables 12,14–17 in Table 1) and, to avoid overlapping, exclude Italian banks' holdings of the same bonds (variable 6 in Table 1). While the latter are taken from the ECB (banks' consolidated balance sheet accounts') and are recorded at market value, the former are at face value and are taken from the Bank of Italy (monthly series of Italy's government bond holders). Bond holdings are included in the VAR after being transformed in real terms and expressed in log values. We distinguish between residents and non-residents holders of government bonds, and consider four types of investors within the resident group: households, the Bank of Italy, Italian banks, other financial institutions. The results from the estimation of this VAR are in Fig. 7; we just report the IRFs of the bond holdings since the responses of the other variables are similar to those plotted in Fig. 3. Since the series of bond holdings are recorded at face value, their responses to spread shocks do not depend on valuation effects but only reflect changes in quantities.

We observe that, following a spread shock, non-residents decrease their holdings of government bonds both at the impact and increasingly over the following year. The contraction is substantial with a 0.4 percent decrease at the impact, i.e. a 2.3 percent for a shock of 100 basis points, which more than doubles ten months later. Looking within the resident group we find that the amount of bonds sold by non-residents is mainly absorbed by domestic banks and, to a lesser extent, by households whose bond purchases are hower slightly not significant. Except for the lack of a negative valuation effect at the impact, bank's bond holdings display the same dynamics observed from the estimation of the smaller VAR (Fig. 5). Notably, since the share of debt held by banks is greater than that of any other investor group, by switching from elasticities to size effects (not reported here), we observe that banks account for the larger part of bond purchases. Finally, the non-significant response of the bond holdings of the Bank of Italy is not surprising, as large asset purchases started in 2015.

To conclude, our results show that Italian banks and, to a lesser extent, households increase their holdings of Italian bonds as the spread increases, while non-resident investors reduce their sovereign exposure. In fact, foreign investors, mainly financial institutions, carry out a dynamic management of their securities portfolio, also because of derivatives on such positions. Then, in a worsening scenario, they are likely to reduce their exposure to risky bonds (Arslanalp and Tsuda, 2012; Arslanalp and Poghosyan, 2014). By contrast, domestic demand increases possibly because of yield-seeking behavior and, in case of banks, because of regulatory incentives and moral suasion. The resilience of residents' demand certainly improves debt sustainability in the short run, as it helps to avoid a rollover crisis. However, this would be without costs only if the demand came from the non-financial sector. If government bonds end up in Italian banks' portfolios, as it seems from our analysis, the sovereign exposure of the banking sector gets larger, and debt vulnerability to future shocks increases.

6. Conclusions

In this paper we examined the effect of sovereign spread shocks on bank activity, the real economy and the debt-to-GDP ratio. Having estimated a Bayesian Proxy-SVAR (Caldara and Herbst, 2019) for the Italian economy over the 2003–2019 period, we find that spread shocks have a significant negative impact on bank lending and economic activity as reflected by an increase in the unemployment rate. Evidence of a significant increase in the cost of credit supports the conclusion that the contraction in bank lending is supply driven. The fall in the market value of banks' holdings of domestic debt, which we detect at the impact, suggests that the credit contraction follows from the deterioration of banks' assets and thus their capital, forcing banks to deleverage. Slowing economic activity makes the government budget worse and this adds to the effect of higher borrowing costs. Consistent with these effects, we observe a substantial increase in the debt-to-GDP ratio that enhances the probability of default and feeds further the sovereign spread, in line with the narrative of the diabolic loop (Brunnermeier et al., 2011, 2016). Finally, we find that foreign investors, unlike residents, sell off domestic bonds in response to sovereign spread shocks. Therefore, the more debt is held by residents the greater the resilience to a rollover crisis but, as our analysis proves, domestic banks' excessive holdings are also a cause of concern to the extent that sovereign exposure increases vulnerability to future spread shocks. Then, we conclude that the spread-credit channel represents a serious threat to debt sustainability in countries where the banking sector is overexposed towards its sovereign.

Declaration of competing interest

None.

Appendix A. Further tables and figures

See Figs. 8 and 9.

Appendix B. Technical details on the Proxy-SVAR estimation

Regarding the estimation of the Proxy-SVAR based on Caldara and Herbst (2019), the prior of the reduced-form coefficients is a Normal-Inverse Wishart:

$$B|\Sigma \sim N\left(b, \Sigma \otimes \Phi_0\right),$$
$$\Sigma \sim IW\left(S_0, \alpha_0\right).$$

Here the mean for the prior coefficients is set as in the Minnesota prior, i.e. equal to 1 for own first lag coefficients and 0 for cross-variables coefficients, and the matrix Ψ_0 is set following the strategy of Karlsson (2013). As regards the variance–covariance matrix of the errors Σ, the scale matrix S_0 is set as a diagonal matrix whose diagonal elements are rescaled residual variances coming from individual AR regressions of the endogenous variables of the model, the degrees of freedom α_0 are $n+2$. This prior specification depends on some hyperparameters λ_i that govern the tightness of the prior (λ_1) and the speed at which the coefficients for lags greater than 1 converge to 0 with greater certainty (λ_3). Here, we set them as $\lambda_1 = 0.1$ and $\lambda_3 = 2$, which are the values conventionally used in the literature. We tested the robustness of our results to marginal changes in the values of the λ_i and the prior mean for the coefficients and we found no relevant differences.

Our Proxy-SVAR model features a measurement equation linking the shock and the proxy together (Eq. (2)). Therefore, a prior distribution is required for the parameters of this equation as well. The prior for the coefficient β is $N(0,1)$ while the standard deviation of the measurement error σ_v is $IG\left(s_1, s_2\right)$ with $s_1 = 2$ and $s_2 = 0.02$, as in Caldara and Herbst (2019). This parameter is crucial as it determines the tightness of the relationship between the proxy and the structural shocks. This setup leads to a prior that is not very informative so that the relevance of the proxy is mainly determined by the likelihood. Alternatively, one could use what Caldara and Herbst (2019) call the "high relevance prior" according to which only half of the variation in the proxy can be attributed to measurement error and therefore the relationship between the proxy and the structural shock becomes tighter. We rather follow the more conservative approach so that our results are not highly influenced by the prior assumptions.

In our baseline estimation, we obtain that the relevance of the proxy is 0.23 at the posterior median, which amounts to a correlation between the proxy and the spread shock of 0.48. We also experiment the high-relevance prior and obtain that the relevance increases to 0.46 at the posterior median, which translates into a correlation of 0.68. As regards the impulse response functions, all the results are confirmed and the credible sets are only marginally tighter, as shown in Fig. 10. Overall, our results are robust to different prior settings, this confirms the reliability of our proxy and that the spread shock has substantial effects on the economy through the credit channel.

Lastly, the Metropolis-within-Gibbs algorithm features a step to draw the variance covariance matrix of the residuals from a mixture proposal distribution. This mixture of proposal distribution consists of a weighted average of the known posterior $\Sigma|Y_{1:T}$ and an Inverse-Wishart distribution for Σ rescaled by the value sampled in the previous iteration Σ^*_{i-1}, governed by the parameter γ. We set this parameter as $\gamma = 0$, we therefore assume that the posterior distribution of $\Sigma|Y_{1:T}$, as specified by the standard inverse Wishart distribution, is a good proposal distribution. We simulate 50000 draws from the Gibbs sampler and the first 10000 are used as burn-in. Furthermore, in order to obtain independent draws, we retain one draw every 10 so that we use 4000 draws for inference.

Data availability

The data and replication codes used for this article are available on Mendeley Data: Cafiso, Gianluca; Rivolta, Giulia; Missale, Alessandro (2024), "The credit channel of the Sovereign Spread: A Bayesian SVAR

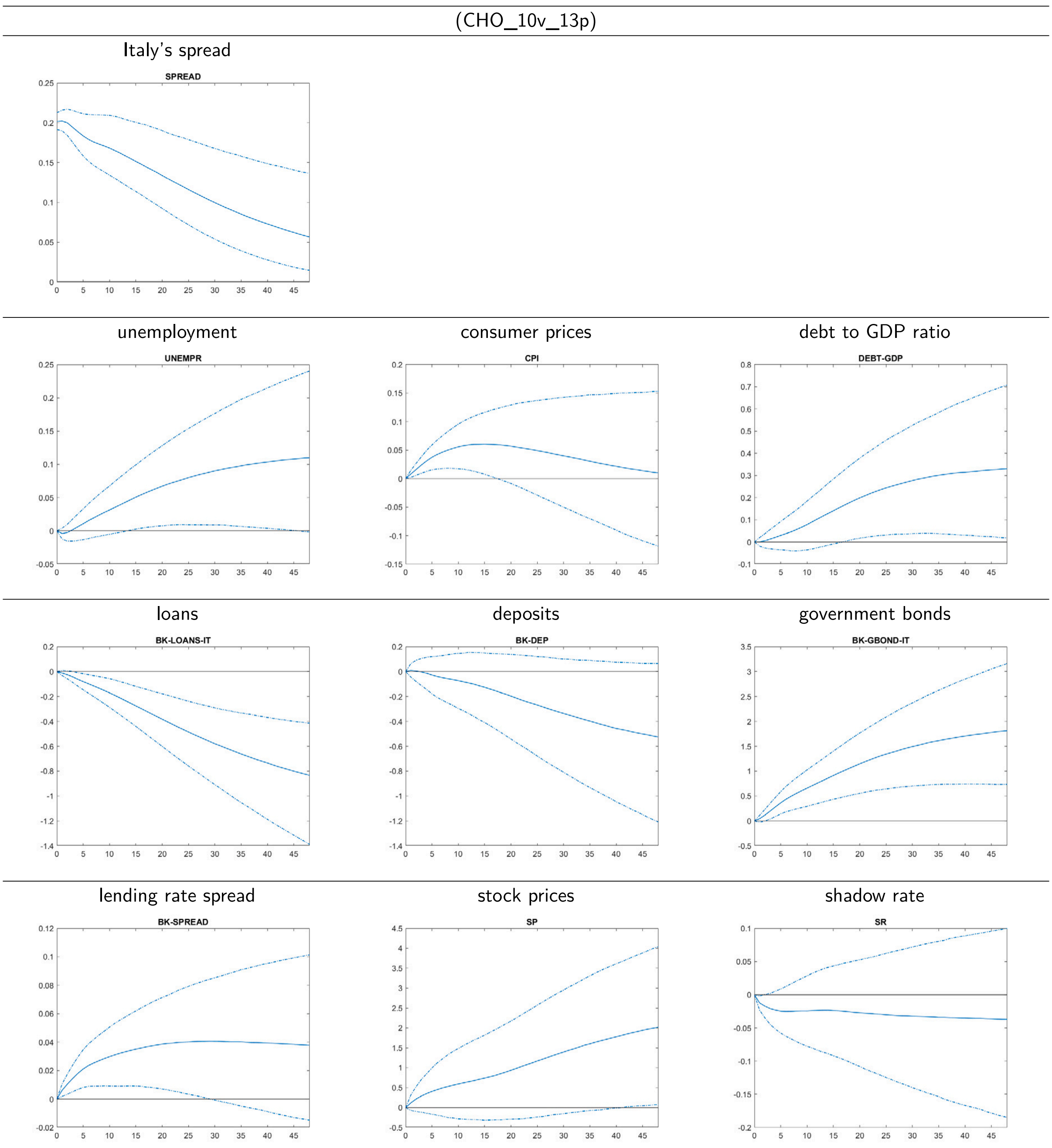

Fig. 8. IRFs, Cholesky. Response to the sovereign shocks. The area between the dotted lines is for the 16–84 interquartile confidence range.

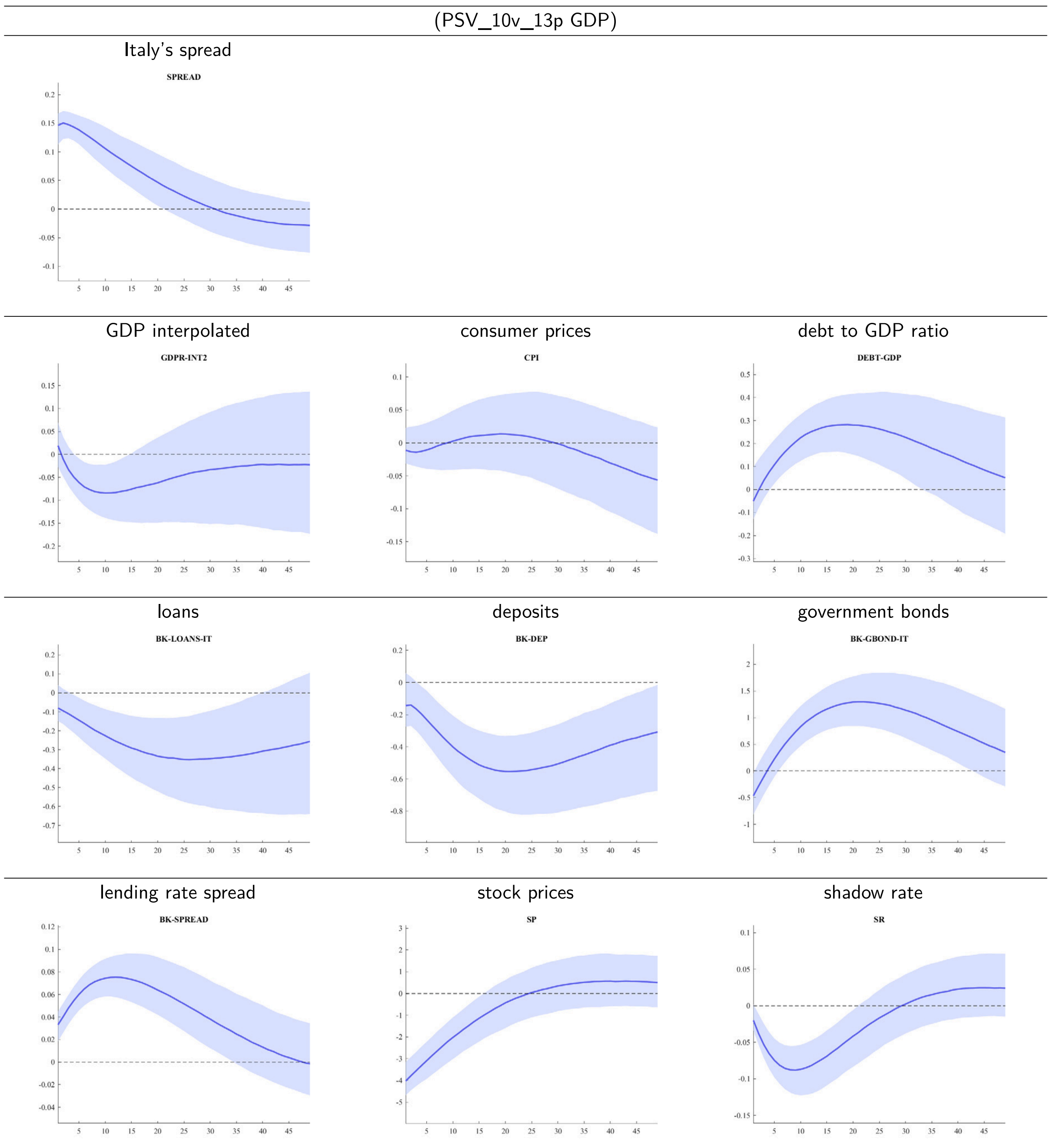

Fig. 9. IRFs, Proxy-SVAR (GDP interpolated). Response to the sovereign shocks. The area between the dotted lines is for the 16–84 interquartile confidence range.

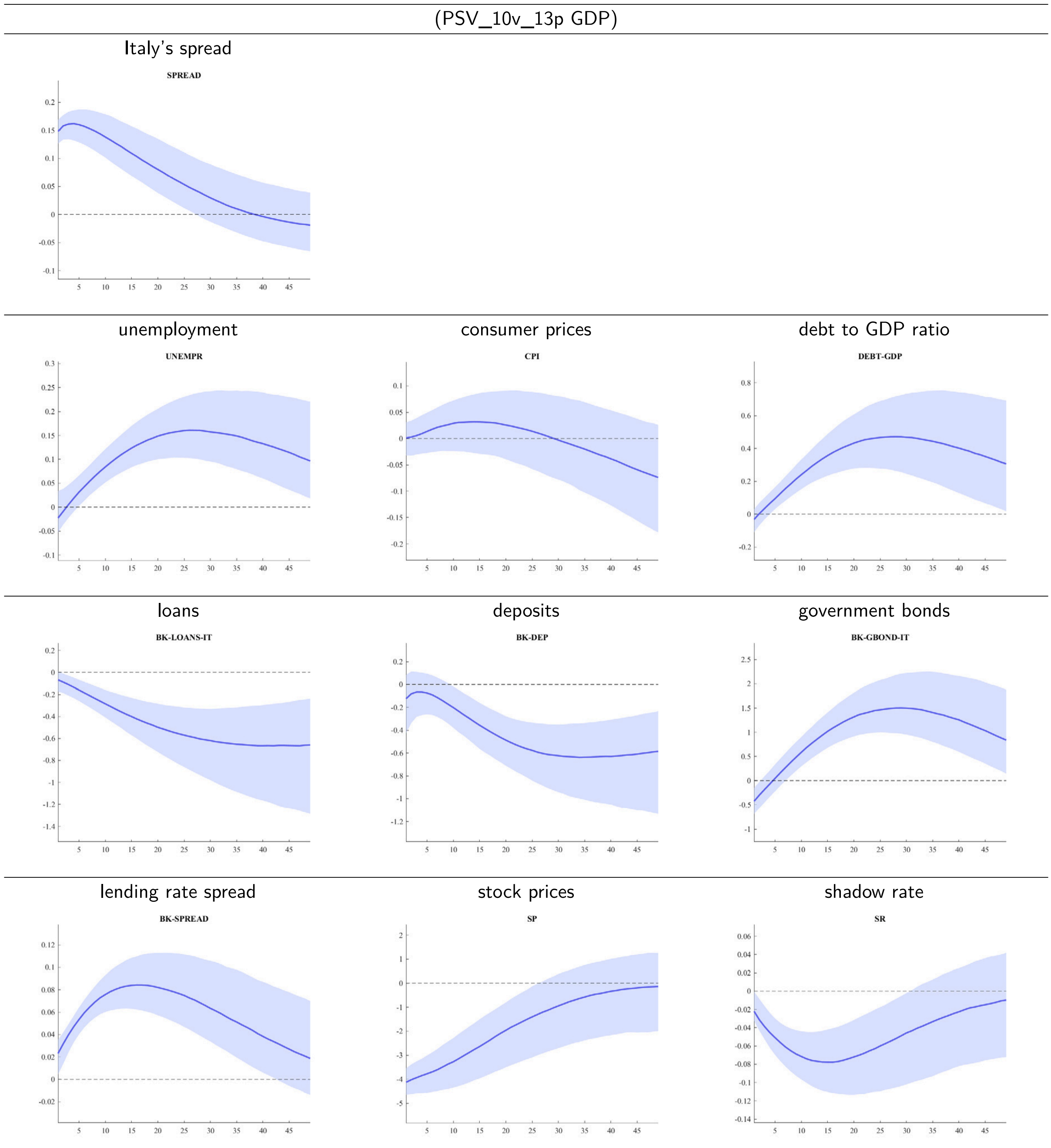

Fig. 10. IRFs, VAR with high relevance prior.
Response to the identified sovereign shocks. 'Households and others' includes individuals and non-financial entities. The darker gray area is for the 16–84 interquartile confidence range.

analysis", Mendeley Data, V1, DOI: 10.17632/4gg3rj7g95.1 https://data.mendeley.com/datasets/4gg3rj7g95/1.

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