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Credit demand and supply shocks in Italy during the Great Recession

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Abstract In this paper, we use Structural VAR analysis to disentangle credit demand and supply shocks and their effect on real economic activity in Italy during the 2008-2014 crisis period. The three endogenous variables considered are the loan interest rate, the loans growth rate and the employment to population ratio. The data are observed at annual frequency for each of 103 Italian provinces. The structural shocks are identified through heteroscedasticity, by letting the variance of the shocks to switch across four Italian macro-regions: North, Centre, South and Islands. Sign restrictions are used to interpret ex post the structural shocks. The empirical findings suggest a more important role of credit supply shocks in shaping the level of real economic activity. Furthermore, the results show that credit crunch hits the North of Italy less than the remaining macro-regions, especially the South-Italy.

Keywords Structural VAR · Identification through heteroscedasticity · Credit shocks · Regional economic activity

Riassunto *Una caratteristica predominante della Grande Recessione è stata una contrazione prolungata del credito al settore privato in diversi paesi. Lo scopo di questo studio, basato su dati disponibili a livello provinciale durante il periodo di crisi 2008-2014, è duplice. In primo luogo, ci concentriamo sull'identificazione degli shocks dal lato della domanda e dell' offerta di credito.*

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In secondo luogo, siamo interessati ad analizzare l'impatto degli shocks dal lato dell'offerta di credito sull'attività reale per l'economia italiana.
Numerosi studi empirici basati su micro-dati studiano l'impatto di una contrazione del credito sull'attività reale dell'economia. Per quanto riguarda l'economia italiana, lo studio di Barone et al. (2016) usa una strategia di identificazione che si basa su dati che catturano le relazioni banca-province e necessita di un periodo campionario che consenta di confrontare un periodo di tranquillità con uno di crisi. Il periodo campionario usato nel presente studio è relativo solo ad un prolungato periodo di crisi. Inoltre, contrariamente allo studio di Barone et al. (2016), l'analisi non si basa su una stima a due stadi, dove, nel primo, viene identificato un indicatore di offerta di credito a livello provinciale e, nel secondo stadio, si esamina l'impatto sull'attività reale dell'economia.
In questo studio, viene utilizzato un modello Vettoriale Autoregressivo Strutturale considerando tre variabili endogene: il tasso di interesse sui prestiti, il tasso di crescita dei prestiti ed il tasso di occupazione osservati annualmente, tra il 2008 ed il 2014, per 103 provincie italiane. Gli shocks strutturali di domanda e offerta di credito ed il loro impatto reale sono simultaneamente identificati attraverso la presenza di eteroschedasticità osservata nei dati a livello di quattro macro-regioni italiane: Nord, Centro, Sud e Isole. Le restrizioni di segno vengono utilizzate per interpretare ex-post gli shock strutturali. I risultati empirici suggeriscono un ruolo più importante degli shock dal lato dell'offerta di credito sul livello di attività economica reale. Inoltre, i risultati mostrano che la crisi del credito colpisce il Nord dell'Italia meno delle rimanenti macro regioni, in particolare del Sud-Italia.

Parole chiave *Modello Vettoriale Autoregressivo Strutturale - Identificazione tramite eteroschedasticità - Shocks al mercato creditizio - Attività economica regionale*

1 Introduction

A predominant feature of the Great Recession has been a prolonged contraction of credit to the private sector in a number of countries. The aim of this paper, based on provincial level data, is twofold. First, we focus on the identification of credit demand and supply shocks in explaining the credit contraction in Italy. Second, we are also interested in analyzing the effects of the identified credit supply shock on real activity for the Italian economy.
The slowdown in bank lending which occurred in many advanced economies has led to a debate about the effects of disturbances in credit markets on business cycles. In spite of the increasing importance of capital markets, the Euro financial system is typically bank-based. Furthermore, bank loans play a non-negligible role in the financing of private investment and consumption in the European countries. The Italian financial system has been dominated by banks: the ratio of loans to non-financial private sector to Italian banks total assets was 76.8 percent in 2014. Hence, bank lending might play an important role in explaining fluctuations of economic cycle. In the aftermath of the financial crisis, the Italian banking system has seen a slackening growth

of bank loans to non-financial corporations and households. The Italian year-on-year growth rate of loans to private sector fell from 9.2 percent in the first quarter of 2008 to 1.1 percent in the first quarter of 2010. After a sharp upturn, the growth rate has become negative since the second quarter of 2012.

A number of empirical studies based on micro-data informing on bank-firm relationship employs the methodology proposed by Khwaja and Mian (2008) to identify credit supply shocks (see Bonaccorsi di Patti and Sette, 2016, for the Italian economy, among the others). The Khwaja and Mian (2008) methodology exploits a sample which includes observation for a pre and post crisis period, and it is based on the estimation of a regression of the change in the loans provided by each bank to its borrowing firms after an exogenous shock (e.g. a crisis event) as a function of bank exposure to that shock. Del Giovane et al. (2017) use Bank Lending Survey (BLS) to identify, through zero exclusion restrictions, the simultaneous equation system fitted to interest rates and loans data for Italy.
While the previous studies are only interested in the identification of a credit supply factor, some authors are also concerned with their real effect using a two-stage estimation analysis. Cingano et al. (2016) use data on bank-firm relationship and they identify credit supply shocks through the variation in bank reliance on the interbank market at the end of 2006, leading to different bank exposure to the July 2007 liquidity shock. The proxy used by Cingano et al. (2016) for the real activity is the private investment. The study of Barone et al. (2016) use bank-province relationship data for the Italian economy to identify a local (province) credit supply indicator. In a second stage of the analysis they assess the impact of credit supply shock on investment, value added and employment.

The Khwaja and Mian (2008) methodology employed by Cingano et al. (2016) and by Barone et al. (2016) relies on an individual bank exposure to an exogenous shock (e.g. crisis event) switching from a no crisis period to one characterized by turmoil. Since we focus only on a prolonged crisis time span, we exploit the heterogeneity in the data across Italian macro-regions. More specifically, ex-ante, we employ identification through heteroscedasticity (see Rigobon, 2003; Lanne and Lütkepohl, 2008) and, ex-post, we give an economic interpretation to the shocks through sign restrictions (see Mumtaz et al., 2015, for a review). In particular, we follow the suggestion of Kick (2016) in setting the sign restrictions: a credit supply (demand) shock moves the price and quantity of credit in opposite (same) directions.
Both methods are popular for the identification of a Structural VAR, which is the model used in this paper. Moreover, we argue that, contrary to the previous studies which rely on a two-stage analysis, our study, based on an estimation in one-shoot, does not suffer from a measurement error affecting the use of an estimated regressor in the second stage regression.

The empirical findings show that credit supply shocks play a more important role than innovations to demand for credit. Furthermore, there is evidence that credit crunch hits the

North of Italy less than the remaining macro-regions, especially the South-Italy.

The paper is structured as follows. Section 2 provides a literature review on identification of shocks to credit markets; Section 3 describes the empirical methodology; Section 4 describes data and the empirical findings and Section 5 concludes.

2 Literature review

As mentioned in the introduction, a number of empirical studies on the Italian credit crunch is only interested in the identification of credit supply shocks. Presbitero et al. (2014) relies on the identification of constrained Italian firms, using firms survey data containing information on loan applications and bank decisions. The authors main focus is the role played by functional distance between the loan office and the headquarters where final lending decisions are made to explain the tightening in lending conditions in Italy. For this purpose, the authors combine survey data on firms with aggregate data on banks informing on the openings and closures of branches at the bank-province level. The authors use a sample of monthly observations from 2008:1 to 2009:4 and the empirical findings show that the credit crunch experienced in Italy after Lehman Brothers collapse has been more severe in provinces with larger shares of branches owned by distantly managed banks. Moreover, there is evidence of a home bias, given that the credit crunch has not been harsher for small and economically weak firms.

The identification methodology put forward by Khwaja and Mian (2008), which is based on Credit Register data for firms that have multiple lenders, has been applied by a number of studies. This approach consists of estimating a regression of the change in the loans provided by each bank to its borrowing firms after an exogenous shock (e.g. a crisis event) as a function of bank exposure to that shock. For this purpose, they use firm fixed effects to capture shifts in the demand for loans and other unobservable borrower characteristics, such as changes in their balance sheet conditions. The identification methodology provides an estimate of the differential change in credit supply for the same firm, associated with a different exposure of the lending banks to the exogenous shock. Albertazzi and Marchetti (2010) present evidence of a contraction of credit supply associated to low bank capitalization and scarce liquidity, over the 6-month period following the Lehman bankruptcy. Bofondi et al. (2013) exploit the differential exposure to the sovereign risk between domestic banks and foreign banks operating in Italy. The authors find that the lending of domestic banks grew less (and their interest rates were higher) than that of foreign banks, after the outbreak of the sovereign debt crisis. Bonaccorsi di Patti and Sette (2016) link banks' balance sheet conditions to the provision of credit and show that Italian banks that relied heavily on securitization prior to the subprime crisis curtailed lending more than other banks.

Del Giovane et al. (2017) estimate a system of two simultaneous equations regarding the interest rates and loan amounts of 11 Italian banks. The authors use demand and supplies dummies obtained from Eurosystem Bank Lending Survey (BLS).[1] In order to identify the simultaneous equations system, the demand dummies are excluded from the equation where the dependent variable is the price and the supply factor dummies are excluded from the equation involving quantity. After a number of robustness checks, the authors acknowledge that they cannot exclude the possibility that their findings are affected to some extent by some residual endogeneity. The authors find that the effects of the supply restriction on both the cost and the availability of credit were, on average, stronger during the sovereign debt crisis than during the Lehman global crisis. Moreover, the authors find that credit crunch was mostly related to the banks' risk perception during the global crisis, whereas funding conditions became predominant during the sovereign debt crisis.

The second empirical issue regarding the impact of the identified credit supply shock on real activity of the Italian economy has been addressed by the following studies. The study of Cingano et al. (2016) use in the first stage the Khwaja and Mian (2008) identification methodology. In particular, the authors use data on bank-firms relationships and they identify credit supply shocks through the variation in bank reliance on the interbank market at the end of 2006, leading to different bank exposure to the July 2007 liquidity shock. The authors' findings show that although credit tightening was homogeneous across firms, investment fell by a much larger amount among smaller and younger firms, and those with higher bank dependence. Bottero et al. (2015) show that the Greek bailout in 2010 led to a fall in loan supply in Italy, which depressed investment and employment for smaller Italian firms.
The methodology suggested by Greenstone et al. (2014) is used to identify and assess the real effects of a credit supply indicator by Barone et al. (2016). The authors use confidential data over 2008-2011, obtained from the Bank of Italy Supervisory Report, on total outstanding loans extended by Italian banks to the private sector (firms and households) aggregated into local credit markets corresponding to provinces. The identification strategy employed by Barone et al. (2016) is based on data capturing bank-provinces relationships (hence it is similar to Khwaja and Mian, 2008). More specifically, the authors focus on the identification of a local (province) credit supply indicator by, first, using a panel regression. The dependent variable is the change in credit granted by one of the 650 banks to households and firms located in a given province and operating in a given economic sector and the explanatory variables are two dummies. The first dummy measures province-year fixed effects that capture the variation in the change of lending due to local economic factors (capturing local demand). The second

[1] Ciccarelli et al. (2015) use Bank Lending Survey (BLS) for the Euro area and the Senior Loan Officer Survey (SLOS) for the U.S. Contrary to Del Giovane et al. (2017) study which employs BLS data for Italy only to identify credit demand and credit supply shocks, Ciccarelli et al. (2015) are also interested in the real effects of credit supply shocks. The qualitative data are transformed into quantitative and treated as endogenous variables together with proxies of output, prices and monetary policy rates in a Vector Autoregression model, VAR, fitted to the Euro area and to the US separately.

dummy measures bank-year fixed effects which identifies nationwide bank lending policies. The authors, then, use the coefficient associated to the second dummy and pre-crisis bank market shares in the province (as weights) to aggregate and to construct a province-year credit supply index. In a second stage, the credit supply real effect are estimated regressing either value added, or investment, or employment (observed for each province) on the estimated local credit supply variable. The empirical findings show that the most severe effect of the credit crunch occurred in the North and Central Italy which have firms relatively more dependent on external finance. The methodology suggested by Greenstone et al. (2014), is also employed by Berton et al. (2017), using a matched data set of job contracts, firms and banks in one Italian region (Veneto). The authors, first, identify and construct a credit supply factor at firm level, and, in a second stage, they assess the impact on employment. The empirical findings (for Veneto region) show that the effects of the credit crunch have been particularly severe for smaller, younger and less productive firms, and those with higher debt overhang and weaker bank-firms relationships have been more vulnerable to the (negative) impact of the credit crunch.
Dörr et al. (2017) use information on loans by individual banks to firms that borrow from multiple Italian banks, which are exposed to foreign borrowers in distressed countries (Greece, Ireland, Portugal and Spain). The authors use a novel identification method suggested by Amiti and Weinstein (2017) which does not rely on a comparison between access to credit during pre-crisis and a crisis period (as in Khwaja and Mian, 2008), but only on loan data over the 2010-2012 period characterized by Euro sovereign debt crisis. The credit supply and demand components are recovered by imposing an additional constraint. The adding-up constraint states that changes in individual loan growth between banks and firms must add up to the overall, economy-wide change in loan growth. After establishing that credit supply shocks reduce firms' loan growth, Dörr et al. (2017) show that credit supply rationing had significant real effects on firms' investment and employment decisions, as well as total factor productivity. Italian firms with higher exposure to troubled banks reduced their investment and employment and they experienced a significant fall in productivity.

Recent empirical studies on the Italian economy (together with Euro area countries) employ macro-time series data and they identify credit supply shocks and their impact on the real economy by imposing sign restrictions to identify a Structural Vector Autoregression model, SVAR. In particular, Bijsterbosch and Falagiarda (2014) use time-varying parameter Vector autoregression model with stochastic volatility, producing results for Euro area countries, including Italy. The studies of Hristov et al. (2012), based on Panel VAR and the study of Kick (2016), based on Global VAR, analyze the dynamic effect of credit supply on real economic activity in Italy as well as a number of Euro area countries.

3 Structural VAR

In this section, we first describe the identification through heteroscedasticity methodology. The first study of identification of structural shocks via changes in volatility is due to Rigobon (2003). Recently, the studies of Lanne and Lütkepohl (2008), Lütkepohl (2012) and Lütkepohl and Netsunajev (2015) show that heteroscedasticity in residuals provides over-identifying restrictions (which can be tested) to traditional SVAR models employed to study the effect of monetary policy shocks. Lütkepohl (2012) identifies shocks by considering changes in volatility in given time periods (with breakpoints specified exogenously). The author considers also a vector generalized autoregressive conditional heteroscedasticity (MGARCH) to model for changes in volatility of residuals. Finally, a third specification model examines changes in volatility by using a Markov regime switching process. Lütkepohl and Netsunajev (2015) use a SVAR to estimate the interaction between US monetary policy and stock market where the identification is obtained by modelling heteroscedasticity in a way similar to Lütkepohl (2012), considering also smooth transition in the variances.

Following Lütkepohl (2005), we carry out with a SVAR analysis, estimating a structural B-model VAR(1) for pooled data, which has the following reduced form representation:

$$Y_{n,i,t} = \delta + AY_{n,i,t-1} + u_{n,i,t} \tag{1}$$

where $Y_n = (interest\ rate_{i,t}, \Delta loans_{i,t}, empl.ratio_{i,t})$ is a vector of three variables in province i at time t, namely interest rate on loans (*interest rate*), a log transformation of loans first order difference ($\Delta loans$) and the employment to population ratio (*empl.ratio*), δ is a 3×1 vector of constant terms, A is a 3×3 parameter matrix and u is a vector of residuals with covariance matrix $E(u_t u_t') = \Sigma_u$, which is not assumed to be diagonal.
According to Lütkepohl (2005), the relationship between the white-noise process and the structural disturbances has the following representation:

$$u_{n,i,t} = B\varepsilon_{n,i,t} \tag{2}$$

where B is a non-singular 3×3 matrix including the contemporaneous interactions between the endogenous variables and ε is a vector of uncorrelated structural shocks.
Hence, the structural form of VAR is:

$$Y_{n,i,t} = \delta + AY_{n,i,t-1} + B\varepsilon_{n,i,t} \tag{3}$$

We estimate a reduced-form of a VAR(1) by Ordinary Least Squares (OLS) for each equations separately.
In an attempt to estimate the model, we need to establish different regimes of volatility. This allows the determination of the covariance matrix structures as well as identifying the system of equations.
Regimes of volatility are selected on the basis of geographical discrimination. Particularly, four

heteroscedastic regimes are defined, corresponding to different Italian macro-areas: North Italy, Central Italy, South Italy and Insular Italy.
The sample of observations is divided into 4 sub-samples, based on geographical characteristics, $S = (S_{North\ Italy}, S_{Central\ Italy}, S_{South\ Italy}, S_{Insular\ Italy})$.
Constructing the covariance matrix structures is carried out by choosing the North Italy as the first regime, whereas the other regimes are: *(i)* Central Italy, *(ii)* Southern Italy and *(iii)* Insular Italy.

The covariance matrix structure has the following representation:

$$\Sigma_1 = BB', \quad \Sigma_i = B\lambda_i B', \qquad i = 2, \ldots, 4 \tag{4}$$

where

$$\Sigma_1 \quad \text{for } i \in S_{North\ Italy} \quad \text{and} \quad \Sigma_i = \begin{cases} \Sigma_2 & \text{for } i \in S_{Central\ Italy} \\ \vdots & \\ \Sigma_4 & \text{for } i \in S_{Insular\ Italy} \end{cases} \tag{5}$$

Once the reduced form of VAR(1) model is estimated by OLS estimation, the corresponding residuals are used in order to estimate the unknown parameters.
The set of unknown parameters includes matrix B coefficients and the variances of the structural error terms.
Assuming normality of the error terms, the structural parameters are obtained by Maximum Likelihood (ML) estimation. The Multivariate Gaussian log-density function at time t and for macro-region i is:

$$log\ l(\beta, \sigma) = -\frac{KT}{2}\ log(2\pi) - \frac{1}{2}\sum_{i=1}^{4} |log(\Sigma_i)| - \frac{1}{2}\sum_{i=1}^{4}(u_i' \Sigma_i^{-1} u_i) \tag{6}$$

where Σ_i is the covariance matrix of the reduced-form residuals, expressed in terms of the structural form coefficients as described in (4) and (5)[2]. As mentioned above, identification through heteroscedasticity is only a statistical tool, and to give an economic interpretation of the structural form shocks we use, ex post, sign restrictions on each column of the impact multiplier matrix B (see Table 1).
The economic identification of credit demand and supply shocks is based on a minimal set of identifying restrictions in line with previous studies (Peersman, 2011; Barnett and Thomas, 2013; Kick, 2016). More specifically, a negative credit demand shock reduces both credit price and the amount of loans. Conversely, a negative credit supply shock produces an increase of

[2] The log density functions are generated by using the **mvtnorm** package in R. The optimization problem is solved by minimizing the negative of the sum of the log densities by using the "BFGS" method. The "BFGS" method is a quasi-Newton method which uses function values and gradients to build up a picture of the surface to be optimize.

the loan interest rate as well as reducing the quantity of bank lending (see Hristov et al., 2012). The real variable is affected by credit supply and demand shocks negatively. Following Kick (2016), we do not expect any prior sign restriction from the responses of the credit variables to the real shocks.
Since the number of unknowns is equal to eighteen and the number of moment conditions (see (4) and (5)) is equal to twenty-four equations, a Likelihood Ratio test is employed to test for the six over-identifying restrictions:

$$LR = -2[ln(\hat{\theta}_R) - ln(\hat{\theta}_{UR})] \tag{7}$$

where $\hat{\theta}_R$ is the ML estimator of the restricted model and $\hat{\theta}_{UR}$ is the ML estimator of the unrestricted model. Under the null hypothesis, the Likelihood ratio statistic has an asymptotic χ^2 distribution with degree of freedom equal to the number of the over-identifying restrictions. We also compute the cumulative standardized impact of each structural shock over two year horizon by estimating $B + AB$. While the standard errors of the parameters of the standardized impact multiplier B are retrieved from inversion of the Hessian of the maximized log-likelihood function, the confidence intervals for the cumulative impulse response are generated through bootstrap. In particular, for each regime, we resample 1000 times the estimated residuals of the VAR(1)[3]. For each draw, we estimate the parameters of the structural form model by maximizing the log likelihood function.
Finally, for each of 103 Italian provinces, we compute the historical decomposition of the endogenous variables as follows:

$$Y_t = \delta \sum_{j=0}^{t-2} A^j + A^{t-1} Y_1 + \sum_{j=0}^{t-2} A^j B \varepsilon_{t-j} \quad , \quad \text{for } t > 1 \tag{8}$$

where $Y_1 = Y_{2008}$ in our analysis. Constructing the historical decomposition allows us to compute the anticipated and unanticipated components of each series.

4 Empirical analysis

4.1 Data

We use a panel data set of observations which contains information on credit aggregates and a real variable for 103 Italian provinces.

For the purpose of disentangling credit supply shock from the demand-side one, we consider two credit market aggregates and one real activity variable. Hence, as endogenous variables, we use as proxies of price and quantity of credit the loan interest rate and the amount of

[3] We keep only the replications (which are 421) in line with the ex post identification of the shocks according to the point estimation results.

loans, respectively; the employment to population ratio is the proxy of real economic activity. The data are at annual frequency, from 2008 to 2014, for each of 103 provinces, for a total of 2163 observations. We use low-frequency data because of the availability of the employment to population ratio: for each province, data are only made accessible with annual frequency. The shortness of the sample period used is due to the loan interest rate series which starts from 2008.

Information on credit aggregates are from the Statistical Database of Bank of Italy. As for the price of credit, we use the lending rates on loans facilities (stock) series for non-MFI resident sectors. Particularly, we consider the interest rate charged by banks at the end of the fourth-quarter as annual observation.
As for the quantity of credit, we consider the first-order difference of loans to non-MFI resident sectors as endogenous variable[4]. In an attempt to include in our model annual observations instead of quarterly data, we consider the value of loans registered at the end of each fourth-quarter. Taking into account the first difference allows us to avoid stationarity problems.
The real aggregate is the employment rate which is defined as the ratio between employed people (aged 15-64) and the corresponding overall resident population. The data are collected from statistical database of the Italian National Institute of Statistics (ISTAT).
Actually, ISTAT makes available Gross Value Added (GVA) data which might be used as a proxy for real economic activity at provincial level. Nonetheless, the value added series is not available for 2014.

Since we seek to identify credit supply and demand shocks, and a real shock, through cross sectional heteroscedasticity, we consider four macro-regions: North Italy, Central Italy, South Italy and Insular Italy.
Fig. 1-2-3 show the boxplots series of the three endogenous variables for each Italian macro-area from 2008 to 2014. The boxplots provide information on each province which belongs to different macro-regions.
Focussing on the mean values of Figure 1, all the Italian macro-regions exhibit the same pattern in the loans interest rate. After a twofold decrease over the 2008-2010, the loan interest rates stabilize around values ranging from 2.8 and 3.5 percent, before exhibiting a temporary upturn in 2011. Afterward, the interest rate on loans values do not exceed 3.7 percent in the 2012-2014 period.
Figure 2 shows a more heterogeneous evolution over time of the loan growth rates by inspection of the boxplots for the macro-regions. Whilst the highest loan growth rate is in South and Insular Italy at the beginning of the crisis, these regions experience the strongest slowdown in the growth rates, starting from 2011. During the last two years of the sample, there is a clear

[4] According to the definitions provided by the Bank of Italy, the loans aggregate is defined as the loans disbursed by banks to non-bank sectors. This variable includes mortgage loans, current account overdrafts, loans secured by pledge of salaries, credit card advances, discounting of annuities, personal loans, leasing, factoring, other financial investment (e.g. commercial paper, bill portfolio, pledge loans, loans granted from funds administered for third parties), bad debts and unpaid and protested own bills.

evidence of a recovery in the loans growth rates.
In Figure 3, we can observe that during the period 2008-2014, all the four macro-areas exhibit a relevant decline of the employment to population ratio, with different levels of decrease in the territorial areas. Whilst North and Central Italy experience a moderate reduction in the employment to population ratio until 2012 and a moderate upturn in 2013-2014, the South and Insular Italy manifest a significant negative trend during the whole period.

4.2 Empirical Evidence from structural VAR

The estimated parameters of the standardized impact multiplier are shown in Table 2 (panel A).
Whilst residuals heteroscedasticity is a statistical tool to identify structural form shocks, ex post interpretation is obtained using the sign based restriction suggested in Table 1. Therefore, according to the sign based restriction, the first, second and third column show the standardized impact of a negative shock to credit demand, credit supply, and real economy, respectively. While the credit demand shock plays a bigger role than the credit supply shock on the loan interest rate, the reverse is true as for the impact on the loan growth rate. Although, on impact, the only statistically significant effect of an innovation to credit demand and credit supply is the one on the interest rate on loans (at 1 percent and 10 percent level of significance, respectively), results from Table 3 show a statistically significant cumulative effect of credit demand and credit supply shocks to both credit aggregates. Moreover, the empirical findings show that credit supply shocks plays a more important role than those to credit demand in reducing the employment to population ratio. In particular, a one standard deviation shock to credit supply implies, on impact, a 1.3 percent change in the employment to population ratio (see Table 2 panel A) and a cumulative impact over a two year horizon equal to 2.4 percent (see Table 3).
The real shock, interpreted as a negative one, due to its marginal depressing effect on the employment to population ratio, raises both the interest rate on loan and the growth in lending. The impact of the real shock on the employment rate is statistically significant over a two year horizon.
Table 2 (panel B) shows that the identification assumption is satisfied because all the estimated parameters, λ_i, measuring the estimated relative variances, are distinct and statistically significant.
The interpretation of the results in Table 2 (panel B) is based on the square root of the relative variances, in order to focus on the magnitude of shocks relative to the one for the North of Italy. The innovation hitting credit supply in Central, South and Insular Italy are all above unity suggesting that credit crunch hits the North of Italy less than the remaining macro-regions. In particular, the largest relative magnitude is observed for the credit supply shock hitting the South of Italy, and the magnitude of the innovation to credit supply in Central and Insular Italy is almost the same. While the largest relative magnitude of the credit demand shock ob-

served is for Insular Italy, the South and Central Italy exhibit credit demand innovation with magnitude lower than the North. Finally, the largest magnitude of the real shock is observed in Central Italy (almost twice than the one for the North). Both South and Insular Italy exhibit a magnitude of the real shock above the corresponding one for the North (although much lower than the one for Central Italy).
Finally, Table 2 (panel C) shows the results of the over-identifying test restrictions using the LR statistic. The value of the log likelihood of the restricted model is equal to 2382.14, whilst the unrestricted log likelihood is equal to 2383.10. Therefore, the over-identifying restrictions are not rejected at 90 percent confidence level.

Following Lütkepohl (2011), we carry out with a historical decomposition (see Fig. 4 and 5) in order to analyse the effects of credit market shocks on the real variable in the Italian provinces. Our main focus is on the contribution of credit demand and supply shocks to the dynamic of the employment to population ratio (de-meaned at provincial level) for each macro-region. A credit demand shock seems to play a non-relevant role (with the exception of Insular-Italy) in explaining the downturn in the employment to population ratio.
We can observe, from historical decomposition, that credit supply shock plays an important role in tracking the dynamics of the employment rate in each macro-region, especially the slackening in employment rate in South and Insular Italy over 2013-2014.

To summarize, contrary to the empirical findings of Kick (2016), we find that credit supply shocks play a more important role than innovations to demand for credit for the dynamics of real economic activity in Italy. Our results are in line with previous papers which focus on the credit crunch effect on real economy across Italian provinces (see Presbitero et al., 2014; Barone et al., 2016; Cingano et al., 2016; Berton et al., 2017). In particular, our findings about regional differences of credit crunch are in line with the ones of the study of Presbitero et al. (2014) who find that the real economy of North Italy is more resilient to credit rationing, since, especially in the Southern regions, banks retracted disproportionally from markets that are more distant from their headquarters. Since our study shows that the Centre and South of Italy exhibit a relative higher magnitude of the credit supply shock, this contrasts the findings of Cingano et al. (2016) related to the territorial impact of rationing in lending. The authors find that the credit cut has been relatively homogeneous across borrowers and the firms with easier access to external finance or with a stronger liquidity position were more able to contain the negative consequences for investment (and, to less, extent on employment) of the drop in credit. Moreover, our findings contrast those from Barone et al. (2016) who find that the most severe credit rationing impact on real value added growth, during the recent financial crisis, occurred in the North and Central Italy which have firms relatively more dependent on external finance.

5 Conclusions

In this paper, we have investigated the role of credit market shocks in explaining the downturn of the Italian economic activity using data at provincial level over 2008-2014. A number of studies of the Italian credit crunch are based on a two-stage estimation approach where in the first stage a credit supply indicator is identified through the Khwaja and Mian (2008) method which requires data on either bank-firms or bank-provinces relationships, observed in a pre and post crisis period. However, since our dataset is constrained only to a period of prolonged recession, our identification scheme is based on the changing variance of the structural shocks to a VAR fitted to interest rates, loans growth rates and employment ratio observed in the Italian macro-regions. Heteroscedasticity is only a statistical tool for the purpose of identification, therefore we have used ex post sign restrictions suggested by theory to identify demand and supply of credit shocks.

Differently from the empirical findings of Kick (2016), we find that credit supply shocks play a more important role than innovations to demand for credit. Our findings related to a sizable and significant effect of credit supply on employment are in line with the studies, based on loans to Italian firms, of Barone et al. (2016), Cingano et al. (2016) and Berton et al. (2017).

Moreover, the empirical evidence shows that credit crunch hits the North of Italy less than the remaining macro-regions, especially the South-Italy. This findings are consistent with those of Presbitero et al. (2014) who find that the real economy of North Italy is more resilient to credit rationing, since, especially in the Southern regions, banks retracted disproportionally from markets that are more distant from their headquarters.

An implication of these findings for Italy is that a key policy priority should therefore take into account the significant role of the credit supply. Taken together, these findings support the implementation of the recent Quantitative Easing adopted by the ECB to stimulate the economy.

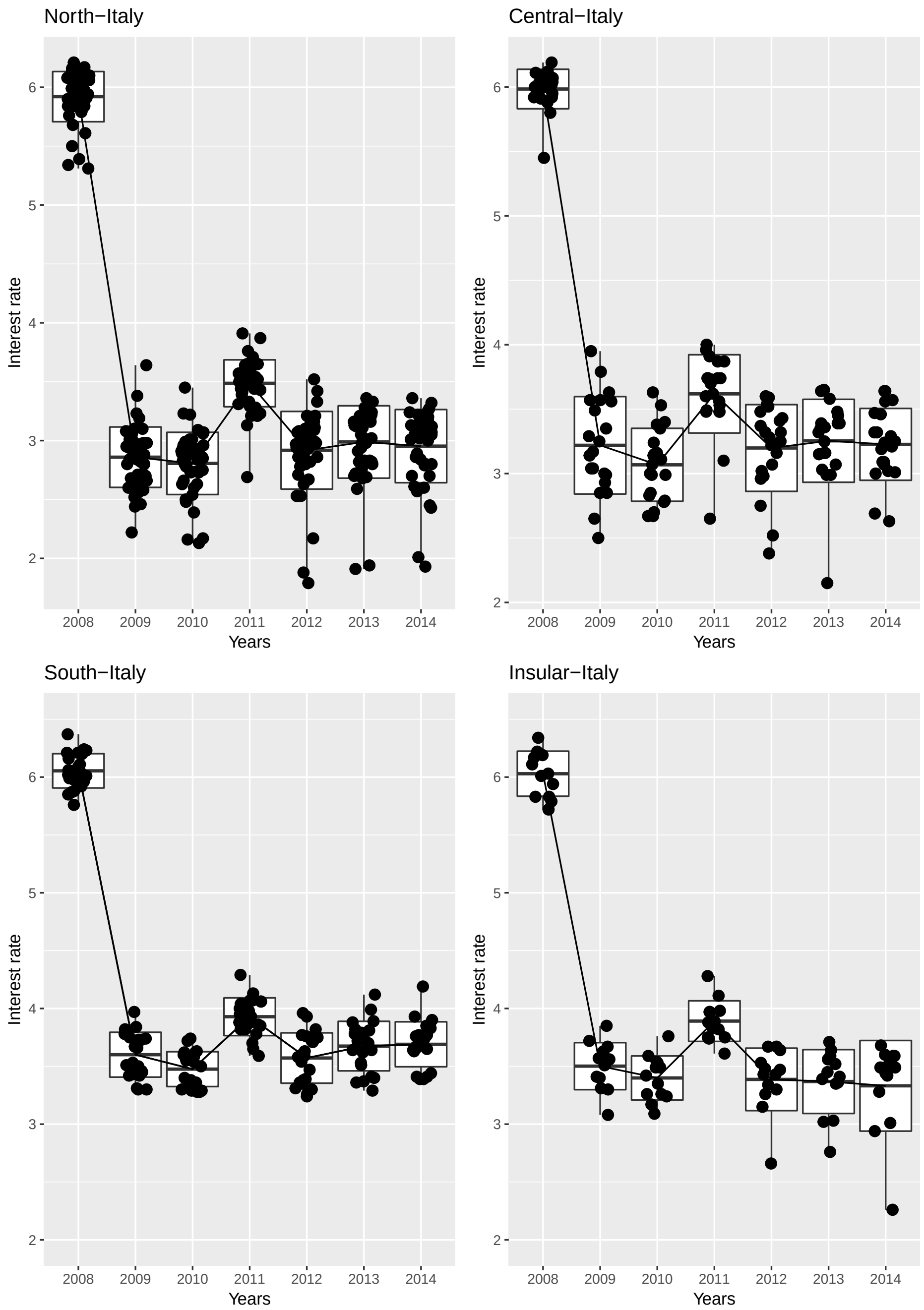

Fig. 1: Boxplots for Loans interest rates, percent, for the Italian macro-areas, 2008-2014.

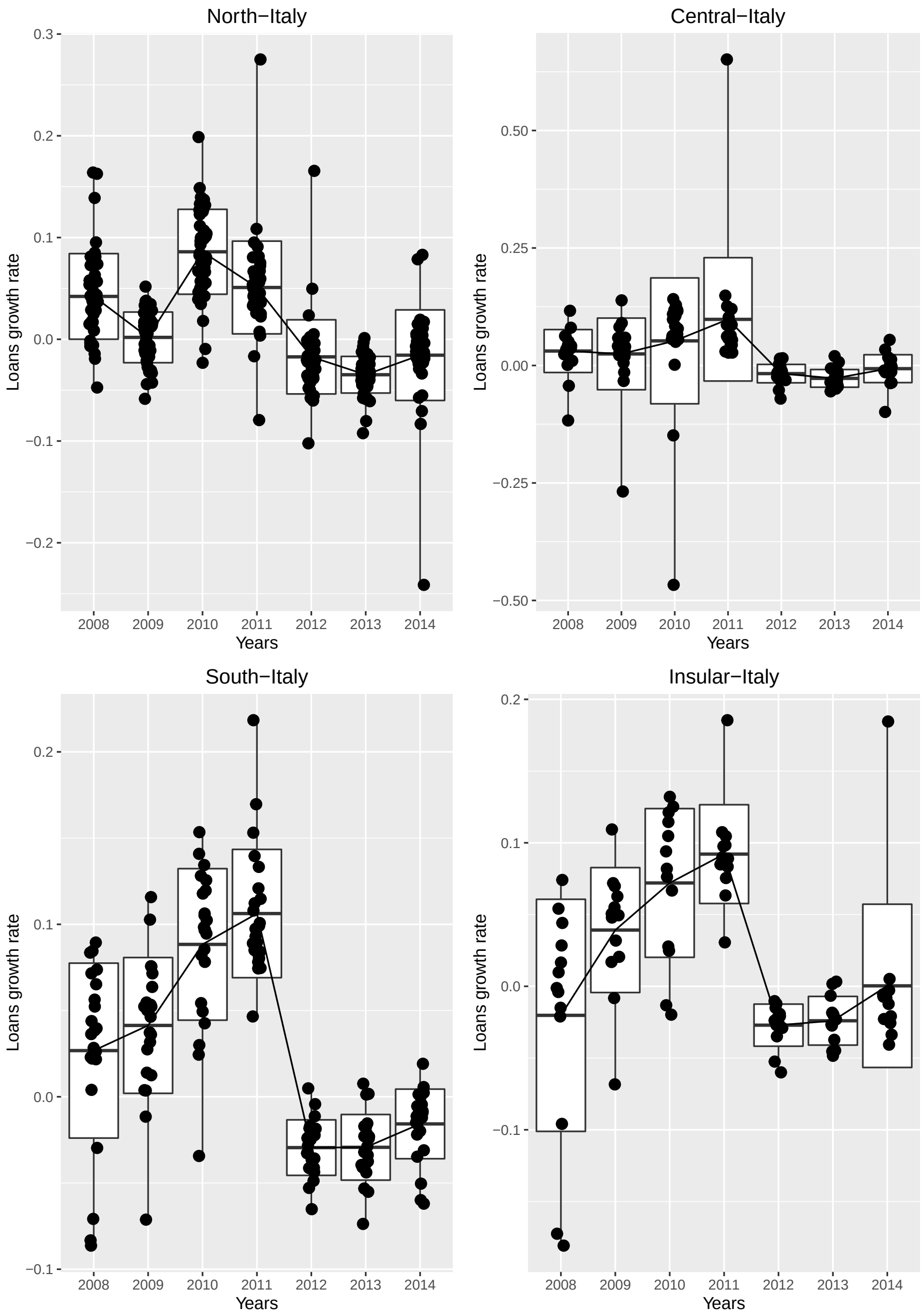

Fig. 2: Boxplots for Loans growth rates, for the Italian macro-areas, 2008-2014.

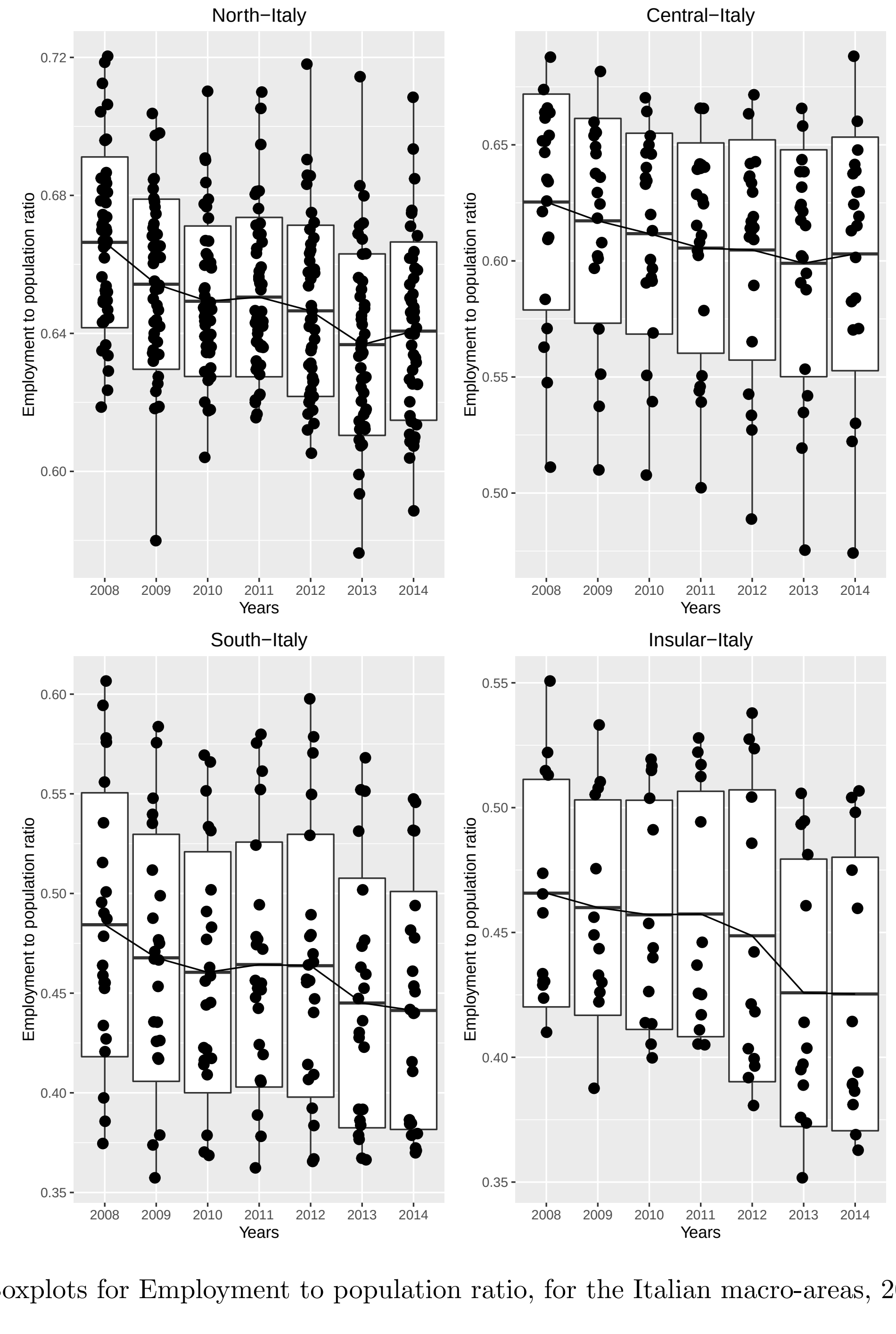

Fig. 3: Boxplots for Employment to population ratio, for the Italian macro-areas, 2008-2014.

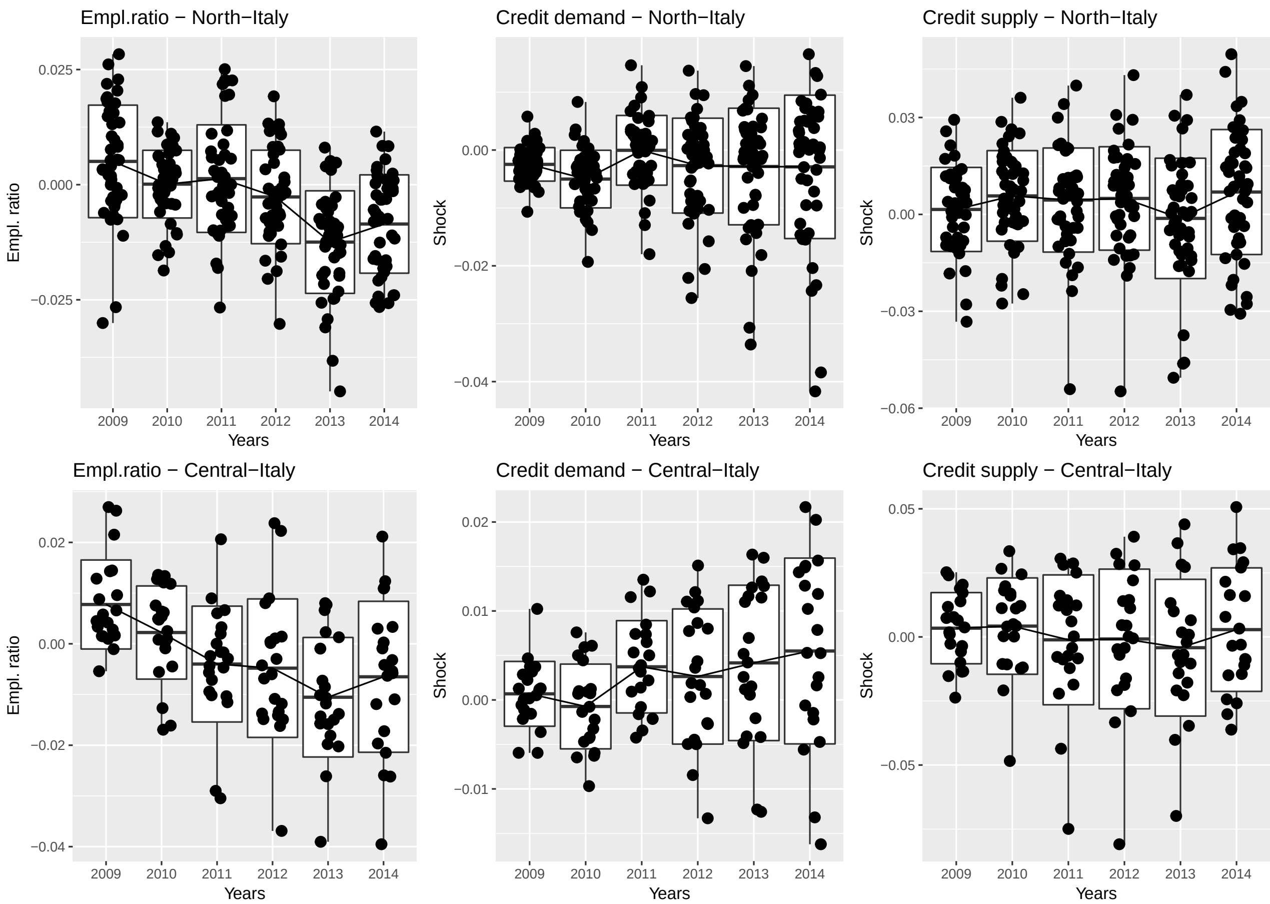

Fig. 4: Contribution of credit demand and supply shocks on historical decomposition of Employment rate, North and Central Italy, 2009-2014.

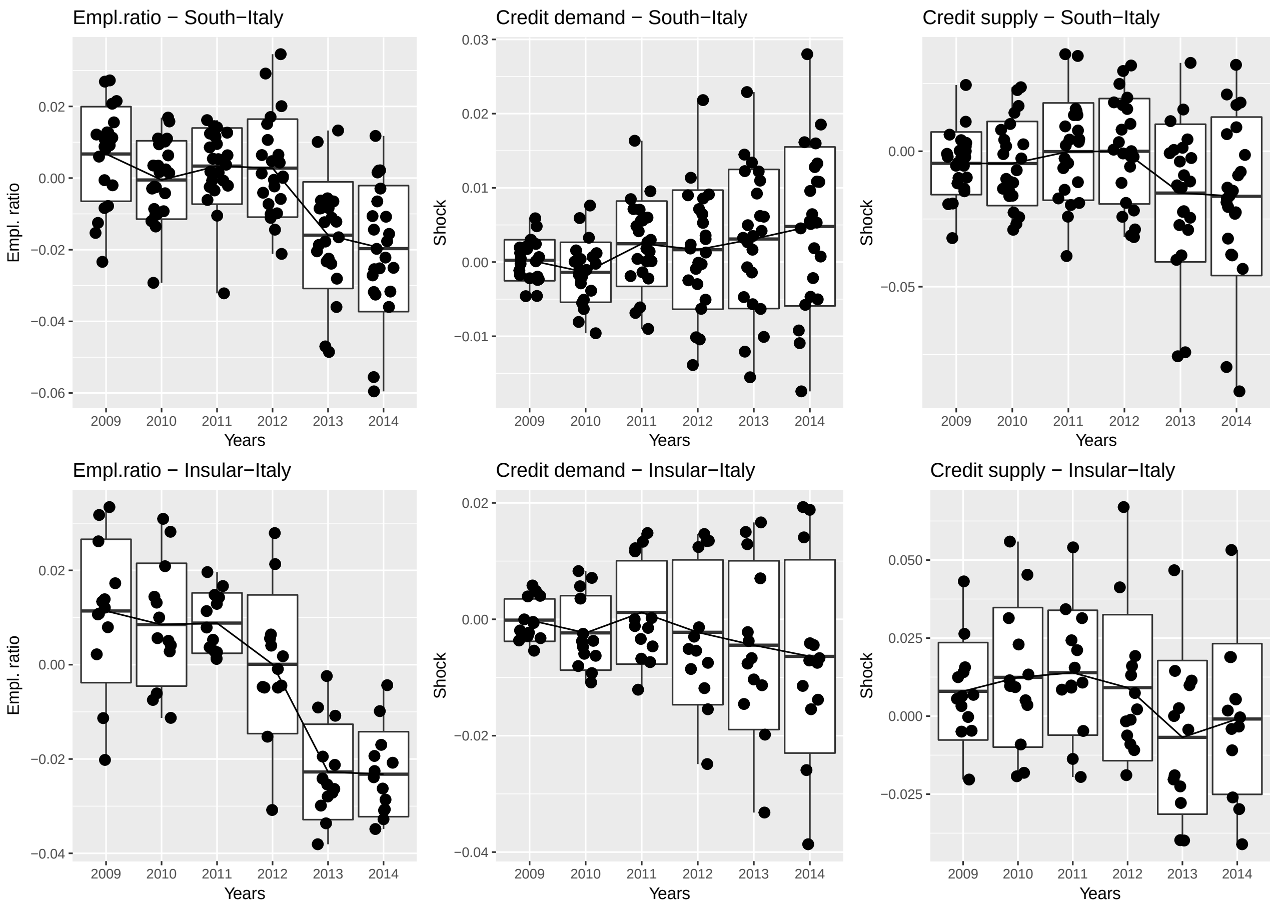

Fig. 5: Contribution of credit demand and supply shocks on historical decomposition of Employment rate, South and Insular Italy, 2009-2014.

Table 1: Theory-driven ex post sign restrictions on B matrix

Impact on	*Credit demand shock*	*Credit supply shock*	*Real shock*
interest rate	**-**	+	***n.a***
Δloans	**-**	**-**	***n.a***
empl. ratio	**-**	**-**	**-**

Note: Here the sign restrictions are related to negative shocks

Table 2: Maximum Likelihood Estimation results of B and λ matrices.

Panel A: Standardized Impact multiplier (B matrix).

	Credit demand shock	Credit supply shock	Real shock
interest rate	-0.323^{****}	0.073^{*}	0.044^{*}
	(0.019)	(0.042)	(0.024)
Δloans			
	-0.001	-0.008	0.054^{****}
	(0.005)	(0.006)	(0.002)
empl. ratio			
	-0.004^{*}	-0.013^{****}	-0.002
	(0.002)	(0.0013)	(0.001)

Panel B: Relative variances and magnitude of the shocks.

	Parameter	Magnitude
Central Italy		
CREDIT DEMAND SHOCK	0.933^{****}	0.966
CREDIT SUPPLY SHOCK	1.238^{****}	1.113
REAL SHOCK	2.963^{****}	1.721
South Italy		
CREDIT DEMAND SHOCK	0.657^{****}	0.810
CREDIT SUPPLY SHOCK	1.404^{****}	1.185
REAL SHOCK	1.234^{****}	1.111
Insular Italy		
CREDIT DEMAND SHOCK	1.405^{****}	1.185
CREDIT SUPPLY SHOCK	1.207^{****}	1.099
REAL SHOCK	1.075^{****}	1.037

Signif. codes: 0 '****' 0.001 '***' 0.01 '**' 0.05 '*' 0.1 ' ' 1

Panel C: Likelihood Ratio Test.

LR Test		Log-likelihood		Value
	Unrestricted model	2382.138	LR statistic	1.931
	Restricted model	2383.104	p-value	0.926

Note: All the parameters are estimated by ML. Asymptotic standard errors are provided in brackets. The relative variances (see panel B) are obtained setting to unity the elements on the first regime structural covariance matrix main diagonal, here refereed to the Northern Italy. The magnitude are obtained by taking the square root of the relative variances (e.g. the parameters in the second column).

Table 3: Cumulative Impact over a two year horizon.

	Mean	Lower bound	Upper bound
Credit demand shock			
interest rate	-0.291	-0.346	-0.262
Δloans	-0.008	-0.013	-0.002
empl. ratio	-0.010	-0.014	-0.004
Credit supply shock			
interest rate	0.123	0.066	0.168
Δloans	-0.013	-0.021	-0.005
empl. ratio	-0.024	-0.027	-0.022
Real shock			
interest rate	0.097	0.067	0.117
Δloans	0.060	0.055	0.066
empl. ratio	-0.004	-0.008	-0.001

Note: The First column is the mean value of bootstrapped distribution of the Cumulative Impact over a two year horizon, the last two columns are 16 percent and 84 percent bootstrapped confidence interval bounds.

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