Default rates spillovers: an analysis based on Italian regional data

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Abstract

In this paper, we estimate the spatial spillovers mechanism across 20 Italian regions using the default rates on loans facilities as proxy of the loans probability of default, over the period 1996-2015. The data, at quarterly frequency, are available for consumer households, non-financial firms and producer households. First, we investigate the presence of spatial dependence across the regional loan default rates. Second, we evaluate whether the Mezzogiorno regions are more affected by spillover effects arising from the Northern regions. For this purpose, we use the connectedness measures proposed by Diebold & Yilmaz (2012) and by Greenwood-Nimmo *et al.* (2015), which are based on the generalized forecast error variance decomposition (GFEVD) obtained from the estimation of a Vector Autoregression model. Given the relatively large number of variables, we use the Adaptive elastic net to estimate the VAR model. The empirical findings reveal an increase in default rates spatial dependence over the 2011Q4 - 2015Q4 (crisis) period, especially for producer households. Moreover, we find evidence of a strong dependence of the Islands from the North of Italy, while the other Southern regions are found to be the most contributor, together with the Northwest of Italy, of financial distress to the remaining macro-regions.

Keywords: Spatial spillovers, Default rates on loans, Diebold-Yilmaz approach, Adaptive Elastic-Net

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1 Introduction

The aim of this paper is the analysis of spatial spillover effects among 20 Italian regional default rates on loan granted to different categories of the private sector: consumer households, non-financial firms and producer households.[1]

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[1]According to the definition provided by Bank of Italy, producer households are defined as individual firms, informal partnership and unregistered company, producers of marketable goods and financial services with up to five employees; activities auxiliary to financial intermediation without employees.

The motivation of the analysis is due to the process of bank consolidation in Italy taking place during the 1990s, leading to a 33% reduction in the number of banks, from 1025 to 684, over the $1992-2013$ period (Papi *et al.*, 2015). The consolidation process was characterized by takeovers of the main distressed banks located in the Mezzogiorno (such as Banco di Napoli, Banco di Sicilia and other major savings banks) by Northern banks (mainly Unicredit and Intesa San Paolo).[2] Nowadays, the bulk of commercial banks located in Mezzogiorno are members of banking groups headquartered in the Northern part of the country (Zazzaro, 2006; Giannola *et al.*, 2013). More specifically, the study of Giannola *et al.* (2013) shows that, in 2010, more than 42% of branches operating in the Mezzogiorno were owned by banks headquartered outside the area and another 38% were attributable to banks which, whilst maintaining their headquarters in the Mezzogiorno, were part of banking groups whose parent bank was in the Center-North. The study of Papi *et al.* (2015) shows, through network analysis, that the overall connectedness of geographical credit markets in Italy has significantly increased over time, whether measured at the provincial or regional level. Moreover, the authors confirm a growing centrality of few Northern Italian banking centers relegating the Southern credit markets and regions to the periphery. These findings support those in the study of Presbitero *et al.* (2014) showing an increasing functional distance (measured by the distance between bank branches and the bank headquarter) over recent years, hence a more striking core-periphery financial and banking divide. In particular, the headquarters of the large Northern banks will be less familiar with the local economic and social environment in the Mezzogiorno. As suggested by Alessandrini *et al.* (2009), physical distance between bank headquarters and local managers makes it difficult to gather and consequently report soft information to those higher up in the management chain and, consequently, monitor local managers. As a consequence, the allocation of decision-making power to local managers in the branches located in Mezzogiorno tends to decrease with distance. Therefore, one might expect a negative relationship between the credit growth and the distance between the centre and the periphery of the bank, especially during a crisis period characterized by credit tightening.

For this purpose, we use the Diebold-Yilmaz methodology, DY, based on the Generalized Forecast Error Variance Decomposition (GFEVD) (see Diebold & Yilmaz, 2012, 2014). The latter is obtained by employing the Adaptive Elastic net shrinkage estimator on a large Vector Autoregression (VAR) model, due to the 20 (region-specific) endogenous variables considered for each private sector category.

Our study can be related to the one of Tola (2010) which is an application of the Pykhtin (2004) model to the Italian banking system to provide a static measure of concentration risk by industry sector and geographic region. For this purpose, the author uses a stationary multifactor structural Portfolio credit risk model, generating an unexpected loss measure that is in line with the Internal ratings-based (IRB) capital requirements.

The use of the DY methodology, based on VAR estimation, is more suitable to address the evidence of non-stationarity we find in the proxies of default rates examined. Moreover, through a dynamic spillover analysis, using the DY methodology, we can assess whether there is evidence of an increase in the index of total default connectedness over $2011-2015$ (crisis period) relative to its long run value estimated by accounting for the whole sample period under investigation ($1996-2015$).

Finally, the DY methodology enables to retrieve indices of directional connectedness and,

[2]Mezzogiorno includes six Southern regions, such as Abruzzo, Apulia, Basilicata, Calabria, Campania and Molise, and the Islands of Sardinia and Sicily.

in particular, to assess whether the Mezzogiorno regions are more dependent (relative to the Northern regions) on shocks arising from the other regions.[3] To detect macro-regional patterns in the spillover analysis, we use the approach proposed by Greenwood-Nimmo *et al.* (2015), say the GNS approach.

In our analysis, we use quarterly data for default rates on loans facilities to three categories of the private sector, that is consumer households, non-financial firms and producer households. The data, collected from the publicly-available Statistical Database of Bank of Italy, contain information on loan default rates for the 20 Italian regions, over the period $1996Q1 - 2015Q4$.

The results show an increase in the Total spillover index (hence there is evidence of a rise in spatial dependence) during the last observations of the sample ($2011Q4 - 2015Q4$), identified as a particular distressful period for the Italian economy.[4] These empirical findings are particularly striking for producer households. Using the approach proposed by Greenwood-Nimmo *et al.* (2015) (GNS), we find that the South and, to less extent, Northwest contribute the most to the financial stress of the other Italian macro-regions. Contrary to the South macro-region, the Islands financial distress largely depends on the others, especially consumer households and non-financial firms. Looking at the directional spillovers, we do not find evidence of a dependence from the North for all the Mezzogiorno regions. The dependence from North is only confirmed for the Islands, while shocks arising from South tend to largely spill over to both the Northwest and the Northeast.

This paper is organized as follows. Section 2 reviews the literature on the pros and cons of bank geographical expansion. Section 3 describes the DY and the GNS approach on studying connectedness as well as the estimation procedure of a LASSO-VAR model. Section 4 describes data. Section 5 describes the empirical findings. Section 6 concludes.

2 Literature review

2.1 Geographical diversification: the evidence within country

Since 1990s, the Italian banking system has been characterized by a consolidation process which has largely involved a geographic expansion of Northern banks in Southern regions, through merger and acquisition (M&A) operations.

Possible explanations might arise from the potential benefits of geographical diversification. In fact, as suggested by the traditional Portfolio Theory, geographical diversification/expansion is positively associated with a reduction in the risk related to a bank portfolio as longs as the different assets display low correlation (Goetz *et al.*, 2016). In particular, the authors find that a geographic diversification of bank's assets across Metropolitan Statistical Areas (MSAs) in the US diminishes a Bank Holding Company (BHC) risk. Using a geographic dispersion measure of deposits at branches level over the $1986-1997$ period, the authors also discover that the reduction of BHC's risk is positively

[3]There has been a growing number of applications of the DY methodology to financial institutions stock market returns and volatilities (see Diebold & Yilmaz, 2014; Demirer *et al.*, 2017, among the others). More recently, Cipollini *et al.* (2015) focused on volatility risk premia.

[4]The choice of the $2011Q4 - 2015Q4$ for the analysis of dynamic connectedness is motivated by the use of rolling regression in line with Diebold & Yilmaz (2012, 2014). Rolling estimation requires the use of a sufficient number of observations which in this study corresponds to a window size of 63 quarters.

associated to a geographic expansion when a BHC diversifies into MSAs that are economically different from its home MSA. In addition, a greater geographic diversification ought mitigate the adverse effects yielded by local business cycles. The study of Meslier *et al.* (2016) confirms the findings of Goetz *et al.* (2016), since there is evidence that (especially) small-size banks benefit from expanding geographically in non-contiguous markets with non-synchronized economic conditions. Consequently, a BHC may decide to extend its subsidiaries and branches across different areas in an attempt to reduce the exposure to its idiosyncratic local market risks. The study of Becchetti *et al.* (2014), focusing on 32 countries over the period $1998-2010$, shows that, in adverse phases of the business cycle, the share of loans to total assets of cooperative banks is higher than the one associated to other category of banks, with a positive effect on the growth of value added in the manufacturing sector and in those most dependent on external finance.
As for the European case, the study of Bonaccorsi di Patti *et al.* (2005) shows that, for Italy, the risk associated to poor geographical portfolio diversification can be particularly high during financial and economic downturns. The study of Illueca *et al.* (2013) highlights the negative effects of the portfolio risk concentration of Spanish banks, characterized by an ownership structure less geared to the attainment of economic performance, a focus on local community funding and an exposure toward the housing sector, particularly hit by the recent crisis.

Another strand of literature has questioned the attractiveness of geographic diversification, since the incentives to loan monitoring might be reduced, due to the difficulty in obtaining "soft-information".
Using data on commercial banks in Texas for the 1998, Brickley *et al.* (2003) suggest that a bank which extends its offer by opening branches and subsidiaries in distant areas ought face difficult in planning incentive-compensation for managers in the new branch, or subsidiary, arising the cost of monitoring their activity. Berger *et al.* (2005) point out that large BHCs which lend money to distant borrowers via their branches/subsidiaries tend to create weak relationships with the customers. By using survey data on small business lending over the $1994-1995$ two-year period, the authors' results show that small banks have comparative advantages in supplying credit based on the "soft information". Moreover, as reported by the authors, there is evidence of a strong relationship between small banks and firms, and this can decisively reduce the probability of a borrower to be rationed. However, the authors find that local banks might be induced in funding obligors without paying attention to creditworthiness just to catch market shares.
The relevant role of local banks is also supported by the research of Berger & Udell (2002). The authors assert the importance of the relationship lending as well as suggesting that small banks might reduce the agency problems, generated by the accumulation of "soft information" by the loan officer, particularly when exogenous disturbances to credit market conditions, such as consolidation processes or changes in regulatory capital requirements, appear (see also Berger & Udell, 2006).
Imai & Takarabe (2011) focus on Japan and they examine how the nationwide city banks transmit large house price shocks to major city centre, intra-nationally, across geographical borders, to local economies in Japan. Presbitero *et al.* (2014) focus on Italy and they assess the role played by functional distance in the transmission mechanism of credit supply shocks across macro-regional economies.

As for the Italian evidence, using data on the asset and loan portfolio compositions of individual Italian banks during the 1993 - 1999 period, Acharya *et al.* (2006) find that diversification/expansion reduces bank returns as well as producing riskier loans, especially for high-risk banks. The study of Presbitero *et al.* (2014) highlights the negative effects of distance between the branches (or subsidiaries) and the BHC's headquarters. The authors find a positive causal relationship between the so-called "functional" distance, that is the distance between loan officer and banks' headquarters, and the tight of credit in Italy during the recent financial crisis. For the period of recession post-Lehman, Demma (2015) finds that, in Italy, local banks can mitigate the negative impact of the crisis on the quality of loans. Therefore, the benefits from soft information more than offset the effects due to adverse selection.

2.2 Geographical diversification: the evidence between countries

A number of studies have investigated the benefits of geographical expansion of large banks in advanced countries for the financial stability of emerging markets. The studies of Kaminsky & Reinhart (2000) and Van Rijckeghem & Weder (2001) were the first to identify a "common lender effects" as a cause of cross-border financial contagion. While the source of shock in the aforementioned studies was typically an emerging market, more recently the literature has also considered advanced countries as the originator of the crisis. This literature has concentrated on a "home bias" effect in credit allocation, implying that global banks exacerbate the transmission of financial shocks across regions, by moving funds from their peripheral to central (headquartered) markets. In particular, the international transmission of shocks may occur simply because internationally active banks suffer capital shortages in their domestic market (due to a crisis to the country where the headquarters are located) and they choose not to alter their portfolio mix of loans to domestic and foreign borrowers by cutting credit lines to both type of borrowers. Cetorelli & Goldberg (2011) use BIS data on cross border lending and they focus on the capital flows reversals from developed to Emerging Asia, Latin America and Emerging Europe, right after the $2007-2008$ crisis period. The authors find that international banks contributed to the spreading of the crisis to emerging market economies. The major contribution of international banks to spreading the crisis was through a loan contraction manifesting through three separate channels: a contraction in direct, cross-border lending by foreign banks; a contraction in local lending by foreign banks' affiliates in emerging markets; and a contraction in lending supply by domestic banks as well, as a result of the funding shock to their balance sheet induced by the decline in interbank, cross-border lending.

Further evidence of a "flight to home" particularly striking during a $2007-2008$ (originated in the US) crisis period is provided by the study of Giannetti & Laeven (2012) which focuses on the syndicated loan market, a highly internationalized financial market, in which large banks lend to a variety of borrowers in a broad set of countries.

The crisis originator in the study of Schnabl (2012) is a liquidity shock originating in one country, Russia. The author, using both bank-to-bank lending and loan-level data, examines the role played by international banks to spreading the crisis in Peru. The author finds that the transmission is strongest for domestically-owned banks that borrow internationally, intermediate for foreign-owned banks, and weakest for locally funded banks. As argued by the author, the results suggest that lending between international

banks establishes a transmission channel for bank liquidity shocks and that foreign bank ownership mitigates, rather than amplifies, the transmission through this channel.
Popov & Udell (2012) analyze the role played by global banks headquartered in Western Europe in spreading the $2007-2008$ crisis to Central and Eastern Europe. The authors find evidence that lending of multinational bank subsidiaries to firms located in these emerging markets was conditioned by the worsening in the balance sheet conditions of foreign parent banks.
The study of De Haas & Van Horen (2011) concentrates on the 118 largest banks in the cross-border syndicated loan market. In particular, the authors dataset allows to compare post-crisis and pre-crisis lending by each bank to each country. The authors find a strong and robust negative effect of geographical distance on lending stability, both in lending to advanced and to emerging markets. The authors find that banks that are further away from their customers are less reliable funding sources during a crisis. A second finding is that international banks with a local presence on the ground may be more stable providers of credit, that is foreign bank subsidiaries provide for a relatively stable credit source themselves, but their presence may also stabilise the cross-border component of bank lending.

3 Empirical methodology

3.1 The DY approach

Following Diebold & Yilmaz (2012, 2014), let us consider a K-multivariate covariance stationary process, $y_t = (y_{1t}, \ldots, y_{Kt})'$, described by a reduced form Vector Autoregression (VAR) model of order p:

$$y_t = \delta + A_1 y_{t-1} + \ldots + A_p y_{t-p} + u_t \tag{1}$$

where A_i, for $i = 1, \ldots, p$, are the $K \times K$ parameter matrices associated to the lagged variables, y_{t-i}, δ is a $K \times 1$ vector of constant terms and $u_t = (u_{1t}, \ldots, u_{Kt})' \sim N(0, \Sigma_u)$ is a vector of independent and identically distributed white noise disturbances, with a non-diagonal covariance matrix, $E(u_t u_t') = \Sigma_u$, which is not assumed to be diagonal.
Fixing $\delta = 0$, a stationary multivariate process admits the following Vector Moving Average representation of infinite order, VMA (∞):

$$y_t = \sum_{i=0}^{\infty} \Psi_i u_{t-i} \tag{2}$$

where Ψ_i, for $i = 1, \ldots, p$, are the $K \times K$ matrices of the VMA(∞) coefficients obtained from the following recursive substitution: $\Psi_i = A_1 \Psi_{i-1} + A_2 \Psi_{i-2} + \ldots + A_p \Psi_{i-p}$, with $\Psi_0 = I_K$ and $\Psi_i = 0$ for $i < 0$.[5]
From the reduced form VMA (∞), one can retrieve the impulse response function, which measures the time profile of a shock at time t on the expected value of the variables in the system after h periods, say $t + h$.
The studies of Diebold & Yilmaz (2012, 2014) follow the suggestions of Koop *et al.* (1996) and Pesaran & Shin (1998), relying on the generalized impulse response function which is not sensitive to the ordering of the variables as other identification scheme, such as the one based on the Cholesky decomposition of residuals covariance matrix (short-run

[5] See Lütkepohl (2005) and Diebold & Yilmaz (2012), for example.

restrictions).
Given a non decreasing information set, Ω_{t-1}, describing the known history of the economy before time t, Koop *et al.* (1996) and Pesaran & Shin (1998) define the generalized impulse response function (GIRF) of a variable at time $t+h$ hit by a shock a time t as follows:

$$GIRF(h, \eta, \Omega_{t-1}) = E(y_{t+h}|u_t = \eta, \Omega_{t-1}) - E(y_{t+h}|\Omega_{t-1}) = \Psi_h \eta \tag{3}$$

where η is a $K \times 1$ vector of shock, $\eta = (\eta_1, \ldots, \eta_K)'$, hitting the economy at time t and Ψ_h is the VMA(∞) coefficients matrix associated at time h. Therefore, the generalized impulse response can be seen as the difference between the expected value of a variable after h periods, conditional on shocks hitting the system at time t and the history up to $t-1$, and its expected value conditional on the previous history (defined as baseline profile). As suggested by Koop *et al.* (1996) and Pesaran & Shin (1998), an alternative approach consists of shocking the single j-th element of the vector of residuals, u_{jt}, for $j = 1, \ldots, K$, and comparing the expected value of a variable at time $t+h$ conditional on the j-th shock and the history of the system with the baseline profile:

$$GIRF(h, \eta_j, \Omega_{t-1}) = E(y_{t+h}|u_{jt} = \eta_j, \Omega_{t-1}) - E(y_{t+h}|\Omega_{t-1}) \tag{4}$$

Assuming a multivariate normal distribution of the residuals:

$$E(u_t|u_{jt} = \eta_j) = (\sigma_{1j}, \sigma_{2j}, \ldots, \sigma_{Kj})'\sigma_{jj}^{-1}\eta_j = \Sigma_u e_j \ \sigma_{jj}^{-1} \ \eta_j \tag{5}$$

where Σ_u is the covariance matrix of residuals in reduced form, σ_{jj} denotes the j-th main diagonal element entering Σ_u and e_j is a $K \times 1$ selection vector which takes value of 1 for the j-th element and zero elsewhere. The K-dimensional vector of generalized impulse responses to a shock arising from the j-th equation at time t after h periods is defined by combining eqs.(3), (4) and (5):

$$GIRF_j = \left(\frac{\Psi_h \Sigma_u e_j}{\sqrt{\sigma_{jj}}}\right)\left(\frac{\eta_j}{\sqrt{\sigma_{jj}}}\right) \tag{6}$$

or alternatively, by setting $\eta_j = \sqrt{\sigma_{jj}}$, it is possible to obtain the corresponding scaled version of the generalized impulse response function:

$$GIRF_j = \sigma_{jj}^{-\frac{1}{2}} \Psi_h \Sigma_u e_j \tag{7}$$

Under the assumption of normality of the residuals and linearity of the VAR model, Pesaran & Shin (1998) define the associated Generalized Forecast Error Variance Decomposition (GFEVD) matrix, $\mathcal{D}^H$, whose generic entry, d_{ij}^H, can be defined as follows:

$$d_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_u e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h \Sigma_u \Psi_h' e_i)} \tag{8}$$

and it measures the portion of the H-step ahead error variances in forecasting y_i due to shocks occurring to y_j, for $i, j = 1, \cdots, K$, such that $i \neq j$, Σ_u is the covariance matrix of the non-orthogonalized VAR residuals, u_t, σ_{jj} is the standard deviation of the error terms for the j-th equation, Ψ_h is the VMA(∞) coefficients matrix at time h and e_i, e_j are selection vectors with i-th and j-th element equal to unity and zero otherwise.
Since the shocks are not orthogonalized, the row sum of the entries in the variance decomposition matrix is not necessary equal to unity, $\sum_{j=1}^{K} d_{ij}^H \neq 1$. Therefore, Diebold

& Yilmaz (2012, 2014) suggest a normalization by row sum of each element of the GFEVD matrix:

$$\tilde{d}_{ij}^{H} = \frac{d_{ij}^{H}}{\sum_{j=1}^{K} d_{ij}^{H}} \tag{9}$$

such that $\sum_{j=1}^{K} \tilde{d}_{ij}^{H} = 1$ and $\sum_{i,j=1}^{K} \tilde{d}_{ij}^{H} = K$, by construction.
The Connectedness table for the forecast horizon H is the GFEVD matrix augmented by a column containing the row sums of the off-diagonal elements of the GFEVD matrix and a row, where the column sums of the matrix off-diagonal entries take place. Finally, the average of all the off-diagonal elements appears, for $i \neq j$ (see Table 1).
The connectedness measures, both pairwise and system-wide, proposed by Diebold & Yilmaz (2012, 2014), can be retrieved directly from the Connectedness table. Each entry provides a *pairwise directional connectedness* measure from j to i:

$$C_{i \leftarrow j}^{H} = \tilde{d}_{ij}^{H} \tag{10}$$

For $i = j$, the pairwise measure explains the "*own share*" of the forecast error variance in a certain variable (e.g. a region) for a given forecast horizon. Generally, the GFEVD matrix ($\mathcal{D}^{H}$) is not symmetric, hence $C_{i \leftarrow j}^{H} \neq C_{j \leftarrow i}^{H}$.
Focusing on row and column sums, Diebold & Yilmaz (2012, 2014) propose the *Total* and *Directional connectedness* measures.
The sum of the GFEVD off-diagonal elements along each row of the Connectedness table, labelled *FROM* index, measures the *Directional connectedness from others to i-th element* of the table:

$$C_{i \leftarrow \bullet}^{H} = \sum_{\substack{j=1 \\ j \neq i}}^{K} \tilde{d}_{ij}^{H} \tag{11}$$

The index in eq.(11) measures the vulnerability (or the exposure) of a certain series to shocks originating in the remaining series for a given forecast horizon. Consequently, this index of directional connectedness can be interpreted as a measure of the vulnerability of series (e.g. regions) to systemic risk. The sum of the off-diagonal entries in the GFEVD matrix along each column, labelled *TO* index, measures, for a given forecast horizon, the *Directional connectedness of the j-th element to others*:

$$C_{\bullet \leftarrow j}^{H} = \sum_{\substack{i=1 \\ i \neq j}}^{K} \tilde{d}_{ij}^{H} \tag{12}$$

The index in eq.(12) measures the contribution of a shock occurring to a series (e.g. region) to the remaining series (e.g. regions).
Finally, the ratio between the sum of the off-diagonal entries in the GFEVD matrix and the sum of its total elements, that is simply the average of the off-diagonal entries in the GFEVD matrix, provides the *Total connectedness* index as:

$$C^{H} = \frac{1}{K} \sum_{\substack{i,j=1 \\ i \neq j}}^{K} \tilde{d}_{ij}^{H} \tag{13}$$

which is a measure of the inter-connectedness degree among different series (e.g. regions) for a given forecast horizon.

3.2 The GNS connectedness measures

For the purpose of interpretation of the results, we follow the approach recently proposed by Greenwood-Nimmo *et al.* (2015) which is based on constructing a block aggregation matrix from the GFEVD matrix, according to a certain aggregation scheme, arbitrarily defined.

In particular, given the K-dimensional vector of endogenous variables, the first step of the Greenwood-Nimmo *et al.* (2015) methodology (GNS) consists of re-normalizing the GFEVD matrix, such that $\mathcal{C}_R^H = K^{-1}\mathcal{D}^H$. The use of the re-normalization allows to obtain the connectedness measures, entering in $\mathcal{C}_R^H$, expressed as a portion of the total H-step forecast error variance (FEV) of the whole system.

After ordering (or re-ordering) the K endogenous variables, $y_t = (y_{1t}, \ldots, y_{Kt})'$, consistently to a selected scheme, it is possible to aggregate the endogenous variables into N groups. Since the generalized FEV approach is not sensitive to the ordering of the variables, the re-ordering procedure is not constrained to a particular scheme.

Suppose that the K endogenous variables are aggregated into N groups, where each n-th group contains a specific number of endogenous variables, K_n, with $n = 1, \ldots, N$. Greenwood-Nimmo *et al.* (2015) suggest to rewrite the above described $K \times K$ generalized forecast error variance decomposition (GFEVD) matrix at H-step ahead, D^H, as follows:

$$\underset{(K\times K)}{\mathcal{C}_R^H} = K^{-1}\begin{bmatrix} C^H_{1\leftarrow 1} & \cdots & C^H_{1\leftarrow K_1} & C^H_{1\leftarrow K_1+1} & \cdots & C^H_{1\leftarrow K_1+K_2} & \cdots & C^H_{1\leftarrow K} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ C^H_{K_1\leftarrow 1} & \cdots & C^H_{K_1\leftarrow K_1} & C^H_{K_1\leftarrow K_1+1} & \cdots & C^H_{K_1\leftarrow K_1+K_2} & \cdots & C^H_{K_1\leftarrow K} \\ C^H_{K_1+1\leftarrow 1} & \cdots & C^H_{K_1+1\leftarrow K_1} & C^H_{K_1+1\leftarrow K_1+1} & \cdots & C^H_{K_1+1\leftarrow K_1+K_2} & \cdots & C^H_{K_1+1\leftarrow K} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ C^H_{K_1+K_2\leftarrow 1} & \cdots & C^H_{K_1+K_2\leftarrow K_1} & C^H_{K_1+K_2\leftarrow K_1+1} & \cdots & C^H_{K_1+K_2\leftarrow K_1+K_2} & \cdots & C^H_{K_1+K_2\leftarrow K} \\ \vdots & \ddots & \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ C^H_{K\leftarrow 1} & \cdots & C^H_{K\leftarrow K_1} & C^H_{K\leftarrow K_1+1} & \cdots & C^H_{K\leftarrow K_1+K_2} & \cdots & C^H_{K\leftarrow K} \end{bmatrix} \tag{14}$$

where the n-th block, labelled as $\mathcal{C}_{n\leftarrow m}$, for $n, m = 1, \ldots N$, can be defined as:

$$\underset{(n\times m)}{\mathcal{C}^H_{n\leftarrow m}} = K^{-1}\begin{bmatrix} C^H_{\tilde{K}_n+1\leftarrow \tilde{K}_m+1} & \cdots & C^H_{\tilde{K}_n+1\leftarrow \tilde{K}_m+K_m} \\ \vdots & \ddots & \cdots \\ C^H_{\tilde{K}_n+K_n\leftarrow \tilde{K}_m+1} & \cdots & C^H_{\tilde{K}_n+K_n\leftarrow \tilde{K}_m+K_m} \end{bmatrix} \tag{15}$$

where $\tilde{K}_n = \sum_{n=1}^{n-1} K_n$[6]. Therefore, the GFEVD matrix can be represented as a block matrix, one for each of the N groups:

$$\underset{(K\times K)}{\mathcal{C}_R^H} = \begin{bmatrix} \mathcal{C}^H_{1\leftarrow 1} & \mathcal{C}^H_{1\leftarrow 2} & \cdots & \mathcal{C}^H_{1\leftarrow N} \\ \mathcal{C}^H_{2\leftarrow 1} & \mathcal{C}^H_{2\leftarrow 2} & \cdots & \mathcal{C}^H_{2\leftarrow N} \\ \vdots & \vdots & \ddots & \vdots \\ \mathcal{C}^H_{N\leftarrow 1} & \mathcal{C}^H_{N\leftarrow 2} & \cdots & \mathcal{C}^H_{N\leftarrow N} \end{bmatrix} \tag{16}$$

As stated by Greenwood-Nimmo *et al.* (2015), the blocks lying on the diagonal of $\mathcal{C}_R^H$ in eq.(16), that is the $\mathcal{C}^H_{n\leftarrow n}$ matrices, provide information on the within-group FEV

[6] As discussed by Greenwood-Nimmo *et al.* (2015), the number of variables for each group can be different among groups.

contributions. For the n-th group, the *Total within-group* FEV contribution is computed as follows:

$$\mathcal{W}_{n\leftarrow n}^{H} = \mathbf{1}_{K_n}^{\prime}\mathcal{C}_{n\leftarrow n}^{H}\mathbf{1}_{K_n} \tag{17}$$

where $\mathbf{1}_{K_n}$ is a $K_n \times 1$ vector of ones. The *Total within-group* measures the contribution of the variables entering a group to its own H-step ahead FEV (see also Park & Shin, 2017). The off-diagonal blocks entering in $\mathcal{C}_R^H$, that is the $\mathcal{C}_{n\leftarrow m}^H$ matrices, with $n \neq m$, provide information on the spillover effects among two different groups. In a similar fashion to the pairwise connectedness measures proposed in the DY approach, Greenwood-Nimmo *et al.* (2015) define the spillover effect *from* group m to group n as:

$$\mathcal{F}_{n\leftarrow m}^{H} = \mathbf{1}_{K_n}^{\prime}\mathcal{C}_{n\leftarrow m}^{H}\mathbf{1}_{K_m} \tag{18}$$

while the spillover effect *to* group m from group n as:

$$\mathcal{T}_{m\leftarrow n}^{H} = \mathbf{1}_{K_m}^{\prime}\mathcal{C}_{m\leftarrow n}^{H}\mathbf{1}_{K_n} \tag{19}$$

It is important to note that $\mathcal{F}_{n\leftarrow m}^H$ and $\mathcal{T}_{n\leftarrow m}^H$ coincide.
Furthermore, Greenwood-Nimmo *et al.* (2015) provide a set of "system-wide" connectedness measures. In particular, the total *From*, *To* and *Net* contributions for group n can be defined as follows:

$$\mathcal{F}_{n\leftarrow\bullet}^{H} = \sum_{m=1,m\neq n}^{N}\mathcal{F}_{n\leftarrow m}^{H} \quad , \quad \mathcal{T}_{\bullet\leftarrow n}^{H} = \sum_{m=1,m\neq n}^{N}\mathcal{T}_{m\leftarrow n}^{H} \quad \text{and} \quad \mathcal{N}_{\bullet\leftarrow n}^{H} = \mathcal{T}_{\bullet\leftarrow n}^{H} - \mathcal{F}_{n\leftarrow\bullet}^{H} \tag{20}$$

where $\mathcal{F}_{n\leftarrow\bullet}^H$ measures the contribution to the FEV of the n-th group from the rest of the system, $\mathcal{T}_{\bullet\leftarrow n}^H$ measures the contribution of the n-th group to the FEV of the remaining groups and $\mathcal{N}_{\bullet\leftarrow n}^H$ measures to what extent the n-th group is a net transmitter or receiver of spillover effects.[7]
Finally, Greenwood-Nimmo *et al.* (2015) introduce two additional measures of connectedness: the *Dependence* and the *Influence* index. The *Dependence* index ($\mathcal{O}_n$) measures to what extent the n-th group is affected by external conditions:

$$\mathcal{O}_{n}^{H} = \frac{\mathcal{F}_{n\leftarrow\bullet}^{H}}{\mathcal{W}_{n\leftarrow n}^{H} + \mathcal{F}_{n\leftarrow\bullet}^{H}} \tag{21}$$

with $0 \leq \mathcal{O}_n^H \leq 1$. In particular, the role of external shocks in the conditions of group n decreases as $\mathcal{O}_n^H$ tends to zero, while the importance of external conditions increases as $\mathcal{O}_n^H$ becomes closer to one. The *Influence* index ($\mathcal{I}_n$) provides a measure of the role played by group n as influencer of the system:

$$\mathcal{I}_{n}^{H} = \frac{\mathcal{N}_{\bullet\leftarrow n}^{H}}{\mathcal{T}_{\bullet\leftarrow n}^{H} + \mathcal{F}_{n\leftarrow\bullet}^{H}} \tag{22}$$

[7]Furthermore, Greenwood-Nimmo *et al.* (2015) define other two aggregate connectedness measures which can be derived from eqs.(17) and (20). The former (labelled aggregate "Heatwave" index) $\mathcal{H}^H = \sum_{n=1}^{N}\mathcal{W}_{n\leftarrow n}^H$, provides a measure of the importance of own (local) conditions for the whole system, while the latter (aggregate "Spillover" index), $\mathcal{S}^H = \sum_{n=1}^{N}\mathcal{F}_{n\leftarrow\bullet}^H \equiv \sum_{n=1}^{N}\mathcal{T}_{\bullet\leftarrow n}^H$, captures the magnitude of spillover effects among groups. Note that $\mathcal{H}^H + \mathcal{S}^H = 1$ and $\sum_{n=1}^{N}\mathcal{N}_{\bullet\leftarrow n}^H = 0$, by construction.

with $-1 \leq \mathcal{I}_n^H \leq 1$. The use of the *Influence* index allows to determine whether the n-th group is a net shock recipient ($-1 \leq \mathcal{I}_n^H < 0$), a net shock transmitter ($0 < \mathcal{I}_n^H \leq 1$) or neither of the two roles ($\mathcal{I}_n^H = 0$) (see Greenwood-Nimmo *et al.*, 2015).

3.3 Estimation procedure

3.3.1 Shrinkage estimators

Given a relatively large number of endogenous variables ($K = 20$) in the VAR model, we use a Lasso-VAR approach where the current values of the K endogenous variables are considered as dependent variables and their lagged values are treated as explanatory variables (Hsu *et al.*, 2008; Davis *et al.*, 2016).
The LASSO (Least Absolute Shrinkage and Selection Operator) regularization technique was originally introduced by the research of Tibshirani (1996). The LASSO, which provides estimation and variable selection, is particularly attractive when the unknown parameters are greater than the number of observations. In such as context, the LASSO shrinks the coefficient to exact zero, generating sparsity in the model representation.
In linear regression models, considering a vector of responses, $y_t = (y_1, \ldots, y_T)' \in \mathbb{R}$, and K independent variables, $x_{jt} = (x_{j1}, \ldots, x_{jT})' \in \mathbb{R}^K$, with $j = 1, \ldots, K$, the LASSO estimator solves the following convex optimization problem:

$$\hat{\beta}_{LASSO} = \underset{(\beta_0, \beta_j) \in \mathbb{R}^{K+1}}{\arg\min} \left\{ \sum_{t=1}^{T} \left(y_t - \beta_0 - \sum_{j=1}^{K} \beta_j x_{jt} \right)^2 \right\} \quad \text{subject to} \quad \sum_{j=1}^{K} |\beta_j| \leq c \tag{23}$$

Alternatively, using the Lagrange multiplier, one can write eq.(23) as follows:

$$\hat{\beta}_{LASSO} = \underset{(\beta_0, \beta_j) \in \mathbb{R}^{K+1}}{\arg\min} \quad \|y - \beta_0 - \sum_{j=1}^{K} \beta_j x_j\|_{\ell_2}^2 + \lambda \|\beta_j\|_{\ell_1} \tag{24}$$

where $\|y - \beta_0 - \sum_{j=1}^{K} \beta_j x_j\|_{\ell_2}^2 = \|u\|_{\ell_2}^2 = (\sqrt{\sum_{t=1}^{T} u_t^2})^2$ is the square of the Euclidean norm of the vector u, while the second part of the minimization problem is the ℓ_1-norm, that is $\|\beta_j\|_{\ell 1} = \sum_{j=1}^{K} |\beta_j|$. Furthermore, $c \geq 0$, or alternatively $\lambda \geq 0$, is a tuning parameter which controls the amount of shrinkage (Tibshirani, 1996).
Although the LASSO estimation procedure has seen a large number of applications in literature during the last two decades, it has also been criticized by some authors.
For example, it has been argued that LASSO does not perform well in terms of prediction power when the variables are highly correlated (Tibshirani, 1996). Furthermore, as Zou & Hastie (2005) point out, in case of high correlation among variables, LASSO does not encourage group selection, that is if two or more variables display high correlation, a selection method should include the whole group whether one of those variables is selected.
To this end, Zou & Hastie (2005) propose the so-called Elastic net (ENET) estimator which solves the following optimization problem:

$$\hat{\beta}_{ENET} = \underset{(\beta_0, \beta_j) \in \mathbb{R}^{K+1}}{\arg\min} \quad \|y - \beta_0 - \sum_{j=1}^{K} \beta_j x_j\|_{\ell_2}^2 + \lambda \sum_{j=1}^{K} \left[\alpha |\beta_j| + (1 - \alpha) \beta_j^2 \right] \tag{25}$$

where the elastic net penalty, $\alpha\|\beta\|_{\ell_1} + (1-\alpha)\|\beta\|^2_{\ell_2}$, is a convex combination of the ℓ_1-norm (LASSO) and ℓ_2-norm (Ridge regression).[8] Whether $\alpha = 1$, the elastic net penalty becomes the LASSO penalty. Oppositely, fixing $\alpha = 0$, the penalty turns into the Ridge regression. In particular, according to Zou & Hastie (2005), the ℓ_1-norm ensures automatic variables selection and shrinkage, simultaneously, while the Ridge regression's penalty encourages group selection, improving the prediction power of the estimator.
Moreover, Fan & Li (2001) argue that the LASSO estimator does not simultaneously respect the so-called oracle-properties, that is an ideal penalized least square procedure must *i)* identify the correct model whenever the right regularization parameter is chosen (consistency in variable selection), and *ii)* it has an asymptotically normal distribution[9]. Zou (2006) proposes an alternative version of the LASSO estimator, the Adaptive LASSO (ALASSO), where different weights are used for the penalization of each coefficient. The ALASSO is the estimator which solves the following convex optimization problem with the ℓ_1 penalty:

$$\hat{\beta}_{ALASSO} = \underset{(\beta_0,\beta_j)\in\mathbb{R}^{K+1}}{\arg\min} \quad \|y - \beta_0 - \sum_{j=1}^{K} \beta_j x_j\|^2_{\ell_2} + \lambda \sum_{j=1}^{K} \hat{w}_j |\beta_j| \tag{26}$$

where $\hat{w}_j$ is a vector of j "adaptive" weights. In literature, the weights are generally defined as $\hat{w}_j = 1/|\hat{\beta}_j|^\gamma$, where $\hat{\beta}$ is a root-n-consistent estimator of β and $\gamma > 0$. As reported in Zou (2006), under specific conditions, that is the weights are data-dependent and suitably defined, the ALASSO estimator is consistent in choosing the right subset of variables and asymptotically normal. Therefore, differently from the Elastic net, the Adaptive LASSO estimator respects the oracle properties.
Nevertheless, the ALASSO penalization does not achieve the performance in terms of stability of the Elastic net. For this reason, Zou & Zhang (2009) propose an alternative penalization which combines the Adaptive LASSO penalization and the ridge regression, the Adaptive Elastic net (AdaEnet). The resulting estimator is defined as follows:

$$\hat{\beta}_{AdaEnet} = \underset{(\beta_0,\beta_j)\in\mathbb{R}^{K+1}}{\arg\min} \quad \|y - \beta_0 - \sum_{j=1}^{K} \beta_j x_j\|^2_{\ell_2} + \lambda \sum_{j=1}^{K} \Big[\alpha\ \hat{w}_j |\beta_j| + (1-\alpha)\beta_j^2\Big] \tag{27}$$

where the adaptive weights are generally constructed as $\hat{w}_j = 1/\hat{\beta}^{\gamma}_{Enet}$, with $\gamma > 0$. As demonstrated by Zou & Zhang (2009), the Adaptive Elastic net has the oracle properties and, at the same time, the use of the ℓ_2 penalty provides stability in case of high-dimensional data.

3.3.2 LASSO-VAR(1) model

Since the K-dimensional time series are not stationary, we estimate a sparse VAR(1) model fitted to the first order difference of the logit transformation of the loan default rates, by using the Adaptive Elastic net estimator proposed by Zou & Zhang (2009). In

[8] The expression in eq.(25) refers to what Zou & Hastie (2005) define the naïve elastic net, which is then rescaled to obtain the elastic net estimator (see also Zou & Zhang, 2009).

[9] Cfr. also Zou (2006) for a further explanation of the oracle properties.

particular, given a K-dimensional vector of time series, $y_t = (y_{1t}, \dots, y_{Kt})'$, the model has the following reduced form representation:

$$\Delta y_t = \delta + A_1 \Delta y_{t-1} + u_t \tag{28}$$

where A_1 is the $K \times K$ coefficients matrix of the lagged variables, Δy_{t-1}, δ is a $K \times 1$ vector of constant terms and $u_t \sim N(0, \Sigma_u)$ are the white-noise disturbances with a non-singular covariance matrix, $E(u_t u_t') = \Sigma_u$, which is not assumed to be diagonal.
Recently, a large number of researchers have shown the attractiveness of estimating the sparse VAR process through the estimation of K separate equations (see Kock & Callot, 2015; Demirer *et al.*, 2017). In line with this strand of literature, we carry out with an equation-by-equation VAR estimation by using the version of the Adaptive Elastic net used in the study of Demirer *et al.* (2017), which solves the following optimization problem for each of the K equations:

$$\hat{\beta}_{k,AdaEnet} = \underset{(\delta,\beta_j)\in\mathbb{R}^{K+1}}{\arg\min} \quad \|\Delta y_t - \delta - \sum_{j=1}^{K} \beta_j \Delta y_{jt-1}\|_{\ell_2}^2 + \lambda \sum_{j=1}^{K} \hat{w}_j \left[\alpha |\beta_j| + (1-\alpha)\beta_j^2 \right] \tag{29}$$

where β_j, $j = 1, \dots, K$, is the j-th row vector of the $K \times K$ coefficient matrix, A_1, and $\hat{w}_j = 1/|\hat{\beta}_{j,OLS}|^\gamma$, with $\gamma = 1$, is the j-dimensional vector of weights. In order to estimate the model, we fix $\alpha = 0.5$ and we select the tuning parameter, λ, by applying a 10-fold cross validation equation by equation, separately (see also Bonaldi *et al.*, 2015).[10]
As stated by Demirer *et al.* (2017), the use of a LASSO-based estimator produces sparsity on the coefficient matrix, however no sparsity is imposed on the resulting covariance matrix of VAR residuals.[11]
Once the sparse VAR(1) model is estimated, we construct the GFEVD matrix, $\mathcal{D}^H$, with a the generic entry defined as follows:

$$d_{ij}^H = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (e_i' \Psi_h^* \Sigma_u e_j)^2}{\sum_{h=0}^{H-1} (e_i' \Psi_h^* \Sigma_u \Psi_h^{*\prime} e_i)} \tag{30}$$

Since the endogenous variables enter the model in their first order difference, we construct the GFEVD by computing the cumulative Moving Average (MA) coefficients matrices, Ψ_h^*, at forecast horizon h. In our analysis, all the connectedness measures retrieved from the GFEVD are computed by considering a four-quarter forecast horizon ($H = 4$).

4 Data

We use data for default rates on loans to three categories of the private sector, that is consumer households (consumers), non-financial firms (nfi) and producer households (producers), in the 20 Italian regions, for a total of 4800 observations. According to the

[10]The computational analysis is run by using the **glmnet** package in R developed by Friedman *et al.* (2010), which uses algorithms based on cyclical coordinate descent methods. We allow the **glmnet** package to standardize the covariates, that is $\frac{1}{T}\sum_{t=1}^{T} x_{jt} = 0$ and $\frac{1}{T}\sum_{t=1}^{T} x_{jt}^2 = 1$. Once standardizing the variables, the **glmnet** package always returns the coefficients to the original scale, automatically.

[11]See Demirer *et al.* (2017) for further details.

definition provided by Bank of Italy, the default rate on loans in a certain quarter t is the ratio between the amount of credit used by borrowers who become "adjusted bad debtors" during the observed quarter t and the amount of credit used by all the borrowers, not classified as "adjusted bad debtors" by the Central Credit Register, at the end of the previous quarter, $t-1$ (see also Bofondi & Gobbi, 2004).

The dataset, collected from the publicly-available database of Bank of Italy, includes quarterly frequency observations over the period $1996Q_1 - 2015Q_4$.[12] In our analysis, we use the NUTS1 and NUTS2 classifications imposed by the European Commission. For the Italian case, the former comprises of 5 groups of regions (or macro-regions), while the latter refers to the 20 regions (see Table 2).

Figures 1, 2 and 3 show the $K = 20$ regional loan default rate time series for each of the three categories of the private sector.

In general, the loan default rates reported by the Southern and Insular regions exhibit the highest values over the whole observed period. The loan default rates for consumer households (see Figure 1) show a decreasing trend with low values of the ratio reported in the last part of the sample. The loan default rates for non-financial firms show a rising pattern, especially the ones reported by the Northern and Central regions, over the last quarters (see Figure 2). Finally, Figure 3 shows that the loans default rate series for producer households tend to remain steady in the most of the Northern and Central regions, with the exception of Lazio, while there is evidence of a decline in the value of the ratio reported by some Southern regions.

Following Virolainen (2004), Foglia *et al.* (2009) and Guarda *et al.* (2012), we apply the logit transformation to the loan default rate series:

$$y_{ikt} = ln\left(\frac{p_{ikt}}{1 - p_{ikt}}\right) \tag{31}$$

where p_{ikt} is the default rate on loan facilities reported in the i-th category of the private sector, for the k-th variable (region) at time t. Since the loan default rate, p_{ikt}, ranges in the interval $[0, 1]$, the "logit transformation" in eq.(31) extends the boundary, moving to an unconstrained space of values, $y_{ikt} \in [-\infty, +\infty]$.

Table 3 shows the results of the Augmented Dickey-Fuller (ADF) test for the presence of unit roots in the time series under investigation. According to the Dickey-Fuller critical values, the null hypothesis, that is the time series are not stationary, is not rejected for almost all the time series. The non-stationarity is also confirmed by the use of the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) unit root test proposed in Kwiatkowski *et al.* (1992), which tests for the null hypothesis that the series is level or trend stationary (see Table 4). Therefore, we fit a VAR model to the first order difference of the logit transform of loan default rate series, "$\Delta logit$". Since the DY methodology, based on the GFEVD, requires the VAR residuals to be Gaussian, we employ the Jarque-Bera (JB) test. As can be seen from Table 5, the null hypothesis, that is the estimated residuals are normally distributed, cannot be rejected at 95% confidence level, for most of the loan default rates series.

[12] The missing values in the default rate on loan facilities series are replaced by linear interpolation.

5 Results

5.1 Total connectedness index

We compute the *Total connectedness* index, e.g. a proxy of the spatial dependence, by taking the average of the off-diagonal elements in the generalized forecast error variance decomposition (GFEVD) matrix. In this analysis, we focus on a forecast horizon equal to four quarters ($H = 4$). The index provides a measure of the total connection between regional default rates on loan facilities (as suggested by Diebold & Yilmaz (2012, 2014), see eq.(13)). First, we focus on the static measure of the *Total connectedness* index which is obtained through the estimation of the lasso VAR(1) model fitted to the $K = 20$ regional default rate series over the full sample period ($1996Q2 - 2015Q4$). The estimation exercise and the corresponding results, reported in the rest of the Section, refer to an analysis conducted for each of the three private sub-sectors (consumer households, non-financial firms and producer households), separately. The static, unconditional, analysis shows that the consumer households sector reports the highest value of the *Total connectedness* measure (54.6%), while the index is relatively lower for producer households (41.3%) and non-financial firms (35.8%).
Following Diebold & Yilmaz (2012, 2014), we also compute a time-varying measure of the *Total connectedness* index as well as of the pairwise and total directional indices suggested by Greenwood-Nimmo *et al.* (2015), using a rolling estimation window width equal to 63 quarters, with a starting sample which covers the $1996Q2 - 2011Q4$ time period. Similarly to the full-sample analysis, we use a forecast horizon equal to four quarters ($H = 4$).
Figure 4 shows the time-varying *Total connectedness* index (black line) for consumer households (panel a), non-financial firms (panel b) and producer households (panel c). For each panel, we also report the unconditional values (dotted line) of the index (the ones reported above), which can be interpreted as the long-run equilibrium. As can be seen from Figure 4 (panel a), the time-varying analysis shows that there is some evidence of an increase of spatial dependence among consumer households, since the *Total connectedness* index is above the long-run equilibrium over the second part of the sample. In particular, the *Total connectedness* index rises from 55.1% to 60.4% between $2012Q2$ and $2015Q1$, before getting back to the long-run value (the index is equal to 55.3% in the last quarter of 2015). Also for producer households (see Figure 4, panel c), there is evidence of an increase in the *Total connectedness* index (the average value, over the $2011Q4 - 2015Q4$, is 45.9%) since it is above the long-run value of 41.3%. Given the long-run value of the *Total connectedness* index for non-financial firms equals 35.8%, this private sector category manifests evidence of an increase in the total default connectedness over $2011Q4 - 2012Q4$, and a subsequent fall in the index over the last three years of the sample under investigation (see Figure 4, panel b).

5.2 GNS Results

In this section, we report the results of the $H = 4$ steps ahead connectedness analysis, conducted by using the approach proposed in the study of Greenwood-Nimmo *et al.* (2015). In particular, these results refer to a specific aggregation scheme of the $K = 20$ regional loan default rate series into $N = 5$ groups of regions, that is Northwest, Northeast, Centre, South and Islands. Similarly to the analysis of the *Total connectedness* index, all the measures reported in this section concern the estimation of the lasso VAR(1) models

for each of the three private sub-sectors (consumer households, non-financial firms and producers households).
We first focus on the static connectedness measures obtained by exploiting the full-sample ($1996Q2 - 2015Q4$) information.

Table 6 shows the group connectedness matrix for consumer households (panel a), non-financial firms (panel b) and producer households (panel c). Each panel shows the *Total within-group* forecast error variance (FEV) contributions, for each of the N groups, that is the elements on the main diagonal (see eq.(17)), and the off-diagonal elements which measure the pairwise spillovers among the groups (see eqs.(18) and (19)). It is important to observe that the values reported in Table 6, together with all the results presented in the rest of the paper, are expressed, given the above-mentioned re-normalization proposed by Greenwood-Nimmo *et al.* (2015) (see Section 3.2), as a percentage of the FEV computed for the whole system. The *Total within-group* index reflects the importance of the local factors in each group, and the higher is the value associated with this measure the stronger is their contribution to the own-group domestic conditions.
The results shown in Table 6 do not reveal large differences among the three categories of the private sector (consumer households, non-financial firms and producer households). More specifically, in each sector, the *Total within-group* indices tend to be larger than the off-diagonal measures, with the highest values recorded in the South of Italy (19%, 24.7% and 22.8%, respectively). Contrary to the South, the other macro-region in the Mezzogiorno, Insular Italy, shows a relatively small contribution of local factors, for all three private sub-sectors (4.4%, 5.9% and 6.9%). The results for Northwest, Northeast and Centre are similar among the three private sub-sectors. The values of the index for consumer households are 10.8%, 12.3% and 10.6%, respectively; the ones for non-financial firms are 13.2%, 14.3% and 13.1%, respectively, and the ones for producer households are 12.4%, 12.8% and 12.5%, respectively.

5.2.1 Static total directional analysis

We also focus on the Dependence score which is presented in Table 7, together with the other aggregate connectedness measures. The Dependence score ($\mathcal{O}_n^H$), with $0 \leq \mathcal{O}_n^H \leq 1$, measures the relative importance of an external shock for a certain group. Large values ($\mathcal{O}_n^H \to 1$) indicates that the group largely depends on external conditions, while small values ($\mathcal{O}_n^H \to 0$) reveal low degree of exposure to external shocks. The results in Table 7 indicate that Insular Italy has the highest dependence value for consumer households (0.57) and non-financial firms (0.41), decisively above the corresponding average values (0.45 and 0.31, respectively), while the scores are more similar for producer households, with the Northwest and Centre of Italy sharing the largest value (0.38). These results are also presented in three quantile maps, one for each private sub-sector (see Figure 5, panel a).
Additional information on the transmission mechanism of spillovers among groups might arise from the aggregate measures presented in Table 7.
In particular, we focus on those measures which provide information on the role played by a specific group as a shock contributor (or receiver).

The contribution of specific-group conditions to the FEV of the whole system is measured by the *To* index. It can be seen from the results in Table 7 that the group contributing the most is the South of Italy, where the values of the *To* index, 13.98% (consumer households), 9.55% (non-financial firms) and 9.52% (producer households), decisively exceed the corresponding average values (8.58%, 5.75% and 6.53%, respectively). The next largest values are reported by the Northwest of Italy: 10.21% (consumer households), 7.99% (non-financial firms) and 8.79% (producer households). Oppositely, we find that Insular Italy has the lowest contribution to the whole FEV for consumer households (4.50%), non-financial firms (2.21%) and producer households (2.84%), less than half of the average values.

These results are confirmed by looking at the *Net* index shown in Table 7. In fact, the net contributor in terms of spillovers is the South of Italy in all the three private sub-sectors: 2.98% (consumer households), 4.27% (non-financial firms) and 2.33% (producer households). These high values, driven by the remarkable relative large magnitude of the *TO* indices, highlight a leading role of the South of Italy in contributing to the system-wide risk. The second ranked is the Northwest of Italy: 1.00% (consumer households), 1.14% (non-financial firms) and 1.14% (producer households). If we focus on the lowest values reported in Table 7, the ranking reveals that the net receiver is the Northeast of Italy for consumer households and producer households, −2.58% and −1.91% respectively, while the smallest *Net* index is reported by the Centre of Italy, −3.54%, for non-financial firms.

Finally, the *Influence* index ($-1 \leq \mathcal{I}_n^H \leq 1$) provides a measure of the role played by a specific group as net receiver ($-1 \leq \mathcal{I}_n^H < 0$), transmitter ($0 < \mathcal{I}_n^H \leq 1$), or neither a net receiver or transmitter ($\mathcal{I}_n^H = 0$). Substantially, for each group this score is computed as the *Net* index normalized by the sum between the *From* and *To* measures. Therefore, the results in Table 7, together with the quantile maps shown in Figure 5 (panel b), display additional evidence of the bigger role played by the South of Italy as net influencer. In fact, for all the private sub-sectors, Southern regions show high values of the index (0.12, 0.29 and 0.14, respectively), decisively above the corresponding average values. Positive values are also reported by the Northwest of Italy: 0.05 (consumer households), 0.08 (non-financial firms) and 0.07 (producer households). The remaining groups of regions report negative values of the *Influence* score. The Northeast of Italy presents large negative values of the score for consumer households (−0.20) and producer households (−0.15), while Central Italy (−0.35) and Insular Italy (−0.30) are the largest net shock recipients for non-financial firms.

5.2.2 Rolling total directional analysis

Figures 6-10 show the time-varying connectedness measures.
Figure 6 shows the time-varying total *Within-group* index for all the three private sub-sectors. From the chart, it can be seen that the results obtained for the unconditional analysis are also valid in the dynamic scenario. In fact, the values of the index reported by consumer households tend to be smaller than the ones showed by non-financial firms and producer households. Furthermore, notwithstanding a reduction reported for consumer households and producer households, the South of Italy shows the highest *Within-group* for all the three private sub-sectors, during the entire sample period.
Figure 6 (panel a), which reports the results for consumer households, highlights a decreasing trend in the *Within-group* index in South of Italy (from 18.84% to 16.75%), with

the exception of the last 3 quarters, when the index increases again reaching 18.20%, and Central Italy (-3.12% is the overall reduction during the whole sample). In the Northwest of Italy, the index is stable around 10.50% until 2014Q4, before increasing by 1.10 point percentage in the subsequent 4 quarters. The results for non-financial firms shown in Figure 6 (panel b) reveal an overall increase in the own-group measure reported by the South of Italy (from 23.24% to 24.47%) and the Northeast of Italy (from 12.64% to 14.43%). For producer households, we find that the index increases in Central Italy by more than 1.50% during the whole period (10.41% is the value reported in 2011Q4). Moreover, there is evidence of a reduction of the *Within-group* index in Insular Italy until 2013Q1 before increasing in the rest of the sample (see Figure 6, panel c). Oppositely, as shown in Figure 6 (panel c), the value of the index falls in South of Italy, from 22.14% to 20.60% between 2011Q4 and 2015Q4.

Figure 7 displays the time-varying *Dependence* score for consumer households (panel a), non-financial firms (panel b) and producer households (panel c). Similarly to the results obtained from the unconditional analysis, if we now turn to the dynamic analysis the results highlight the large level of dependence reported by Insular Italy (around 0.60), during the whole sample period, together with Central Italy (the index increases from 0.45 to 0.60 since 2011Q4, see Figure 7, panel a). For non-financial firms, the results show that Insular Italy is the group reporting the largest degree of dependence from the system, with an average value equal to 0.50 for the entire period (see Figure 7, panel b). The results in Figure 7 (panel c) show that for producer households the group which reports the highest score is Central Italy, with values of the index ranging from 0.40 to 0.50. High *Dependence* scores are also reported by the Northwest and Northeast of Italy, with the same average value reported during the whole sample (0.38). Finally, the Insular Italy shows an increasing trend in the *Dependence index* over the period 2011$Q4-2013Q$1 reaching its peak (0.49), before reducing to 0.30 at the end of the sample period.
Figure 8 presents the *To* connectedness index obtained from the rolling-window estimation. The charts shown in Figure 8 (panel a) validate the unconditional results, that is a relevant contribution to the system-wide FEV arising from the South of Italy during the whole period (14% on average), for consumer households. In Central Italy, the index is relatively stable around $8-9\%$, before falling in the last 2 quarters of the sample (from 9.02% to 6.19%). Oppositely, Insular Italy shows a marked increase by 3.37% in the value of the index (the value is 4.71% at the begin of the sample period). For non-financial firms, Figure 8 (panel b) highlights relative low values of the *To* index, in particular those reported by Central Italy (4.07%, on average) and Insular Italy (2.56%, on average), together with a sharp decline reported by the South of Italy since 2012Q3 (from 12.37% to 8.82%). Similarly, the results for producer households (Figure 8, panel c) show that the index falls by 3.84 point percentage in South of Italy, after reaching a peak in 2013Q1, while there is evidence of a relevant increase in Northwest of Italy during the 2014$Q1-2015Q$4 time span, when the index reaches its maximum value (11.87%).
Figures 9 and 10 show the results for the time-varying *Net* and *Influence* index. As mentioned before, these connectedness measures provide information on the role played by a group (or entity) as net shocks transmitter or receiver. The *Net* and *Influence* index are similar by construction (see Figures 9 and 10). In fact, the *Influence* score for the i-th group is the ratio of its *Net* index to the importance of spillovers for that group (measured by the sum of its *From* and *To* index). This normalization allows to obtain values ranging from -1 to 1.

For these reasons, let us focus on commenting the results shown in Figure 10. The predominant role played by South of Italy in the static analysis is not confirmed in the dynamic estimation, for all the three private sub-sectors. For example, for consumer households there is evidence of an increasing trend of the *Influence* score reported by the Northwest of Italy since 2012$Q2$ (from around zero to 0.17 in 2015$Q4$), reaching values of the index higher than the ones presented by Southern regions (see Figure 10, panel a). Similarly, the relevant role played by South of Italy sharply decreases for producer households. In fact, as shown in Figure 10 (panel c), in spite of relative large values reported in the first part of the sample (with values of the score ranging around 0.20), the *Influence* score declines, reaching negative values in the last two quarters. For non-financial firms, as can be seen from Figure 10 (panel b), the South of Italy presents the highest *Influence* score (0.24, on average), together with the Northwest of Italy (0.17, on average). Oppositely, Central Italy presents large negative values of the index for all the three private sub-sectors during the whole time span. However, closer inspection of the charts show that for consumer households and producer households, also Insular Italy plays a negative role as net influencer, at least in the first part of the sample, say since $2013-2014$, before becoming positive in the last few quarters (see Figure 10, panel a and panel c). For non-financial firms, Insular Italy shows negative values, sharing the role of the group most influenced by the system together with Central Italy (see Figure 10, panel b).

The total directional indices provide aggregate information on dependence (influence) of one macro-region from (to) the rest of the country. Since our aim is to detect spatial dependence arising from an increase in the "functional" distance (due to the Consolidation process involving the Italian banking system), we focus on pairwise spillover analysis. The full sample (static analysis) will explore all pairwise effects and the dynamic analysis based on rolling regression will focus only on the effects between Northern and Mezzogiorno regions.

5.2.3 Pairwise static analysis

We investigate the pairwise spillovers between groups, that is the measures entering in the off-diagonal elements of the group connectedness matrix (see Table 6). Each of those elements measures the contribution to the FEV of group i arising from group j (see eqs.(18) and (19)).
Since the group connectedness matrix is not row-standardized, to better compare the single contribution of a certain group to the FEV of the others, we need to compute spillover measures that are normalized with respect, for example, to the importance of each within-group condition. To this end, we compute the ratio between the contribution of group j to the FEV of group i and the total *Within-group* index reported by group i (see Table 8).
In general, the pairwise spillover analysis shows a large contribution of the Southern regions to the FEV of the other macro-regions, with the exception of the Northest which is more affected by the Northwest. Whilst there is evidence of spatial spillover from South to Northern regions, this is not true for the Islands, which are strongly affected by Northern regions, especially for consumer households and non-financial firms.

As for consumer households (see Table 8, panel a), Southern regions show a large contribution to FEVs of other groups. For example, the spillover from South to Northwest accounts for 35.4% of the importance of local factors in Northwest, while the contribution from Northwest to Southern regions is 19.8%. Large values are reported also from South to Centre (48.4%) and from South to Islands (56.1%). The only exception is the largest contribution from Northwest to Northeast (21.9%), slightly above than the spillover that Northeast receives from South (20.9%). Central Italy reports large values of the cross-group measures, including: the contribution to the FEV of Northwest (23.8%) and the one of South (20.1%). The Islands are largely affected by Northern regions (especially from the Northwest), with spillover indices equal to 37% (from Northwest) and 12.3% (from Northeast). Oppositely, there is no evidence of default spillovers from the Islands to Northern regions.

The largest contribution from Northwest to Northeast is more evident looking at the results for non-financial firms (see Table 8, panel b). In fact, the value of the cross-group measure is equal to 15.1%, decisively larger than the spillover from South to Northeast (11.4%). Focusing on the other pairwise measures, there is evidence of a large contribution from South to Northwest, 26.7% (the spillover from Northwest to South accounts for less than 1/10 of its within-group measure), and from South to Islands, 29.2% (the spillover from Islands to South is only equal to 3.3%). The Centre of Italy largely receives from both South (20.3%) and Northwest (17.8%), while its contribution to the FEVs of other groups is negligible. Similarly to the results obtained for consumer households, there is a large spillover effect from Northwest to Islands, 20.3% (the index measuring the spillover from Islands to Northwest is only 3.3%), while the spillover from the Northeast to Islands is lower, 16% (still above the spillover arising from Islands to Northeast).

Finally, the results corresponding to pairwise spillover for producer households (see Table 8, panel c) are similar to the results for non-financial firms. More specifically, there is evidence of a large contribution from Northwest to Northeast, 21.2% (the spillover from Northeast to Northwest is 14.5%). Once again, Southern regions show the largest pairwise contributions, including: the one to the FEV of the Northwest (24.2%), the Central Italy (25%) and the Islands (15.9%). The Islands are affected, also, by shocks arising from Central Italy (the value of the spillover is 11.8%) and, to less extent, from Northeast (9.3%) and Northwest (7.7%). Large spillover effects are also from Northwest to Central Italy (19%).

5.2.4 Pairwise rolling analysis

The static results are confirmed by using the time-varying cross-group spillovers computed over the $2011Q4 - 2015Q4$ period, with a forecast horizon equal to four quarters ($H = 4$) (see Figure 11).

As for consumer households (see Figure 11, panel a), the dynamic spillover index from South to Northern regions is permanently above than the one from North to South, over the whole forecast period. In particular, the average value of the spillover from South to Northwest is 37.6% (slightly above the long-run value which is equal to 35%), while the spillover from South to Northeast is 21.5% (the corresponding long-run value is 20.9%). Oppositely, both Northwest and Northeast show a dynamic spillover effect to the Islands larger than the one measured from the Islands to the Northern regions. The difference between the spillover effects is particularly evident looking at the dynamic cross-group measure from Northwest to Islands, whose average value is equal to 41.6% (above the

static pairwise measure, 37%).
The large contribution from South to Northern regions is confirmed also for non-financial firms (see Figure 11, panel b). However, whilst the spillover from South to Northwest is above its long-run value (26.7%) over the period $2011Q4-2013Q1$, the dynamic spillover decreases since the next quarter, showing an average value equal to 19.4%, over the rest of the forecast period. The spillover from Northwest to South is in line with its long-run value (9.3%). A similar pattern is found in the causality relationship between Northeast and South-Italy. In particular, the spillover from South to Northeast decreases from 24% to 10.2% over the entire forecast period (the long-run value is equal to 11.4%). The spillover from Northern regions to Islands is confirmed, given that we find an average (over the whole forecast period) spillover from Northwest to Islands equal to 25.5% (the long rung value is 20.3%), while the average spillover from Northeast is 22.5% (largely above its long-run value, 16%).
Different results on the comparison between Northwest and South arise from the analysis conducted on the producer households (see Figure 11, panel c). The Southern regions show a large spillover to the Northeast over the whole forecast period (with an average dynamic spillover, 20.2%, in line with the corresponding long-run value). The spillovers from South to Northwest decreases over the forecast period. In fact, after increasing in the $2011Q4-2013Q1$, the value of the spillover from South to Northwest shows an average value of 21.7% (lower than the long-run value, 24.2%). The spillover from Northwest to South reports an increase from 16% to 24.4% over the $2011Q4-2015Q4$. We also find a decrease in the spillovers from the Northeast to the Islands, especially in the second part of the sample. The spillover from Northeast to Islands shows a large increase in the $2011Q4-2013Q1$, before converging to similar values of the spillover arising from the Islands. Finally, the comparison between the dynamic spillovers computed for the Northwest and the Islands does not reveal any additional information with respect to the full sample analysis. In fact, both of the two spillover measures are similar, reporting values in line with the corresponding long-run equilibria.

To summarize, we find evidence of an increase in default rates spatial dependence (relative to the long-run value) for Italian regional default rates over a crisis period ($2011Q4-2015Q4$) associated with the last part of the observed sample. These empirical findings are observed for all the three private sector categories, especially for the producer households.
Furthermore, the aggregated total directional indices suggest different dynamics for the two macro-regions of the Mezzogiorno. While the *Influence* index suggests that the South is the largest contributor of shocks to the other macro-regions, Insular Italy shows the highest degree of dependence from the rest of the system (this is particularly true for consumer households and non-financial firms). As for the Northern regions, the *Influence* index suggests that the Northwest is among the largest contributor of shocks to the other macro-regions and the Northeast shows a degree of dependence from the rest of the system similar to Insular Italy.
Furthermore, the comparison of pairwise indices sheds further light on the issue of increasing vulnerability of the Mezzogiorno from the North of Italy as a consequence of the bank consolidation process. In particular, the hypothesis of a bank consolidation process detrimental for the Mezzogiorno is partially supported by the dependence of only Insular Italy on the Northern regions. Moreover, we find evidence of large spillover from the

South to the Northwest and Northeast macro-regions.

6 Conclusions

In this paper, we have investigated the spatial spillover effects among 20 Italian regions, by using loans default rates series for consumer households, non-financial firms and producer households, over the $1996Q1-2015Q4$ time span. In particular, we use the Diebold-Yilmaz methodology, DY, based on the generalized forecast error variance decomposition (GFEVD) obtained from the estimation, through the Adaptive Elastic net, of a large VAR model, to retrieve a measure of total spatial connectedness among the 20 Italian regional default rates series. Furthermore, the GNS approach enables to compute indices of directional connectedness and, in particular, to assess whether the Mezzogiorno regions are more dependent (relative to the Northern regions) on shocks arising from the other regions.

Using the DY approach to compute an index of total connectedness, the empirical evidence shows an increase in spatial dependence (over the $2011Q4-2015Q4$ period) relative to its long-run value. In particular, these empirical findings are more striking for producer households.

We have also focused on indices of directional causality. In this respect, our work is along the lines of Imai & Takarabe (2011) and of Presbitero *et al.* (2014) since the focus is on the role played by large national banks in spreading the crisis from one region to the others within the same country. More specifically, using the GNS approach, we find that Northwest and South are the largest donor of financial stress. These findings, coupled with the analysis of pairwise aggregate spillover effect, partially support the hypothesis of a core-periphery divide and, in particular, the hypothesis of the Mezzogiorno's dependence from the North, triggered by the geographic expansion of Northern banks. This might be motivated by the evidence of large spillovers (both for static and dynamic analysis) from Northern regions only to Insular Italy.

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Appendices

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Figure 1: Default rates on loan facilities (in percentage) for Consumer households in the Italian regions, from 1996$Q1$ to 2015$Q4$.

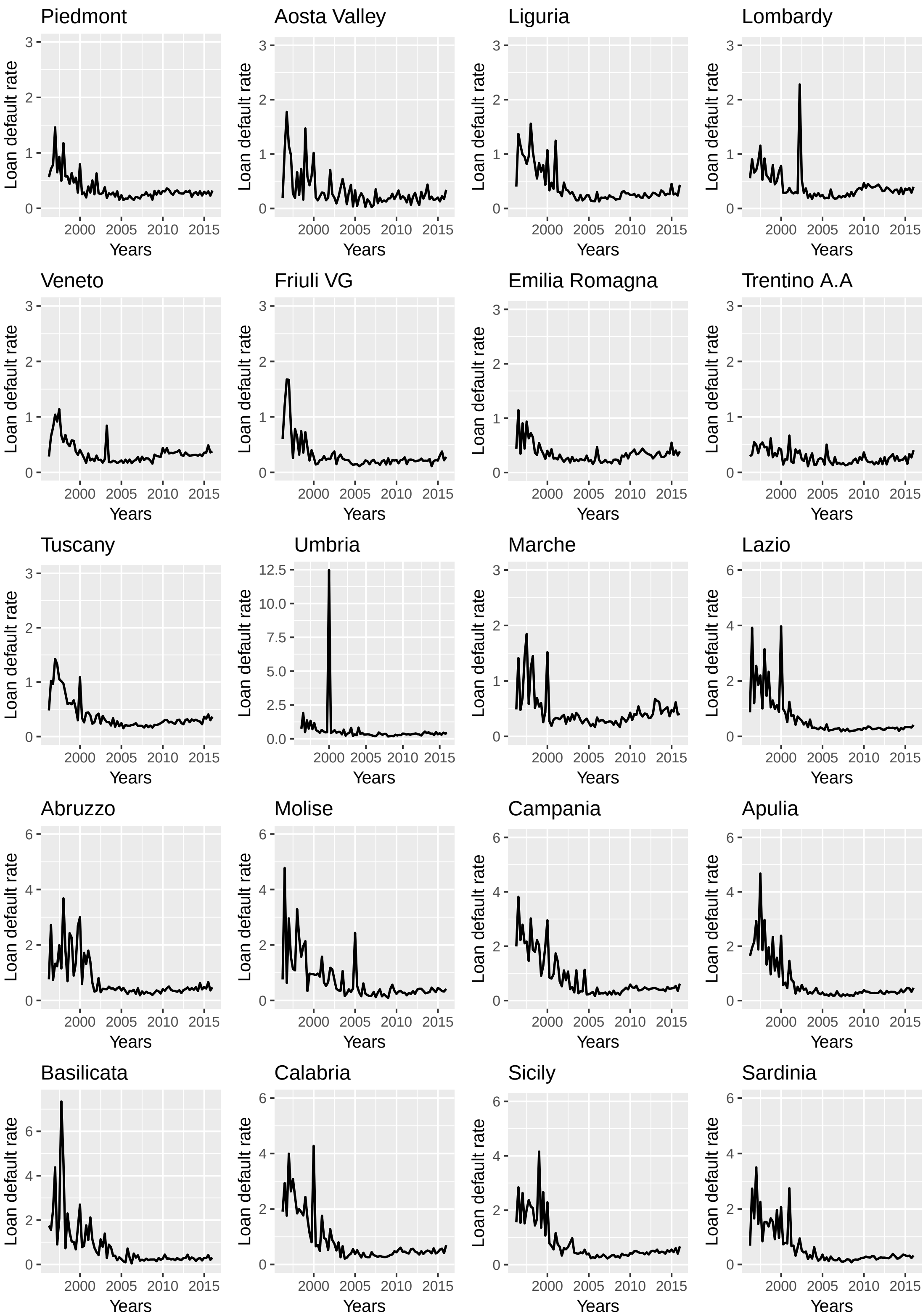


Figure 2: Default rates on loan facilities (in percentage) for Non-financial firms in the Italian regions, from 1996$Q1$ to 2015$Q4$.

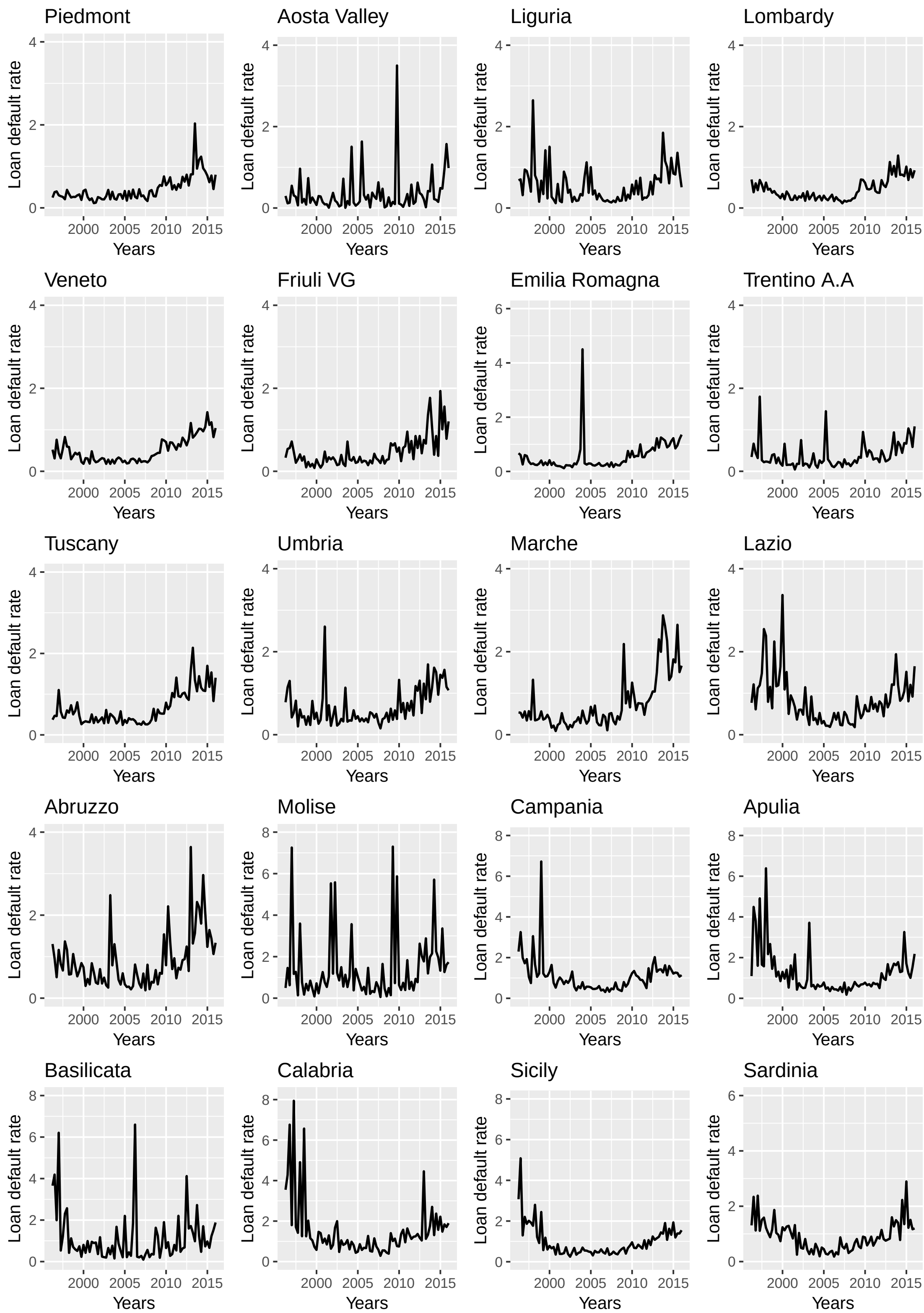


Figure 3: Default rates on loan facilities (in percentage) for Producer households in the Italian regions, from 1996$Q1$ to 2015$Q4$.

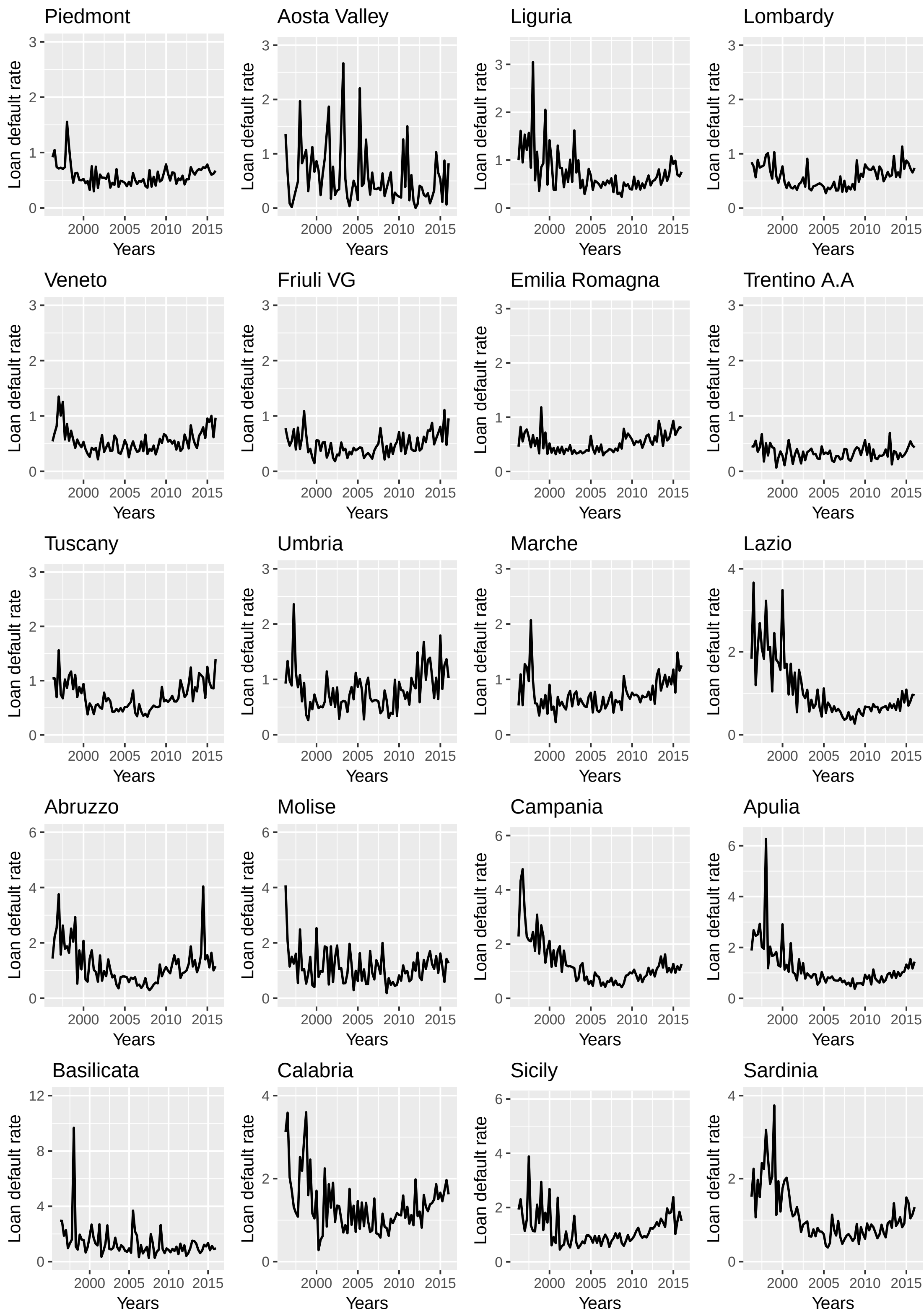
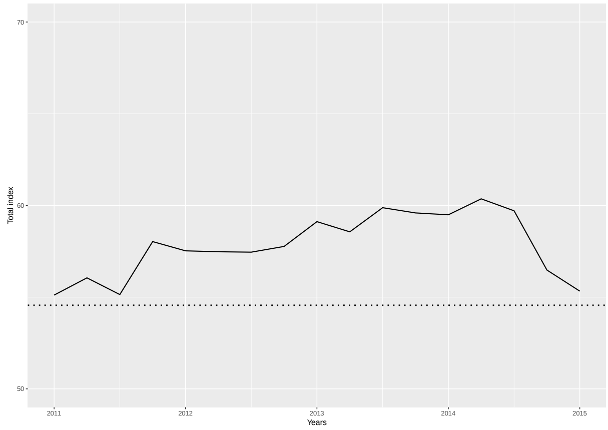
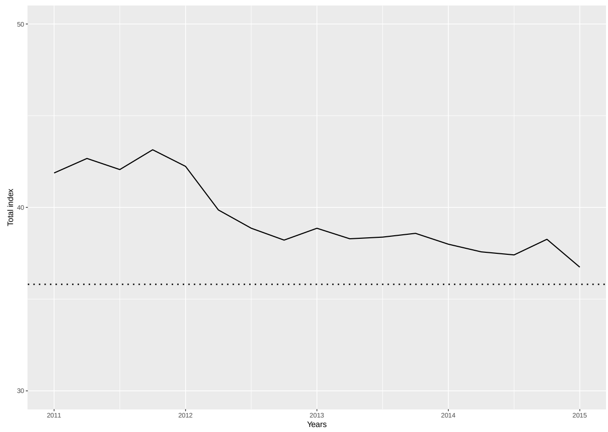


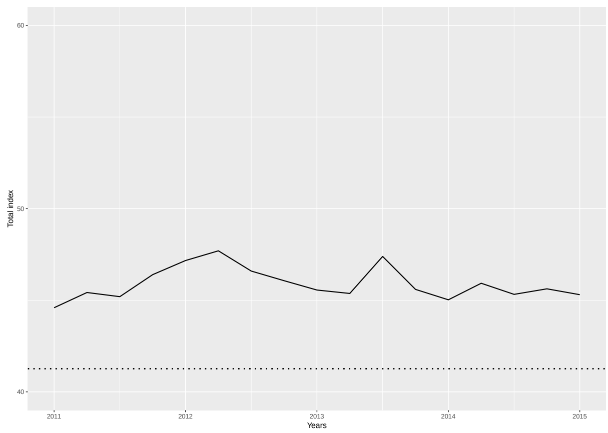
Figure 4: Time-varying *Total connectedness* index (in percentage) at $H = 4$ steps ahead, $2011Q4 - 2015Q4$.



(a) Consumers households



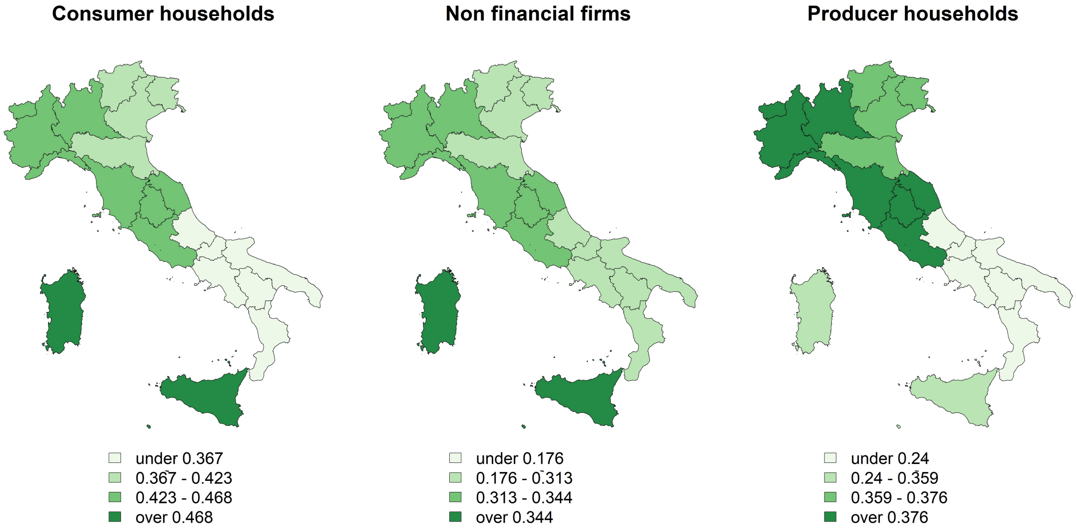
(b) Non-financial firms



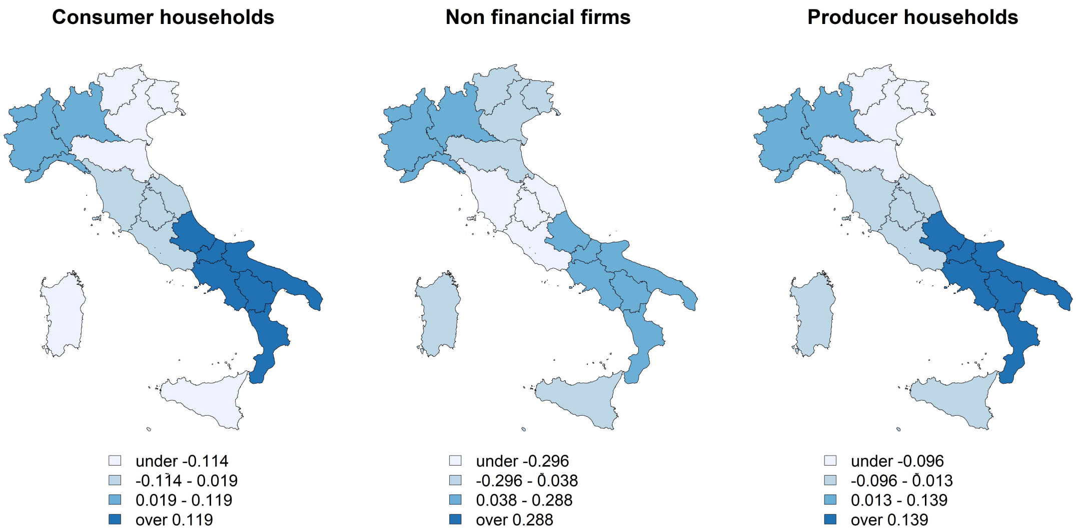
(c) Producers households

Note. The figure shows the time-varying *Total connectedness* index (black line) using a rolling estimation window width equal to 63 quarters, with a starting sample which covers $1996Q2 - 2011Q4$, and a forecast horizon equal to four quarters ($H = 4$). The time-varying *Total connectedness* index is reported for each of the three private sub-sectors: consumer households (panel a), non-financial firms (panel b) and producer households (panel c). The static, unconditional, *Total connectedness* index values (dotted line) are also reported: 54.6% (consumer households), 35.8% (non-financial firms) and 41.3% (producer households).

Figure 5: Dependence and Influence indices. Full sample estimation (1996Q2−2015Q4), $H = 4$ steps ahead. $N = 5$ Italian groups of regions.

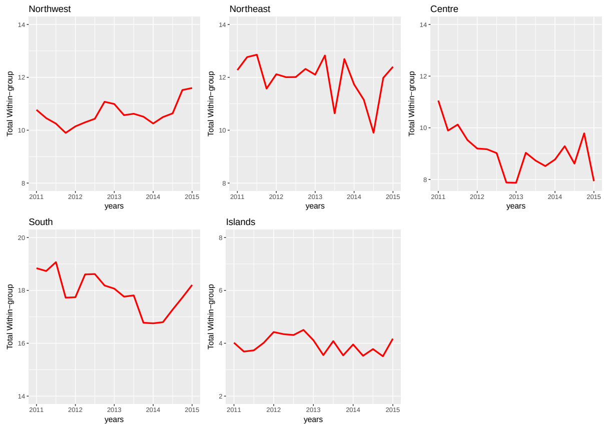


(a) Dependence index quantile maps.

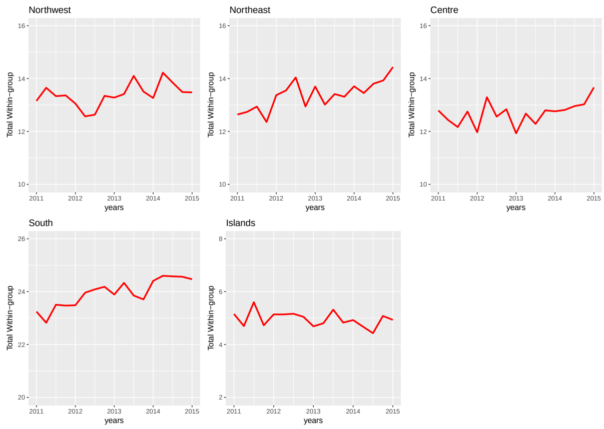


(b) Influence index quantile maps.

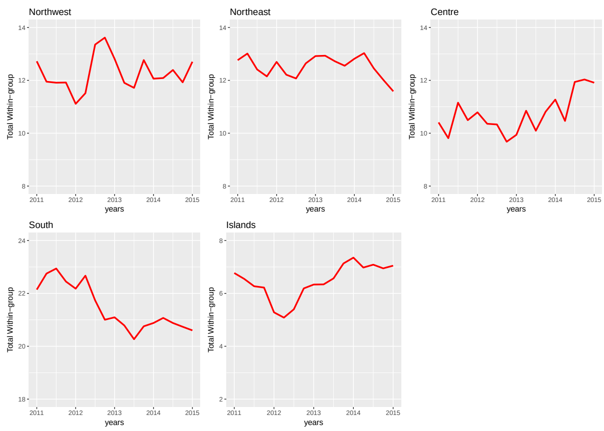
Figure 6: Time-varying total *Within-group* index at $H = 4$ steps ahead, $2011Q4 - 2015Q4$. $N = 5$ Italian groups of regions.



(a) Consumer households



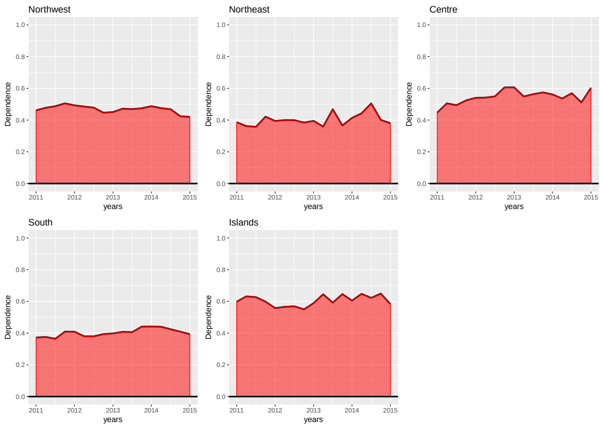
(b) Non-financial firms



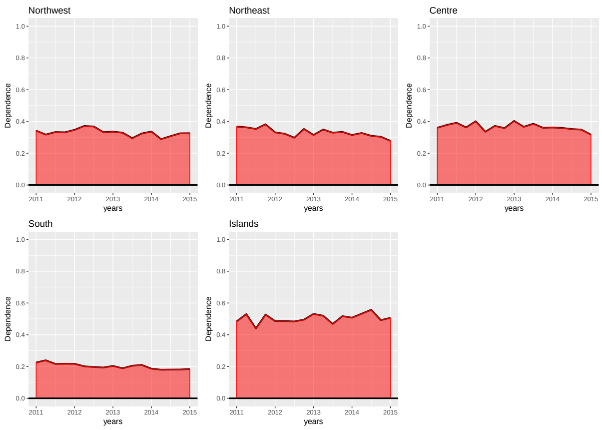
(c) Producer households

Note. The figure shows the time-varying total *Within-group* index (see eq.(17)) using a rolling estimation window width equal to 63 quarters, with a starting sample which covers $1996Q2 - 2011Q4$, and a forecast horizon equal to four quarters ($H = 4$). The index is reported for each of the three private sub-sectors: consumer households (panel a), non-financial firms (panel b) and producer households (panel c). The values are expressed as a percentage of the FEV computed for the whole system.

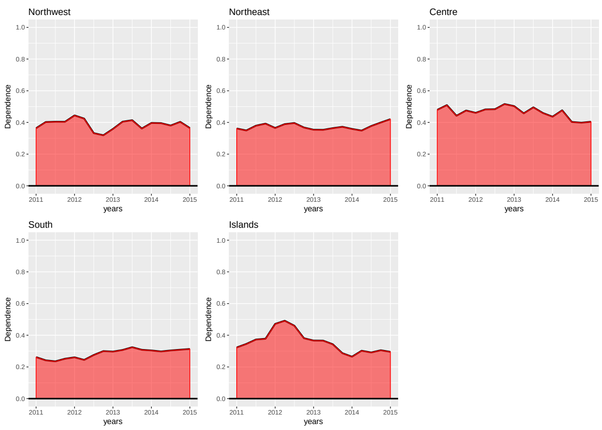
Figure 7: Time-varying Dependence index at $H = 4$ steps ahead, $2011Q4 - 2015Q4$. $N = 5$ Italian groups of regions.



(a) Consumer households



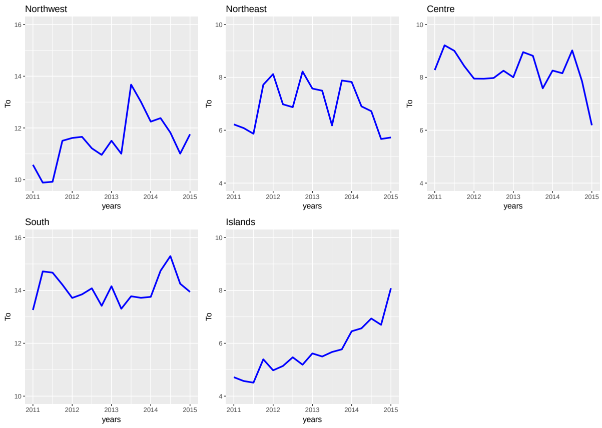
(b) Non-financial firms



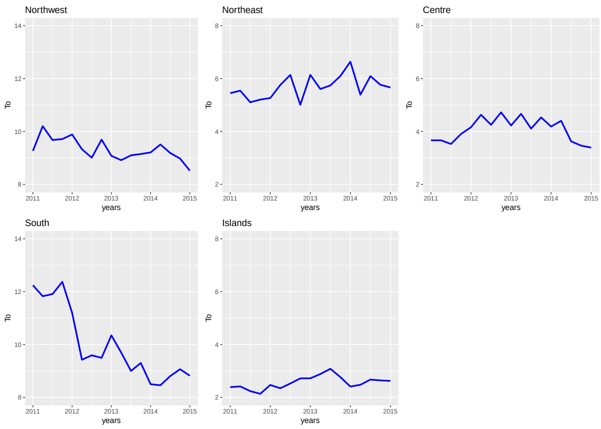
(c) Producer households

Note. The figure shows the time-varying Dependence index (see eq.(21)) using a rolling estimation window width equal to 63 quarters, with a starting sample which covers $1996Q2-2011Q4$, and a forecast horizon equal to four quarters ($H = 4$). The index is reported for each of the three private sub-sectors: consumer households (panel a), non-financial firms (panel b) and producer households (panel c).

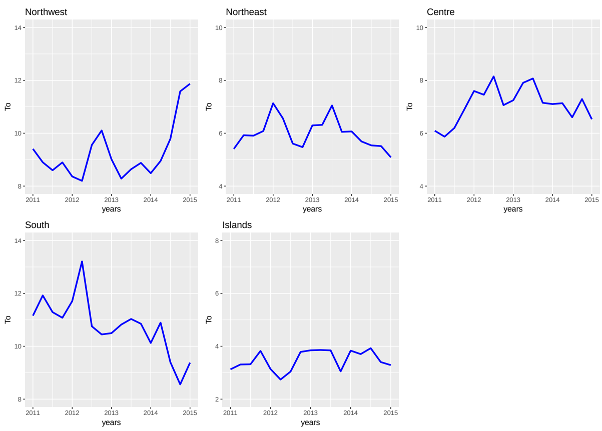
Figure 8: Time-varying *To* index at $H = 4$ steps ahead, $2011Q4 - 2015Q4$. $N = 5$ Italian groups of regions.



(a) Consumer households



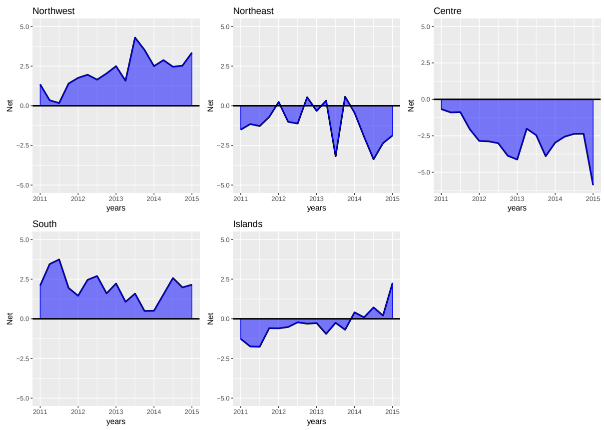
(b) Non-financial firms



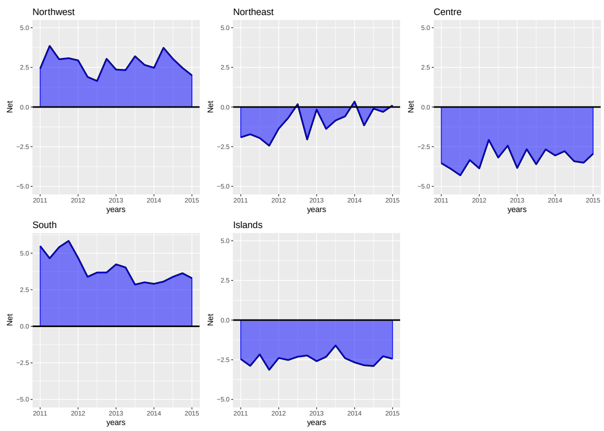
(c) Producer households

Note. The figure shows the time-varying *To* connectedness index (see eq.(20)) using a rolling estimation window width equal to 63 quarters, with a starting sample which covers $1996Q2 - 2011Q4$, and a forecast horizon equal to four quarters ($H = 4$). The index is reported for each of the three private sub-sectors: consumer households (panel a), non-financial firms (panel b) and producer households (panel c). The values are expressed as a percentage of the FEV computed for the whole system.

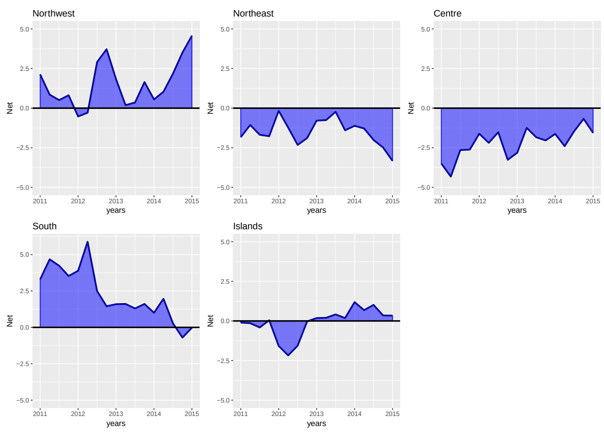
Figure 9: Time-varying *Net* index at $H = 4$ steps ahead, $2011Q4 - 2015Q4$. $N = 5$ Italian groups of regions.



(a) Consumer households



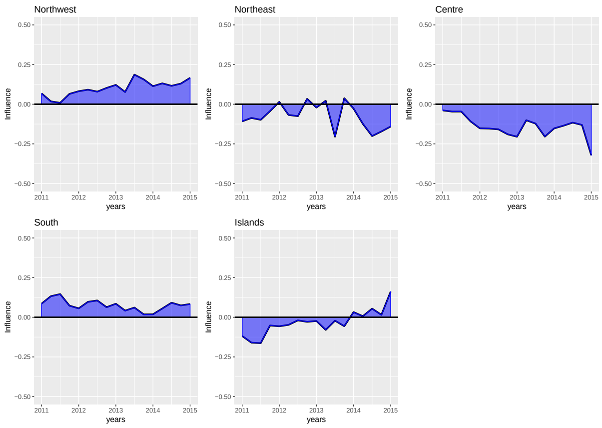
(b) Non-financial firms



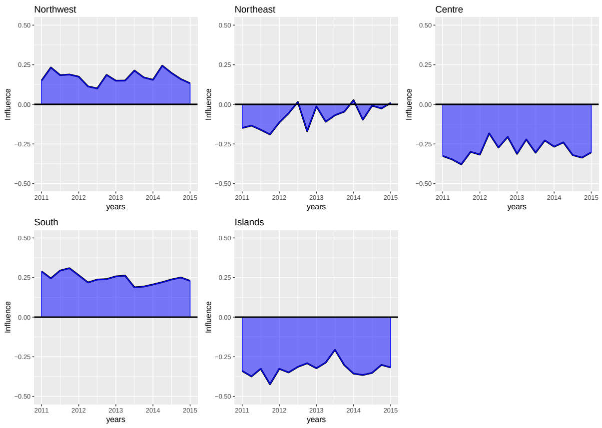
(c) Producer households

Note. The figure shows the time-varying *Net* index (see eq.(20)) using a rolling estimation window width equal to 63 quarters, with a starting sample which covers $1996Q2 - 2011Q4$, and a forecast horizon equal to four quarters ($H = 4$). The index is reported for each of the three private sub-sectors: consumer households (panel a), non-financial firms (panel b) and producer households (panel c). The values are expressed as a percentage of the FEV computed for the whole system.

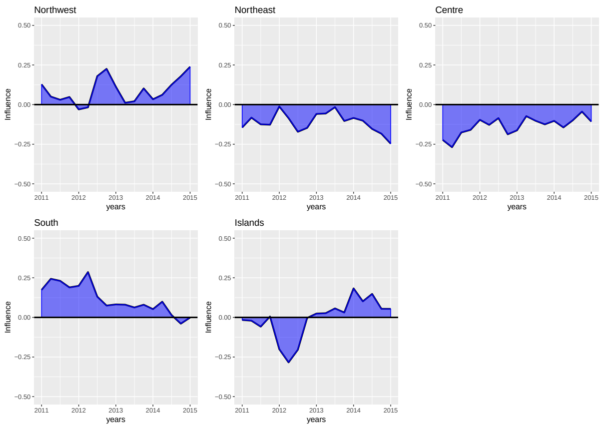
Figure 10: Time-varying *Influence* index at $H = 4$ steps ahead, $2011Q4 - 2015Q4$. $N = 5$ Italian groups of regions.



(a) Consumer households



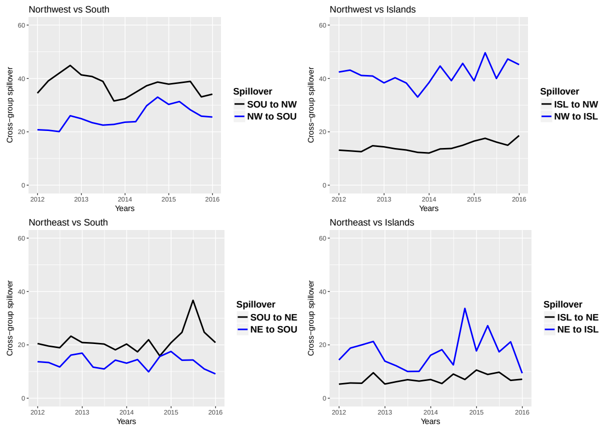
(b) Non-financial firms



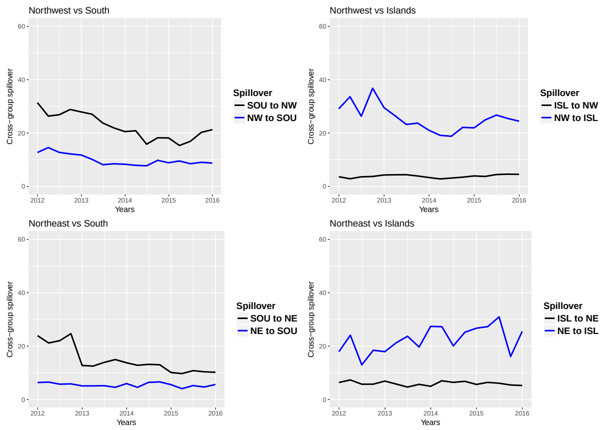
(c) Producer households

Note. The figure shows the time-varying *Influence* index (see eq.(22)) using a rolling estimation window width equal to 63 quarters, with a starting sample which covers $1996Q2 - 2011Q4$, and a forecast horizon equal to four quarters ($H = 4$). The index is reported for each of the three private sub-sectors: consumer households (panel a), non-financial firms (panel b) and producer households (panel c).

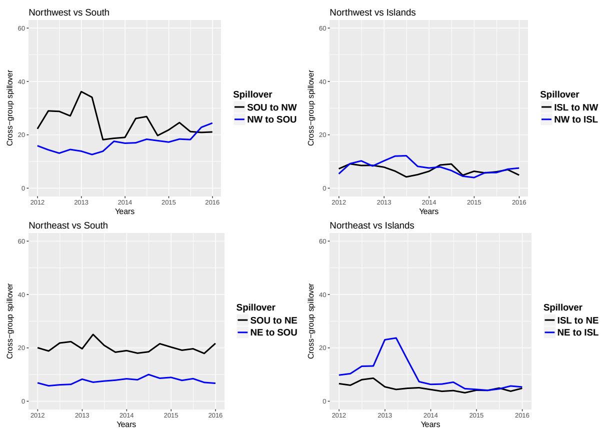
Figure 11: Time-varying Cross-group spillovers at $H = 4$ steps ahead, $2011Q4 - 2015Q4$. North vs Mezzogiorno.



(a) Consumer households



(b) Non-financial firms



(c) Producer households

Note. The figure shows the time-varying cross-group spillovers reported in Table 8, using a rolling estimation window width equal to 63 quarters, with a starting sample observed over $1996Q2 - 2011Q4$, and a forecast horizon equal to four quarters ($H = 4$). In particular, the figure shows the pairwise spillovers between the Northern regions (Northwest and Northeast) and the Mezzogiorno regions (South and Islands). The measures (in percentage) are reported for each of the three private sub-sectors: consumer households (panel a), non-financial firms (panel b) and producer households (panel c).

Table 1: Connectedness Table

	y_1	y_2	$\cdots$	y_K	From others
y_1	$\tilde{d}_{11}^H$	$\tilde{d}_{12}^H$	$\cdots$	$\tilde{d}_{1K}^H$	$\sum_{j=1}^K \tilde{d}_{1j}^H, j \neq 1$
y_2	$\tilde{d}_{21}^H$	$\tilde{d}_{22}^H$	$\cdots$	$\tilde{d}_{2K}^H$	$\sum_{j=1}^K \tilde{d}_{2j}^H, j \neq 2$
$\vdots$	$\vdots$	$\vdots$	$\ddots$	$\vdots$	$\vdots$
y_K	$\tilde{d}_{K1}^H$	$\tilde{d}_{K2}^H$	$\cdots$	$\tilde{d}_{KK}^H$	$\sum_{j=1}^K \tilde{d}_{Kj}^H, j \neq K$
To others	$\sum_{i=1}^K \tilde{d}_{i1}^H$	$\sum_{i=1}^K \tilde{d}_{i2}^H$	$\cdots$	$\sum_{i=1}^K \tilde{d}_{iN}^H$	$\frac{1}{K}\sum_{i,j=1}^K \tilde{d}_{ij}^H$
	$i \neq 1$	$i \neq 2$		$i \neq K$	$i \neq j$

Table 2: Italian regions grouped at NUTS 1 (macro-regional) level.

Northwest	Northeast
Aosta Valley	Emilia-Romagna
Liguria	Friuli Venezia-Giulia
Lombardy	Trentino Alto-Adige
Piedmont	Veneto
Centre	**South**
Lazio	Abruzzo
Marche	Apulia
Tuscany	Basilicata
Umbria	Calabria
	Campania
Islands	Molise
Sardinia	
Sicily	

Note. Mezzogiorno includes the Southern regions and the islands of Sardinia and Sicily.

Table 3: Augmented Dickey Fuller (ADF) test on the logit trasformation of the regional loan default rates series.

Hypothesis	Statistic	Critical values 1%	5%	10%
$H_0 : \beta = 0$	t-based	-3.51	-2.89	-2.58
$H_0 : \alpha = 0$	t-based	3.22	2.54	2.17
$H_0 : \alpha = \beta = 0$	F-based	6.70	4.71	3.86

Regions	Consumer Households				Non Financial Firms				Producer Households			
	$H_0 : \beta = 0$	$H_0 : \alpha = 0$		$H_0 : \alpha = \beta = 0$	$H_0 : \beta = 0$	$H_0 : \alpha = 0$		$H_0 : \alpha = \beta = 0$	$H_0 : \beta = 0$	$H_0 : \alpha = 0$		$H_0 : \alpha = \beta = 0$
	τ	t-value	p-value	Γ	τ	t-value	p-value	Γ	τ	t-value	p-value	Γ
PIEDMONT	-3.017	-3.099	0.003	5.437	-1.065	-1.011	0.316	0.728	-2.215	-2.222	0.030	2.480
AOSTA VALLEY	-3.358	-3.413	0.001	5.950	-2.616	-2.581	0.012	3.501	-4.124	-4.071	0.000	8.536
LIGURIA	-2.521	-2.635	0.010	4.070	-2.620	-2.612	0.011	3.433	-2.653	-2.675	0.009	3.609
LOMBARDY	-2.416	-2.450	0.017	3.093	-1.262	-1.236	0.221	0.825	-1.756	-1.757	0.083	1.544
VENETO	-2.955	-3.004	0.004	4.715	-0.205	-0.122	0.903	0.411	-2.241	-2.247	0.028	2.528
FRIULI VG	-4.546	-4.622	0.000	11.173	-1.096	-1.057	0.294	0.667	-2.856	-2.847	0.006	4.087
EMILIA-ROMAGNA	-2.072	-2.104	0.039	2.353	-1.446	-1.400	0.166	1.115	-1.397	-1.391	0.169	0.981
TRENTINO AA	-1.994	-2.011	0.048	2.066	-2.262	-2.251	0.028	2.561	-3.224	-3.220	0.002	5.197
TUSCANY	-3.706	-3.833	0.000	8.343	-0.491	-0.435	0.665	0.278	-1.257	-1.245	0.217	0.806
UMBRIA	-2.435	-2.470	0.016	3.115	-1.106	-1.068	0.289	0.703	-2.369	-2.372	0.020	2.814
MARCHE	-2.339	-2.376	0.020	2.910	-0.954	-0.858	0.394	0.698	-2.199	-2.192	0.032	2.421
LAZIO	-2.674	-2.898	0.005	5.339	-1.374	-1.355	0.180	0.949	-1.899	-1.994	0.050	2.293
ABRUZZO	-1.477	-1.552	0.125	1.343	-1.874	-1.845	0.069	1.771	-1.973	-2.010	0.048	2.057
MOLISE	-2.054	-2.136	0.036	2.413	-2.122	-2.105	0.039	2.252	-2.992	-3.001	0.004	4.507
CAMPANIA	-2.462	-2.642	0.010	4.186	-1.980	-2.008	0.049	2.031	-2.244	-2.314	0.024	2.840
APULIA	-2.340	-2.493	0.015	3.550	-2.054	-2.093	0.040	2.212	-2.371	-2.443	0.017	3.223
BASILICATA	-1.653	-1.821	0.073	2.092	-2.782	-2.782	0.007	3.880	-2.963	-2.984	0.004	4.482
CALABRIA	-2.564	-2.718	0.008	4.200	-2.742	-2.800	0.007	3.990	-2.971	-2.963	0.004	4.414
SICILY	-1.990	-2.113	0.038	2.607	-1.473	-1.492	0.140	1.120	-1.621	-1.622	0.109	1.317
SARDINIA	-2.329	-2.559	0.013	4.241	-1.282	-1.286	0.203	0.827	-1.449	-1.464	0.148	1.075

Note. The table reports the ADF statistics computed for the logit transformation of the 20 regional series of Default rate on loan facilities for each of the three private sector categories, which run from $1996Q_1$ to $2015Q_4$, considering a model with an intercept and a number of lags equal to 4. The model has the following representation: $\Delta y_t = \alpha + \beta y_{t-1} + \Theta_1 \Delta y_{t-1} + \Theta_2 \Delta y_{t-2} + \Theta_3 \Delta y_{t-3} + \Theta_4 \Delta y_{t-4} + \varepsilon_t$. In particular, three hypotheses are tested: *1)* $H_0 = \beta = 0$, *2)* $H_0 : \alpha = 0$ and *3)* $\alpha = \beta = 0$. The table reports the statistics of interest: τ refers to the hypothesis (1), that is the presence of a unit root in the processes, t-value refers to the hypothesis (2), that is the significance of the intercept (p-values for this statistic are also reported), and Γ refers to the hypothesis (3), that is the joint hypothesis that there is a non-stationary process without drift. Each statistic is compared with the corresponding critical values reported in the upper-right sub-table.

Table 4: KPSS unit root test on the logit transformation of the regional default rates series.

	Consumer Households			Non Financial Firms			Producer Households		
	$\ell = 2$	$\ell = 4$	$\ell = 6$	$\ell = 2$	$\ell = 4$	$\ell = 6$	$\ell = 2$	$\ell = 4$	$\ell = 6$
PIEDMONT	0.532	0.351	0.269	0.368	0.264	0.215	0.427	0.306	0.244
AOSTA VALLEY	0.346	0.280	0.240	0.152	0.173	0.168	0.057	0.061	0.072
LIGURIA	0.583	0.382	0.287	0.381	0.271	0.224	0.420	0.319	0.264
LOMBARDY	0.446	0.309	0.245	0.553	0.354	0.271	0.513	0.336	0.259
VENETO	0.491	0.324	0.251	0.578	0.375	0.282	0.403	0.281	0.226
FRIULI VG	0.456	0.319	0.257	0.333	0.255	0.217	0.384	0.297	0.259
EMILIA ROMAGNA	0.529	0.350	0.265	0.341	0.244	0.203	0.477	0.330	0.262
TRENTINO AA	0.402	0.300	0.245	0.352	0.272	0.234	0.135	0.124	0.120
TUSCANY	0.600	0.386	0.294	0.529	0.346	0.264	0.569	0.373	0.286
UMBRIA	0.408	0.318	0.266	0.417	0.322	0.260	0.278	0.206	0.173
MARCHE	0.525	0.345	0.267	0.407	0.289	0.233	0.330	0.243	0.207
LAZIO	0.613	0.401	0.301	0.554	0.367	0.278	0.592	0.384	0.290
ABRUZZO	0.514	0.337	0.257	0.435	0.303	0.243	0.529	0.358	0.274
MOLISE	0.448	0.329	0.266	0.203	0.160	0.135	0.228	0.196	0.169
CAMPANIA	0.611	0.397	0.296	0.575	0.380	0.290	0.608	0.401	0.306
PUGLIA	0.625	0.401	0.301	0.583	0.386	0.294	0.601	0.393	0.299
BASILICATA	0.496	0.343	0.269	0.344	0.273	0.229	0.178	0.211	0.209
CALABRIA	0.601	0.391	0.296	0.554	0.370	0.287	0.345	0.268	0.236
SICILY	0.606	0.391	0.294	0.607	0.387	0.291	0.531	0.367	0.280
SARDINIA	0.595	0.388	0.289	0.609	0.395	0.296	0.564	0.372	0.284

Note. The table reports the KPSS unit root test statistic, computed for the logit transformation of the 20 regional series of loan default rates, where the null hypothesis is that the series is stationary around a trend. The test statistics are reported for each of the three private sector categories and for different lag parameter truncation, $\ell = 2$, $\ell = 4$ and $\ell = 6$ (see Kwiatkowski *et al.*, 1992). The critical value at 5% (0.146) is also reported.

Table 5: Jarque-Bera test on the residuals of the VAR model fitted to the Δ logit transformation of the regional loan default rates series.

	Consumer Households		Non Financial Firms		Producer Households	
	Statistic	p-value	Statistic	p-value	Statistic	p-value
PIEDMONT	2.498	0.287	4.03	0.133	5.114	0.078
AOSTA VALLEY	1.558	0.459	0.493	0.781	28.634	0.000
LIGURIA	2.785	0.248	1.233	0.540	1.076	0.584
LOMBARDY	480.093	0.000	1.117	0.572	1.592	0.451
VENETO	105.406	0.000	0.206	0.902	1.075	0.584
FRIULI VG	5.101	0.078	3.179	0.204	1.164	0.559
EMILIA ROMAGNA	0.141	0.932	350.322	0.000	13.798	0.001
TRENTINO AA	0.031	0.985	1.584	0.453	6.079	0.048
TUSCANY	7.053	0.029	1.108	0.575	0.466	0.792
UMBRIA	125.254	0.000	0.011	0.994	0.121	0.941
MARCHE	3.091	0.213	1.768	0.413	0.577	0.75
LAZIO	58.893	0.000	0.207	0.902	0.176	0.916
ABRUZZO	4.565	0.102	25.587	0.000	3.246	0.197
MOLISE	0.049	0.976	2.787	0.248	0.275	0.871
CAMPANIA	6.514	0.038	24.836	0.000	1.171	0.557
APULIA	1.890	0.389	8.829	0.012	0.507	0.776
BASILICATA	8.429	0.015	0.672	0.715	4.229	0.121
CALABRIA	4.315	0.116	1.274	0.529	17.018	0.000
SICILY	3.450	0.178	3.247	0.197	1.928	0.381
SARDINIA	0.260	0.878	1.946	0.378	1.843	0.398

Note. The table reports the Jarque-Bera (JB) test statistic computed for the series of residuals obtained through the estimation of a sparse VAR(1) model for the three private sector categories. The statistics are compared with the critical value of a Chi-squared distribution with 2 degrees of freedom, that is $\chi^2(2) = 5.99$, at 5% significance level. P-values are also reported.

Table 6: Group connectedness matrix. Full sample estimation ($1996Q2 - 2015Q4$), $H = 4$ steps ahead.

	Northwest	Northeast	Centre	South	Islands
Northwest	10.786	1.485	2.567	3.817	1.346
Northeast	2.701	12.312	1.665	2.569	0.752
Centre	2.148	1.221	10.642	5.153	0.836
South	3.756	1.867	3.826	18.994	1.557
Islands	1.609	0.535	1.064	2.441	4.350

(a) Consumer households.

	Northwest	Northeast	Centre	South	Islands
Northwest	13.150	1.832	1.065	3.513	0.440
Northeast	2.162	14.341	1.109	1.633	0.755
Centre	2.331	1.690	13.120	2.665	0.194
South	2.292	1.172	1.001	24.717	0.818
Islands	1.206	0.951	0.163	1.737	5.942

(b) Non-financial firms.

	Northwest	Northeast	Centre	South	Islands
Northwest	12.354	1.787	1.986	2.986	0.887
Northeast	2.720	12.816	1.539	2.310	0.615
Centre	2.372	1.493	12.479	3.121	0.535
South	3.167	1.356	1.867	22.812	0.798
Islands	0.530	0.641	0.818	1.101	6.910

(c) Producers households.

Note. The table reports the static group connectedness matrix obtained through a full sample estimation ($1996Q2-2015Q4$), by using a forecast horizon equal to four quarters ($H = 4$). The measures are reported for each of the three private sector categories: consumer households (panel a), non-financial firms (panel b) and producer households (panel c). In each panel, the main diagonal elements give the *Total within-group* forecast error variance (FEV) contributions, for each of the $N = 5$ groups (see eq.(17)). The off-diagonal elements give the spillover effects among the groups (see eqs.(18) and (19)). The values are expressed as a percentage of the FEV computed for the whole system.

Table 7: Aggregate connectedness measures. Full sample estimation ($1996Q2-2015Q4$), $H = 4$ steps ahead.

	Within	From	To	Net	Dep.	Infl.
Consumers						
Northwest	10.786	9.214	10.214	1.000	0.461	0.051
Northeast	12.312	7.688	5.108	-2.580	0.384	-0.202
Centre	10.642	9.358	9.122	-0.236	0.468	-0.013
South	18.994	11.006	13.980	2.974	0.367	0.119
Insular	4.350	5.650	4.491	-1.158	0.565	-0.114
Average	11.417	8.583	8.583	0.000	0.449	-0.032
Firms						
Northwest	13.150	6.850	7.991	1.141	0.343	0.077
Northeast	14.341	5.659	5.645	-0.014	0.283	-0.001
Centre	13.120	6.880	3.339	-3.541	0.344	-0.347
South	24.717	5.283	9.549	4.266	0.176	0.288
Insular	5.942	4.058	2.206	-1.852	0.406	-0.296
Average	14.254	5.746	5.746	0.000	0.310	-0.056
Producers						
Northwest	12.354	7.646	8.789	1.143	0.382	0.070
Northeast	12.816	7.184	5.277	-1.907	0.359	-0.153
Centre	12.479	7.521	6.210	-1.311	0.376	-0.096
South	22.812	7.188	9.518	2.330	0.240	0.139
Insular	6.910	3.090	2.835	-0.255	0.309	-0.043
Average	13.474	6.526	6.526	0.000	0.333	-0.017

Note. The table reports the values of the Within, From, To and Net measures computed according to eqs.(17) and (20), for each of the three private sector categories: consumer households, non-financial firms and producer households. The values of these four indices are expressed as a percentage of the FEV computed for the whole system. Dep. denotes the dependence index, O_n^H, $0 \leq O_n^H \leq 1$ (see eq.(21)), while Infl. denotes the influence index, I_n^H (see eq.(22)).

Table 8: Relative (to *Within-group* index) group connectedness matrix. Full sample estimation ($1996Q2 - 2015Q4$), $H = 4$ steps ahead.

	Northwest	Northeast	Centre	South	Islands
Northwest	100.000	13.766	23.798	35.385	12.480
Northeast	21.940	100.000	13.521	20.866	6.111
Centre	20.182	11.471	100.000	48.420	7.858
South	19.774	9.829	20.143	100.000	8.195
Islands	36.983	12.307	24.464	56.119	100.000

(a) Consumer households.

	Northwest	Northeast	Centre	South	Islands
Northwest	100.000	13.931	8.101	26.717	3.346
Northeast	15.077	100.000	7.733	11.388	5.263
Centre	17.764	12.879	100.000	20.313	1.479
South	9.273	4.742	4.051	100.000	3.308
Islands	20.305	16.011	2.741	29.242	100.000

(b) Non financial firms.

	Northwest	Northeast	Centre	South	Islands
Northwest	100.000	14.464	16.075	24.167	7.184
Northeast	21.223	100.000	12.011	18.024	4.797
Centre	19.010	11.968	100.000	25.010	4.286
South	13.883	5.946	8.184	100.000	3.496
Islands	7.667	9.270	11.835	15.936	100.000

(c) Producers households.

Note. The table reports the static group connectedness matrix obtained through a full sample estimation ($1996Q2 - 2015Q4$), by using a forecast horizon equal to four quarters ($H = 4$). This table is constructed through a re-normalization of Table 6. In particular, the (i, j)-th element entering each panel is normalized with respect to the *Total within-group* index of group i. The measures (in percentage) are reported for each of the three private sub-sectors: consumer households (panel a), non-financial firms (panel b) and producer households (panel c).