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Spatio-temporal Analysis of Regional Systems: A Multiregional Spatial Vector Autoregressive Model for Spain

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Abstract:

This paper contributes to the recent literature in spatial econometrics that focuses on space-time data modeling implementing a multi-location time-series statistical framework to analyze a regional system. Therefore, taking as a point of departure the Global Vector Autoregression approach introduced in Pesaran et al. (2004), a multiregional spatial vector autoregressive model (MultiREG-SpVAR) is formulated and then applied to study the spatio-temporal transmission of macroeconomic shocks across the regions in Spain.

The empirical application analyzes the extent to which a region's economic output growth is influenced by the growth of its neighbors (*push-in* or inward growth effect), and also investigates the relevance of spillovers derived from temporary region specific output growth shocks (*push-out* or outward growth effect). Our results identify some regions that perform as 'growth generating' within the Spanish regional system since growth shocks from these regions spill over to a large number of regions of the country, playing a key role in transmitting regional business cycles. The policy implications of our results suggest that national and/or regional governments should stimulate economic activity in these leading regions in order to favor the economic recovery process of the whole Spanish economy.

Keywords:

Regional growth; Spatial econometrics; Vector Autoregressions; Spillovers.

JEL Classification:

C33; C51; R11; R15

1. Introduction

There has been a growing interest over the last decade to address with the modeling of spatio-temporal data in applied economic analysis (see, for example, Anselin et al. (2008), Mur and López (2010), Rey and Janikas (2010), or Elhorst (2010, 2012), and the references contained therein). This interest can be explained, at least in part, by the fact that these types of data permit the modeling of the dynamic interdependencies existing between spatial units, incorporating simultaneously the presence of serial

correlation and spatial dependence between the observations over time and at each point of time, respectively.

Within the vector autoregressive (VAR) approach introduced by Sims (1980), that makes it possible to handle the complete set of possible temporal interactions of a set of geo-referenced data, a number of efforts have been made in order to explore more flexible models of this type. As a result, a new class of spatial vector autoregressive (SpVAR) models has recently appeared in the spatial econometrics literature. SpVARs are a general type of multivariate vector autoregressions that include spatial as well as temporal lags of the state variables. In contrast to standard VARs, that do not allow the joint modeling of dynamic spatio-temporal interdependencies within a group of connected economies (regions, states, metropolitan areas or local districts), in SpVAR models endogenous variables can exhibit co-movements over time and also over space.

At the moment, there have been few studies incorporating space in VAR specifications. Among these one finds the contributions of Carlino and DeFina (1995) who fitted a traditional VAR for a single variable observed in several regions and than LeSage and Pan (1995), subsequently generalized by LeSage and Krivelyova (2002), who introduced spatial priors in standard univariate Bayesian VAR models with the aim of improving the out-of-sample predictive performance of the estimated models.

Conley and Dupor (2003) and Neusser (2008), based on earlier work of Chen and Conley (2001), use a semi-parametric spatial VAR framework to examine sectoral interdependencies. In their models, the effect of one sector on another is a function of the economic distance between them, and these distances are used to impose *a priori* restrictions in order to estimate (in a semi-parametric way) the proposed SpVAR models. More recently, Azomahou et al. (2009) use this semi-parametric approach to study the spatial effects of the demographic system on economic growth.

Di Giacinto (2003, 2006, and 2010) uses spatial prior information in structural VAR models in order to provide parameter restrictions that permit the identification of the impulse responses derived from the estimated models. Márquez et al. (2010) also use structural VAR models, but rather than using spatially lagged variables in order to model spatial dependence, bi-regional specifications are used which allow more information on spatial dependence to be incorporated and tested.

Pesaran et al. (2004) and Dees et al. (2007) introduced global VAR specifications to study international macroeconomic fluctuations, where spatial information is used to model the regional interdependencies that can exist between the variables considered. The SpVAR model used in Dewachter et al. (2012) to analyze the propagation through space and time of macroeconomic shocks in Europe is a restricted version of this type of global models.

Beenstock and Felsenstein (2007) develop general multivariate spatial VAR models which include spatial as well as temporal lags and which can contain spatial error components. Kuethe and Pede (2011) use a similar approach but within a simpler reduced-form specification to model regional housing price cycles. Brady (2011) uses a simple spatial autoregressive specification to measure the diffusion of housing prices across space and over time. Also in Márquez et al. (2013) SpVAR models are estimated, in this case with the aim of analyzing the effects of shocks to the relative productive capacity of different regions, trying to uncover the pattern of regional competition within a country.

Finally, Canova and Ciccarelli (2009) introduced very general multi-area Bayesian panel VAR models, which allow cross-unit interdependencies, unit-specific dynamics and time variations in the parameters. However, contrary to LeSage and Pan (1995) or Di Giacinto (2003, 2006, and 2010), they imposed non-spatial prior information to obtain posterior distributions for the parameters.

In this paper, a multiregional spatial vector autoregressive model (MultiREG-SpVAR) is built. The model is composed of individual Spatial VAR (SpVAR) specifications, namely vector autoregressive models augmented by spatially-lagged explanatory variables that are combined in a consistent manner following the linking approach followed by Pesaran *et al.* (2004) and Dees *et al.* (2007).

The paper is organized as follows. Section 2 outlines the proposed multiregional SpVAR model. In Section 3, an illustration of the methodology is provided based on estimating a MultiREG-SpVAR model for the Spanish regional system. Prior to the analysis of the spatio-temporal propagation of macroeconomic shocks across regions in Spain, firstly a brief discussion about regional business cycles and growth spillovers is made. Thereafter, information is provided on the data (and their properties) and the spatial weights matrices used in the empirical application and a simple correlation

analysis between the output growth rates of the Spanish regions is made. Next, the results of the different estimates of spatial spillovers are presented and discussed. Section 4 concludes the paper

2. The multiregional spatial vector autoregressive (MultiREG-SpVAR) model

2.1. Econometric specification

In the proposed MultiREG-SpVAR model the regions are considered as small open economies, though allowing for feedbacks between the variables of different regions: each region is linked with the others in the regional system under study by including external variables in the econometric specification, in such a way that all regions are potentially affected by developments in the other regions of the system. These external variables are spatial lags of the state variables that have been constructed using spatial weights, which specify the neighborhood set for each location.

Specifically, we consider N regions, indexed by $i=1,2,\dots,N$, and the SpVAR(p_i, q_i) multivariate space-time model for region i at time t ($t=1,2,\dots,T$) is formulated incorporating temporal as well as spatial dynamics as

$$\mathbf{Y}_{it} = \mathbf{\Lambda}_{0i} + \mathbf{\Lambda}_{1i} \mathbf{t} + \mathbf{\Gamma}_{1i} \mathbf{Y}_{i,t-1} + \dots + \mathbf{\Gamma}_{pi} \mathbf{Y}_{i,t-p_i} + \mathbf{\Phi}_{0i} \mathbf{Y}_{it}^* + \mathbf{\Phi}_{1i} \mathbf{Y}_{i,t-1}^* + \dots + \mathbf{\Phi}_{qi} \mathbf{Y}_{i,t-q_i}^* + \mathbf{u}_{it} \quad (1)$$

where $\mathbf{Y}_{it} = (y_{1,it}, y_{2,it}, \dots, y_{G,it})'$ is the $G \times 1$ vector of internal state variables, $\mathbf{Y}_{it}^* = (y_{1,it}^*, y_{2,it}^*, \dots, y_{G,it}^*)'$ is the $G \times 1$ vector of external spatially-lagged variables, \mathbf{t} is the vector of the deterministic time trends, $\mathbf{\Lambda}_{ji}$ ($j=0,1$), $\mathbf{\Gamma}_{ji}$ ($j=1,2,\dots,p_i$) and $\mathbf{\Phi}_{ji}$ ($j=0,1,2,\dots,q_i$) are conformable matrices of parameters, and \mathbf{u}_{it} is the $G \times 1$ vector of shocks assumed to be serially uncorrelated with a zero mean and a non-singular covariance matrix, $\mathbf{\Sigma}_{ii} = Cov(u_{k,it}, u_{l,it}) = (\sigma_{ii,kl})$. In (1), the $\mathbf{\Gamma}_{ji} \mathbf{Y}_{i,t-j}$ terms represent the temporal dynamics, the $\mathbf{\Phi}_{0i} \mathbf{Y}_{it}^*$ term indicates the presence of spatial dynamics and, finally, the $\mathbf{\Phi}_{ji} \mathbf{Y}_{i,t-j}^*$ terms represent the temporal-spatial dynamics.

For each region, the vector of external variables is built as $\mathbf{Y}_{it}^* = \sum_{j=1}^N w_{ij} \mathbf{Y}_{jt}$. The region specific weights w_{ij} form a row-standardized $N \times N$ connectivity matrix \mathbf{W} with

elements known a priori satisfying $w_{ii} = 0$ and $\sum_{j=1}^N w_{ij} = 1$. This matrix reflects the network of relationships in the regional system. Then, the spatially lagged vector \mathbf{Y}_{it}^* summarizes the state of the economy in the neighboring regions, and their components, $y_{g,it}^* = \sum_{j=1}^N w_{ij} y_{g,jt}$, are a weighted average of y_g in all regions except the i^{th} . The specification of the spatial weights matrix will be addressed in section 3.

It can be seen from (1) that spatially heterogeneous model dynamics is allowed because parameters in the SpVAR models are assumed to vary unrestrictedly at the level of the individual regions. Also cross-region correlation among the disturbances is allowed, given by $\boldsymbol{\Sigma}_{ij} = \text{Cov}(\mathbf{u}_{it}, \mathbf{u}_{jt})$ for $i \neq j$. Therefore, the isolated region-specific SpVAR models allow for cross-unit contemporaneous interdependencies through two channels: (i) correlation among internal and external variables (Φ_{0i} matrices); (ii) correlation of shocks in different regions ($\boldsymbol{\Sigma}_{ij}$ matrices).

To build the MultiREG-SpVAR model, first internal and external variables are grouped as $\mathbf{Z}_{it} = (\mathbf{Y}'_{it}, \mathbf{Y}_{it}^*)'$ in order to put all the regional models together as a system

$$\left\{ \begin{array}{l} \mathbf{A}_{01} \mathbf{Z}_{1t} = \boldsymbol{\Lambda}_{01} + \boldsymbol{\Lambda}_{11} \mathbf{t} + \mathbf{A}_{11} \mathbf{Z}_{1,t-1} + \dots + \mathbf{A}_{r1} \mathbf{Z}_{1,t-r} + \mathbf{u}_{1t} \\ \mathbf{A}_{02} \mathbf{Z}_{2t} = \boldsymbol{\Lambda}_{02} + \boldsymbol{\Lambda}_{12} \mathbf{t} + \mathbf{A}_{12} \mathbf{Z}_{2,t-1} + \dots + \mathbf{A}_{r2} \mathbf{Z}_{2,t-r} + \mathbf{u}_{2t} \\ \dots \\ \mathbf{A}_{0N} \mathbf{Z}_{Nt} = \boldsymbol{\Lambda}_{0N} + \boldsymbol{\Lambda}_{1N} \mathbf{t} + \mathbf{A}_{1N} \mathbf{Z}_{N,t-1} + \dots + \mathbf{A}_{rN} \mathbf{Z}_{N,t-r} + \mathbf{u}_{Nt} \end{array} \right. \quad (2)$$

where $\mathbf{A}_{0i} = (\mathbf{I}_G, -\Phi_{0i})$, $\mathbf{A}_{ki} = (\boldsymbol{\Gamma}_{ki}, \Phi_{ki})$ ($i=1, \dots, N$; $k=1, \dots, r$) and $r = \max(p_i, q_i)$.

Secondly, link matrices \mathbf{L}_i of order $(2 \times G) \times (N \times G)$ are constructed on the basis of the regional weights connection w_{ij} in order to obtain the identity $\mathbf{Z}_{it} = \mathbf{L}_i \mathbf{Y}_t$ that relates the region-specific variables \mathbf{Z}_{it} to the 'global' variable $\mathbf{Y}_t = (\mathbf{Y}'_{1t}, \mathbf{Y}'_{2t}, \dots, \mathbf{Y}'_{Nt})'$, \mathbf{Y}_t being a vector of order $(N \times G) \times 1$ containing all the endogenous variables of the multiregional model. Thus, the system of individual models (2) yields a compact specification in terms of \mathbf{Y}_t given by

$$\mathbf{G}_0 \mathbf{Y}_t = \boldsymbol{\Lambda}_0 + \boldsymbol{\Lambda}_1 \mathbf{t} + \mathbf{G}_1 \mathbf{Y}_{t-1} + \dots + \mathbf{G}_r \mathbf{Y}_{t-r} + \mathbf{u}_t \quad (3)$$

where $\mathbf{G}_j = ((\mathbf{A}_{j1}\mathbf{L}_1)', (\mathbf{A}_{j2}\mathbf{L}_2)', \dots, (\mathbf{A}_{jN}\mathbf{L}_N)')'$ ($j=0,1,\dots,r$), $\mathbf{\Lambda}_j = (\mathbf{\Lambda}'_{j1}, \mathbf{\Lambda}'_{j2}, \dots, \mathbf{\Lambda}'_{jN})'$ ($j=0,1$), and $\mathbf{u}_t = (\mathbf{u}'_{1t}, \mathbf{u}'_{2t}, \dots, \mathbf{u}'_{Nt})'$ with $\mathbf{\Sigma}_u = Cov(\mathbf{u}_t)$.

Finally, since it can be shown that \mathbf{G}_0 is a $(N \times G) \times (N \times G)$ non-singular matrix if the global model is to be complete (that is, if it is possible to uniquely solve the state variables of all the regions), the following integrated reduced form can be obtained by premultiplying expression (3) by the matrix \mathbf{G}_0^{-1} :

$$\mathbf{Y}_t = \mathbf{\Pi}_0^1 + \mathbf{\Pi}_0^2 \mathbf{t} + \mathbf{\Pi}_1 \mathbf{Y}_{t-1} + \dots + \mathbf{\Pi}_r \mathbf{Y}_{t-r} + \mathbf{e}_t \quad (4)$$

where $\mathbf{\Pi}_0^j = \mathbf{G}_0^{-1} \mathbf{\Lambda}_j$ ($j=0,1$), $\mathbf{\Pi}_j = \mathbf{G}_0^{-1} \mathbf{G}_j$ ($j=0,1,\dots,r$) and $\mathbf{e}_t = \mathbf{G}_0^{-1} \mathbf{u}_t$ with $\mathbf{\Sigma}_e = Cov(\mathbf{e}_t)$, a non-restricted covariance matrix.

Having reparametrized the original system (2) as (4), the multiregional spatial vector autoregressive model can be seen as a reduced-form VAR model for the regional system vector $\mathbf{Y}_t = (\mathbf{Y}'_{1t}, \mathbf{Y}'_{2t}, \dots, \mathbf{Y}'_{Nt})'$. This expression is the basis for the analysis of the dynamic properties of the multiregional model, and can be utilized among other things for the simulation of the response of the regional system to shocks in specific regions, as set out in section 3.

2.2. Relationship with the spatial econometrics literature

Although our proposed MultiREG-SpVAR model shares some similarities with other models proposed in the spatial econometric literature, it also has important differences.¹

In this regard, the Beenstock and Felsenstein (2007) SpVAR models are similar to (1), including spatial as well as temporal lags, but only homogeneous dynamics is permitted (coefficients do not vary across locations). The MultiREG-SpVAR model is more general than the one proposed by Beenstock and Felsenstein because it allows heterogeneous dynamics, a distinctive feature of multiregional time series (panel) data.

Moreover, the Canova and Ciccarelli (2009) multicountry VAR models use an econometric specification as in (4), allowing cross-unit lagged interdependencies, heterogeneous dynamics, and structural time variations. Due to the high dimensionality

¹ We do not include in this comparison some previous contributions due to the univariate nature of the proposal (Carlino and DeFina, 1995; LeSage and Pan, 1995; LeSage and Krivelyova, 2002; Chen and Conley, 2001; Conley and Dupor, 2003).

of the proposed models, the framework of the analysis is Bayesian. Abstracting from the statistical framework, our specification is in one sense more general than that proposed by Canova and Ciccarelli because cross-region contemporaneous (and also time-lagged) spatial interdependencies are allowed, but it is more restricted in other sense because no time variations are allowed in the parameters.

Finally, the Di Giacinto (2010) structural SpVAR specifications are comparable to (3), but assume a block-triangular structure for the matrix of simultaneous interactions \mathbf{G}_0 , thus restricting the spatial interaction coefficients. Although spatial heterogeneity is allowed, permitting all model parameters to vary unrestrictedly at the level of the individual regions, the recursive identification scheme (causal ordering of the endogenous variables) makes the De Giacinto' specification less general than the MultiREG-SpVAR model.

In conclusion, the suggested multivariate specification occupies an intermediate position in the spatial econometrics literature, being more general in some senses (cross-unit interdependencies and heterogeneity in the underlying dynamic process), and having some restrictions in other sense (time variations in the coefficients).

2.3. Example

To illustrate the proposed approach we present a simple MultiREG-SpVAR(1,1) model composed of $N=3$ regions in $G=2$ state variables.

For region $i=1,2,3$ the SpVAR structure is given by:

$$\begin{pmatrix} y_{1,it} \\ y_{2,it} \end{pmatrix} = \begin{pmatrix} \Lambda_{0i}^1 \\ \Lambda_{0i}^2 \end{pmatrix} + \begin{pmatrix} \Lambda_{1i}^1 \\ \Lambda_{1i}^2 \end{pmatrix} (t) + \begin{pmatrix} \Gamma_{1i}^1 \\ \Gamma_{1i}^2 \end{pmatrix} \begin{pmatrix} y_{1,it-1} \\ y_{2,it-1} \end{pmatrix} + \begin{pmatrix} \Phi_{0i}^1 \\ \Phi_{0i}^2 \end{pmatrix} \begin{pmatrix} y_{1,it}^* \\ y_{2,it}^* \end{pmatrix} + \begin{pmatrix} \Phi_{1i}^1 \\ \Phi_{1i}^2 \end{pmatrix} \begin{pmatrix} y_{1,it-1}^* \\ y_{2,it-1}^* \end{pmatrix} + \begin{pmatrix} u_{1,it} \\ u_{2,it} \end{pmatrix}$$

where $y_{1,it}^* = w_{i1}y_{1,1t} + w_{i2}y_{1,2t} + w_{i3}y_{1,3t}$ and $y_{2,it}^* = w_{i1}y_{2,1t} + w_{i2}y_{2,2t} + w_{i3}y_{2,3t}$, and w_{ij} are a set of spatial weights forming a matrix:

$$\mathbf{W} = \begin{pmatrix} 0 & w_{12} & w_{13} \\ w_{21} & 0 & w_{23} \\ w_{31} & w_{32} & 0 \end{pmatrix}$$

with the properties that $w_{12} + w_{13} = 1$, $w_{21} + w_{23} = 1$ and $w_{31} + w_{32} = 1$.

Written in disaggregated form, each SpVAR(1,1) takes the form:

$$\begin{cases} y_{1,it} = \Lambda_{0i}^1 + \Lambda_{1i}^1 t + \Gamma_{1i,1}^1 y_{1,it-1} + \Gamma_{1i,2}^1 y_{2,it-1} + \Phi_{0i,1}^1 y_{1,it}^* + \Phi_{0i,2}^1 y_{2,it}^* + \Phi_{1i,1}^1 y_{1,it-1}^* + \Phi_{1i,2}^1 y_{2,it-1}^* + u_{1,it} \\ y_{2,it} = \Lambda_{0i}^2 + \Lambda_{1i}^2 t + \Gamma_{1i,1}^2 y_{1,it-1} + \Gamma_{1i,2}^2 y_{2,it-1} + \Phi_{0i,1}^2 y_{1,it}^* + \Phi_{0i,2}^2 y_{2,it}^* + \Phi_{1i,1}^2 y_{1,it-1}^* + \Phi_{1i,2}^2 y_{2,it-1}^* + u_{2,it} \end{cases}$$

The three region-specific SpVAR models can be written together as:

$$\begin{cases} \begin{cases} y_{1,1t} - \Phi_{01,1}^1 y_{1,1t}^* - \Phi_{01,2}^1 y_{2,1t}^* = \Lambda_{01}^1 + \Lambda_{11}^1 t + \Gamma_{11,1}^1 y_{1,1t-1} + \Gamma_{11,2}^1 y_{2,1t-1} + \Phi_{11,1}^1 y_{1,1t-1}^* + \Phi_{11,2}^1 y_{2,1t-1}^* + u_{1,1t} \\ y_{2,1t} - \Phi_{01,1}^2 y_{1,1t}^* - \Phi_{01,2}^2 y_{2,1t}^* = \Lambda_{01}^2 + \Lambda_{11}^2 t + \Gamma_{11,1}^2 y_{1,1t-1} + \Gamma_{11,2}^2 y_{2,1t-1} + \Phi_{11,1}^2 y_{1,1t-1}^* + \Phi_{11,2}^2 y_{2,1t-1}^* + u_{2,1t} \end{cases} \\ \begin{cases} y_{1,2t} - \Phi_{02,1}^1 y_{1,2t}^* - \Phi_{02,2}^1 y_{2,2t}^* = \Lambda_{02}^1 + \Lambda_{12}^1 t + \Gamma_{12,1}^1 y_{1,2t-1} + \Gamma_{12,2}^1 y_{2,2t-1} + \Phi_{12,1}^1 y_{1,2t-1}^* + \Phi_{12,2}^1 y_{2,2t-1}^* + u_{1,2t} \\ y_{2,2t} - \Phi_{02,1}^2 y_{1,2t}^* - \Phi_{02,2}^2 y_{2,2t}^* = \Lambda_{02}^2 + \Lambda_{12}^2 t + \Gamma_{12,1}^2 y_{1,2t-1} + \Gamma_{12,2}^2 y_{2,2t-1} + \Phi_{12,1}^2 y_{1,2t-1}^* + \Phi_{12,2}^2 y_{2,2t-1}^* + u_{2,2t} \end{cases} \\ \begin{cases} y_{1,3t} - \Phi_{03,1}^1 y_{1,3t}^* - \Phi_{03,2}^1 y_{2,3t}^* = \Lambda_{03}^1 + \Lambda_{13}^1 t + \Gamma_{13,1}^1 y_{1,3t-1} + \Gamma_{13,2}^1 y_{2,3t-1} + \Phi_{13,1}^1 y_{1,3t-1}^* + \Phi_{13,2}^1 y_{2,3t-1}^* + u_{1,3t} \\ y_{2,3t} - \Phi_{03,1}^2 y_{1,3t}^* - \Phi_{03,2}^2 y_{2,3t}^* = \Lambda_{03}^2 + \Lambda_{13}^2 t + \Gamma_{13,1}^2 y_{1,3t-1} + \Gamma_{13,2}^2 y_{2,3t-1} + \Phi_{13,1}^2 y_{1,3t-1}^* + \Phi_{13,2}^2 y_{2,3t-1}^* + u_{2,3t} \end{cases} \end{cases}$$

Then, defining the vectors $\mathbf{Z}_{it} = (y_{1,it}, y_{2,it}, y_{1,it}^*, y_{2,it}^*)'$, we have:

$$\begin{cases} \mathbf{A}_{01} \mathbf{Z}_{1t} = \Lambda_{01} + \Lambda_{11} \mathbf{t} + \mathbf{A}_{11} \mathbf{Z}_{1,t-1} + \mathbf{u}_{1t} \\ \mathbf{A}_{02} \mathbf{Z}_{2t} = \Lambda_{02} + \Lambda_{12} \mathbf{t} + \mathbf{A}_{12} \mathbf{Z}_{2,t-1} + \mathbf{u}_{2t} \\ \mathbf{A}_{03} \mathbf{Z}_{3t} = \Lambda_{03} + \Lambda_{13} \mathbf{t} + \mathbf{A}_{13} \mathbf{Z}_{3,t-1} + \mathbf{u}_{3t} \end{cases}$$

where $\mathbf{A}_{0i} = (\mathbf{I}_2, -\Phi_{0i})$, $\mathbf{A}_{1i} = (\Gamma_{1i}, \Phi_{1i})$ for $i=1,2,3$.

Now the full regional system vector $\mathbf{Y}_t = (y_{1,1t}, y_{2,1t}, y_{1,2t}, y_{2,2t}, y_{1,3t}, y_{2,3t})'$ is defined, and link matrices \mathbf{L}_i of order 4×6 are constructed in order to obtain the identity $\mathbf{Z}_{it} = \mathbf{L}_i \mathbf{Y}_t$ for $i=1,2,3$. In this example, these matrices have the form:

$$\mathbf{L}_1 = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & w_{12} & 0 & w_{13} & 0 \\ 0 & 0 & 0 & w_{12} & 0 & w_{13} \end{pmatrix} = \begin{pmatrix} \mathbf{I}_2 & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & w_{12} \mathbf{I}_2 & w_{13} \mathbf{I}_2 \end{pmatrix}$$

$$\mathbf{L}_2 = \begin{pmatrix} 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 \\ w_{21} & 0 & 0 & 0 & w_{23} & 0 \\ 0 & w_{21} & 0 & 0 & 0 & w_{23} \end{pmatrix} = \begin{pmatrix} \mathbf{0} & \mathbf{I}_2 & \mathbf{0} \\ w_{21}\mathbf{I}_2 & \mathbf{0} & w_{23}\mathbf{I}_2 \end{pmatrix}$$

$$\mathbf{L}_3 = \begin{pmatrix} 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \\ w_{31} & 0 & w_{32} & 0 & 0 & 0 \\ 0 & w_{31} & 0 & w_{32} & 0 & 0 \end{pmatrix} = \begin{pmatrix} \mathbf{0} & \mathbf{0} & \mathbf{I}_2 \\ w_{31}\mathbf{I}_2 & w_{32}\mathbf{I}_2 & \mathbf{0} \end{pmatrix}$$

After that, the individual models are stacked to yield a model for \mathbf{Y}_t given by:

$$\begin{pmatrix} \mathbf{A}_{01}\mathbf{L}_1 \\ \mathbf{A}_{02}\mathbf{L}_2 \\ \mathbf{A}_{03}\mathbf{L}_3 \end{pmatrix} \mathbf{Y}_t = \begin{pmatrix} \boldsymbol{\Lambda}_{01} \\ \boldsymbol{\Lambda}_{02} \\ \boldsymbol{\Lambda}_{03} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\Lambda}_{11} \\ \boldsymbol{\Lambda}_{12} \\ \boldsymbol{\Lambda}_{13} \end{pmatrix} \mathbf{t} + \begin{pmatrix} \mathbf{A}_{11}\mathbf{L}_1 \\ \mathbf{A}_{12}\mathbf{L}_2 \\ \mathbf{A}_{13}\mathbf{L}_3 \end{pmatrix} \mathbf{Y}_{t-1} + \begin{pmatrix} \mathbf{u}_{1t} \\ \mathbf{u}_{2t} \\ \mathbf{u}_{3t} \end{pmatrix}$$

or, more compactly, given by:

$$\mathbf{G}_0 \mathbf{Y}_t = \boldsymbol{\Lambda}_0 + \boldsymbol{\Lambda}_1 \mathbf{t} + \mathbf{G}_1 \mathbf{Y}_{t-1} + \mathbf{u}_t$$

where $\mathbf{G}_0 = \begin{pmatrix} \mathbf{A}_{01}\mathbf{L}_1 \\ \mathbf{A}_{02}\mathbf{L}_2 \\ \mathbf{A}_{03}\mathbf{L}_3 \end{pmatrix}$, $\boldsymbol{\Lambda}_0 = \begin{pmatrix} \boldsymbol{\Lambda}_{01} \\ \boldsymbol{\Lambda}_{02} \\ \boldsymbol{\Lambda}_{03} \end{pmatrix}$, $\boldsymbol{\Lambda}_1 = \begin{pmatrix} \boldsymbol{\Lambda}_{11} \\ \boldsymbol{\Lambda}_{12} \\ \boldsymbol{\Lambda}_{13} \end{pmatrix}$, $\mathbf{G}_1 = \begin{pmatrix} \mathbf{A}_{11}\mathbf{L}_1 \\ \mathbf{A}_{12}\mathbf{L}_2 \\ \mathbf{A}_{13}\mathbf{L}_3 \end{pmatrix}$, and

$$\mathbf{u}_t = \begin{pmatrix} \mathbf{u}_{1t} \\ \mathbf{u}_{2t} \\ \mathbf{u}_{3t} \end{pmatrix}.$$

Premultiplying the equation for \mathbf{Y}_t by \mathbf{G}_0^{-1} , the following reduced-form VAR model is obtained:

$$\mathbf{Y}_t = \boldsymbol{\Pi}_0^1 + \boldsymbol{\Pi}_0^2 \mathbf{t} + \boldsymbol{\Pi}_1 \mathbf{Y}_{t-1} + \mathbf{e}_t$$

that in disaggregated form can be written as:

$$\begin{pmatrix} y_{1,1t} \\ y_{2,1t} \\ y_{1,2t} \\ y_{2,2t} \\ y_{1,3t} \\ y_{2,3t} \end{pmatrix} = \begin{pmatrix} \pi_{01}^1 \\ \pi_{02}^1 \\ \pi_{03}^1 \\ \pi_{04}^1 \\ \pi_{05}^1 \\ \pi_{06}^1 \end{pmatrix} + \begin{pmatrix} \pi_{01}^2 t \\ \pi_{02}^2 t \\ \pi_{03}^2 t \\ \pi_{04}^2 t \\ \pi_{05}^2 t \\ \pi_{06}^2 t \end{pmatrix} + \begin{pmatrix} \pi_{1,11} & \pi_{1,12} & \pi_{1,13} & \pi_{1,14} & \pi_{1,15} & \pi_{1,16} \\ \pi_{1,21} & \pi_{1,22} & \pi_{1,23} & \pi_{1,24} & \pi_{1,25} & \pi_{1,26} \\ \pi_{1,31} & \pi_{1,32} & \pi_{1,33} & \pi_{1,34} & \pi_{1,35} & \pi_{1,36} \\ \pi_{1,41} & \pi_{1,42} & \pi_{1,43} & \pi_{1,44} & \pi_{1,45} & \pi_{1,46} \\ \pi_{1,51} & \pi_{1,52} & \pi_{1,53} & \pi_{1,54} & \pi_{1,55} & \pi_{1,56} \\ \pi_{1,61} & \pi_{1,62} & \pi_{1,63} & \pi_{1,64} & \pi_{1,65} & \pi_{1,66} \end{pmatrix} \begin{pmatrix} y_{1,1t-1} \\ y_{2,1t-1} \\ y_{1,2t-1} \\ y_{2,2t-1} \\ y_{1,3t-1} \\ y_{2,3t-1} \end{pmatrix} + \begin{pmatrix} e_{1,t} \\ e_{2,t} \\ e_{3,t} \\ e_{4,t} \\ e_{5,t} \\ e_{6,t} \end{pmatrix}$$

3. An illustrative application of the MultiREG-SpVAR methodology: the transmission of shocks in the Spanish regional system

To place the application in context, first a brief discussion is made in this section about regional business cycles and growth spillovers. Thereafter, the Spanish regional system, the data (and their statistical properties) and the spatial weights matrices used in the empirical application are presented. Then, a short exploratory analysis of the Spanish regional cycles is made through a simple correlation approach. Finally, in subsections 3.6 and 3.7 the estimation results and simulations derived from the MultiREG-SpVAR model applied to the Spanish regional system are presented. Given the very large number of regressions and intermediate results involved in the estimation, only the main estimation and specification tests results are presented. Specifically, only output shocks are analyzed, although employment or capital (private or public) could also be investigated. Then, our empirical application concentrates on the relevance of growth spillovers within Spain.

3.1. Regional business cycles and growth spillovers

Over the recent years, considerable attention has been paid to the degree of co-movement of economic activity across regions (Montoya and de Haan, 2008). This fact can be explained because the analysis of regional business cycles is an important issue for policy makers (for example, Kouparitsas, 1999, and Mihov, 2001). The majority of studies have focused on the research into economic integration (Darvas and Szapáry, 2004) and regional business cycle synchronization (Clark and van Wincoop, 2001), with their corresponding derivations on economic policy (Larsson et al., 2009) and trade recommendations (spurred by the seminal articles of Frankel and Rose, 1997,1998). In addition, a few studies have examined the extent to which different factors may lead to changes in regional business cycles (Artis et al., 2011).

Much less attention has been devoted to the impact of regional shocks on regional economic cycles. Motivated by recent empirical literature using aggregate-level data at

the international level (see for instance Arora and Vamvakidis (2005) and Bagliano and Morana (2012)), we go beyond existing regional studies by considering growth spillovers within a country. Effectively, notwithstanding the fact that regional business cycles is a topic with an extensive economic literature, to our knowledge, no studies can be found that directly allow the joint modeling of dynamic interdependencies of business cycles within a regional system trying to analyze the spatial and temporal responses in all regions to a temporary shock in an state variable of one specific region.

In this context, the main underlying hypothesis in our empirical application is the existence of regional growth spillovers, where the evolution of one regional economy influences the growth of neighboring regional economies (Cheshire and Carbonaro, 1996). According to Capello (2009) growth spillovers would make reference to influences from a single regional economy on the growth of neighboring regional economies through trade linkages and market relationships. In the particular case of the Spanish economy, a question emerges: Can positive growth shocks from some regions in Spain spill over to other regions, stimulating the economic growth of the Spanish regional system?

3.2. Data for the Spanish regions

The database used consists of yearly time series for the Spanish Autonomous Communities. This corresponds with a NUTS2 level of disaggregation in the Eurostat nomenclature of statistical territorial units.² Spain is a decentralized state composed of 17 regions and Ceuta and Melilla (two Spanish North African cities), and they constitute the so-called Autonomous Communities (see figure 1). These regions have achieved the status of self-governed territories, sharing governance with the Spanish central government within their respective territories. Due to the transfer of important economic responsibilities from the central government to the regional executives, the NUTS2 level of disaggregation in Spain is the most interesting level from a political economy perspective.

<<insert figure 1 about here>>

² Although the Spanish national statistical office (INE) and other institutions provide some information at NUTS3 level (provinces in the Spanish nomenclature), there is not enough information available to assemble a complete database for output and all productive factors considered.

The data for the 17 Spanish regions cover the period 1964-2003 and for each region the macroeconomic variables used are the following: gross value added, GVA , measured at basic prices in thousands of year 2000 constant euros; total employment (E), in thousands of employed persons; and private (KPR) and public (KPU) net capital stocks, in thousands of year 2000 constant euros. The regional series for GVA and E have been drawn from the *BD.MORES* database (Bustos et al., 2008) and the time series for KPR and KPU have been taken from the *Fundación BBVA-Ivie* database (Mas et al., 2009). Some summary statistics of these and other variables (population – POP - and relative GVA per capita – $GVApc$) on the seventeen Spanish regions are shown in Table 1.

<<insert table 1 about here>>

3.3. Spatial weights

With respect to the matrix \mathbf{W} reflecting the spatial connectivity structure between regions necessary to build the region-specific spatially-lagged variables ($\mathbf{Y}_{it}^* = \sum_{j=1}^N w_{ij} \mathbf{Y}_{jt}$) used in the MultiREG-SpVAR model, we experiment with two alternative definitions of spatial weights, and then we use ‘goodness-of-fit’ statistics to choose the model that best represents the data.³

The first spatial weights matrix is based on a pure geographical criterion (physical distance), a standard first-order contiguity scheme, this being defined by the existence of a common border between each two regions.⁴ Then, a binary neighborhood-based spatial weights matrix is built defining non-normalized weights w_{ij}^* as (by convention, self-neighbors are excluded, so $w_{ii}^* = 0$):

$$w_{ij}^* = \begin{cases} 1 & \text{if regions } i \text{ and } j \text{ are geographical neighbors} \\ 0 & \text{otherwise} \end{cases}$$

and next a $\mathbf{W}_{geog} = (w_{ij})$ row-standardized weights matrix is defined as $w_{ij} = w_{ij}^* / \sum_j w_{ij}^*$.

³ Some recent discussions about the different approaches in constructing the spatial weights matrix can be found in Elhorst (2010), Harris et al. (2011) or Corrado and Fingleton (2012).

⁴ In the geographical case, we only use the first-order contiguity weights matrix because Stakhovych and Bijmolt (2008) show in a Monte Carlo simulation research that this matrix performs better on average than those using the K -nearest neighbors and inverse distance weights matrices in terms of their probabilities of finding the true model and the lower mean squared error of the parameters.

The second weights matrix is based on an economic criterion, hypothesizing that the spillover effect a region has on another depends on the ‘economic’ distance between them, such as technological proximity or the intensity of economic activity. So the \mathbf{W}_{econ} matrix has been built using information on trade linkages among the regions in order to capture the economic interaction of region j with the i^{th} region’s economy and not only the geographic interaction.⁵ The trade-based weights were computed using data on interregional trade in Spain drawn from the *C-Intereg* database (Llano et al., 2008, 2010).

Initially, we used a fully-connected trade-share weights matrix based on the averages of regional goods trade flows in Spain. Thus, mean trade shares \bar{s}_{ij} were computed as portions of region j in the total trade (exports plus imports) of region i over the period 2004-2007 (measured in millions of euros), and the spatial weights were defined as $w_{ij}^* = \bar{s}_{ij}$ (and $w_{ii}^* = 0$). The resulting multiregional model was not dynamically stable (some eigenvalues of the model were slightly above unity) so we decided to transform the trade-share matrix into a more sparse matrix, trying at the same time to mitigate the potential endogeneity problem caused by using a weight matrix determined by one variable (trade) directly related with the phenomenon under study (regional economic growth).⁶

As a result, a binary trade-based spatial weights matrix with a cut-off point was built defining non-normalized weights w_{ij}^* as

$$w_{ij}^* = \begin{cases} 1 & \text{if } \bar{s}_{ij} \geq \alpha \\ 0 & \text{if } \bar{s}_{ij} < \alpha \end{cases}$$

⁵ The relationship between trade and business cycle synchronization has been well documented in the literature (see, for example, Baxter and Kouparitsas, 2004, Imbs, 2004, or Calderón et al., 2007). For the Iberian case, Barrios and De Lucio (2003) show that trade and industrial specialization play an important role in determining regional economic fluctuations. Then, the intensity and pattern of trade between Spanish regions can influence the size and the shape of shocks across them.

On the other hand, the literature on technological diffusion documents that economies exchanging goods take advantages of technological improvements and market (pecuniary) externalities in other economies (Vayá et al., 2004). Then, changes in the state variables of trading partners can spread out to the regional system.

⁶ Anselin and Rey (1991) and Farber et al. (2009) show that high connectivity of the weights matrix has a negative impact on the probability of detecting the true model specification. Smith (2009) also shows that strongly connected matrices introduce a downward bias for the estimates of spatial parameters. These results, along with the instability of the model using the full-connected trade matrix, reinforce our decision to use a sparser binary trade-contiguity matrix as the proposed below.

and then a $\mathbf{W}_{econ} = (w_{ij})$ row-standardized weights matrix was defined as $w_{ij} = w_{ij}^* / \sum_j w_{ij}^*$. In the application we have used as trade-neighbors of region i those regions j that have a mean trade share above 10% ($\alpha = 0.1$) of the total trade. This criterion is based on the idea that only ‘relevant traders regions’ have non-negligible spatio-temporal effects on their neighbors, the remaining regions being less important and assumed to have negligible individual impacts. The 10% critical cut-off point yields a set of 3 to 5 (not necessarily geographically contiguous) neighbors.⁷

Table 2 presents in two panels the 17×17 weight matrices (for the seventeen Spanish regions) used in this work, where weights are displayed in row-normalized form by region, such that the elements of each row sum to one. Note that, contrary to the purely geographical case, the trade-based spatial weights matrix is non-symmetric, reflecting asymmetry in the weight importance of the trade relationship between regions. Moreover, the data of the trade-based matrix highlight the key role played by six regions (Andalusia, Catalonia, Castile and León, Madrid, the Basque Country and the Valencian Community), which are the more integrated with the rest of Spanish regional economies. If a major transmission mechanism for externalities is trade, we should expect that spatial spillovers will often emanate from these six core regions in terms of the exporting and importing of goods and services across geographical space (and also in terms of size and performance), playing an important role in the propagation of shocks across the Spanish regional system.

<<insert table 2 about here>>

The weights matrix finally used in the construction of the multiregional model has been selected by estimating the corresponding individual SpVAR models, and subsequently evaluating the results using information criteria. Following Stakhovych and Bijmolt (2008), this information criteria checking is the best statistical procedure to find the correct specification of the weights matrix, increasing both the probability of identifying its true specification and the precision of the parameter estimates.

Table 3 presents the AIC statistics obtained in both cases. An inspection of the numbers in this table shows that in most cases the econometric specifications utilizing

⁷ To check the robustness of our results we have used two other values ($\alpha=0.05$ and $\alpha=0.15$), and the results were qualitatively similar to those presented in this paper, so we omit them for the sake of brevity.

trade-based weights work better than those using geographic-based weights. Then, we employ only the \mathbf{W}_{econ} matrix in the rest of the application.

3.4. Unit root analysis

As a step prior to the VAR analysis of subsection 3.6, the integration properties of all the variables have been examined in order to determine the existence of unit roots [I(1)] or stationarity [I(0)] in their time-series behavior.

First, we investigated the order of integration of each variable (in logs) by means of the standard Augmented Dickey-Fuller (ADF) test (Dickey and Fuller, 1979) and also we used the Weighted Symmetric Dickey-Fuller (WS) test (Park and Fuller, 1995) in order to increase the small-sample power performance of the unit root analysis. Both type of tests provided evidence favoring the hypothesis that the vast majority of the series under study behave as I(1) non-stationary variables.

Further, we used some panel unit-root tests to test the presence of unit roots in the series (Breitung and Pesaran, 2008). These panel unit-root results provide again general evidence for not rejecting the hypothesis that the variables in the database behave in a non-stationary manner.⁸ Hence, all the SpVAR models that make up the multiregional specification have been estimated in log first differences, and not levels.⁹

3.5. Spanish regional business cycle comovements through time

In this subsection we analyze, in a very simple descriptive manner, business cycle comovements through time between the Spanish regions.¹⁰ Column 2 of table 4 shows the Pearson's correlation coefficients for yearly real *GVA* growth rates between Spain and its seventeen regional economies for various sub-periods. It appears that economic growth in the regions is quite correlated with that in the national economy in the four subintervals considered. Moreover, the correlation coefficients generally are slightly lower in the 1976-1985 period, and clearly declined in the post-1996 period.

⁸ For the sake of brevity, we omit the details of this and other intermediate outputs. Complete results can be obtained on request from the authors.

⁹ Although stationarity is not required in the multi-location methodology, because vector error correction methods can be used for cointegrated series (Pesaran et al., 2004), due to the limited length of the time series we decided to postpone such long-run analysis for future works.

¹⁰ An exhaustive investigation into regional business cycles within Spain over the 1991-2009 period can be found in the recent work of Gadea et al. (2012).

Since it would be more illustrative to develop a correlation analysis conducted by filtering out the irregular variations in *GVA* growth data, the asymmetric time varying band-pass filter of Christiano and Fitzgerald (2003) was applied to the original growth data. This filter is an optimal linear approximation to the ideal band-pass filter, and is designed to eliminate low-frequency trend variation and to smooth high-frequency irregular variation, while retaining intermediate business cycle components.

Column 3 of table 4 contains the calculated correlation coefficients for the transformed data, and figure 2 shows the frequency filtered time series. After removing the irregular variations in the real *GVA* growth data, the pattern of business cycle synchronization that emerge from these correlation coefficients is the same as in the un-filtered series: there is a high degree of economic comovement within the Spanish regional system, suggesting that there is over time an increased degree of economic linkages between the Spanish regions and also increased growth spillovers.

<<insert table 3 about here>>

<<insert figure 2 about here>>

While this discussion reveals important information regarding the relationships and the degree of business cycle synchronization in the Spanish regional system, the correlation analysis does not provides a measure of the spillover effects of individual regions and does not indicate how economic shocks are transmitted across the regional system; this will be addressed in the next two sections.

3.6. Model specification and estimation

Since we are considering $N=17$ regions, seventeen individual SpVAR(p_i, q_i) models need to be estimated before the construction of the multiregional model. All regional models contain the four domestic variables $\mathbf{Y}_{it} = (gva_{it}, e_{it}, kpr_{it}, kpu_{it})$, where $gva_{it} = \log(GVA_{it})$, $e_{it} = \log(E_{it})$, $kpr_{it} = \log(KPR_{it})$ and $kpu_{it} = \log(KPU_{it})$, and the corresponding region-specific external variables contained in \mathbf{Y}_{it}^* . Due to data limitations, we initially set the lag order of the domestic and external variables to two ($p_i=2$) and one ($q_i=1$), respectively. The optimum lag was chosen according to AIC choice criterion; table 5 presents the finally selected lags for each regional SpVAR model.

<<insert table 5 about here>>

According to Pesaran et al. (2004), three requirements need to be met for the validity of the multi-location methodology.¹¹ First, the global model must be dynamically stable; this condition implies that the eigenvalues of the model (4) must be less than or equal to unity: in this application, the moduli of the 136 (17x8) eigenvalues were all on or within the unit circle; specifically, the number of unitary roots was as expected 68 (17x4). Secondly, the weights must be relatively small; as reported in table 2 the binary trade-based weights are not close to one, the largest weight being 0.33 for some regions. Thirdly, the cross-dependence of the idiosyncratic shocks must be sufficiently small: in our application, several sets of average pairwise cross-section correlations were calculated, related to the endogenous variables in levels and in differences and to the SpVARX residuals obtained from each individual model; very low cross-section correlations between residuals were observed, allowing us to simulate shocks which are mainly region-specific.

In summary, given that all the mathematical conditions for the validity of the approach are met, the estimation of the MultiREG-SpVAR is justified, and the dynamic properties of the estimated model can be investigated.

3.7. Impulse responses: spatio-temporal propagation of shocks

In this section, we simulate how macroeconomic shocks are transmitted across the regions of Spain. To accomplish this task, we use the econometric results outlined in the previous section.

Push-in spillover effects

From the estimation of the regional models, we can obtain the estimates of the contemporaneous effects of external variables on their region-specific counterparts (the diagonal elements of the matrices Φ_{0i} in equation 1). These short-run inward elasticities measure the impact variation of the internal variables due to a one percent change in its

¹¹ The weak exogeneity of the region-specific external variables is another key assumption of this approach: in our case, because no cointegrating relation between internal and external variables is assumed, this exogeneity hypothesis cannot be tested but is automatically assured.

corresponding external counterpart; this is an important step in order to identify co-movements in the macroeconomic variables across different regions.¹²

Table 6 reports the estimated push-in spillover effects derived from each individual SpVAR model. When positive, values greater than one indicate that the internal variables of a region are more sensitive to a variation on their external counterparts; the opposite holds when impact elasticities are lower than one (and positive).

In our case, except for two negative but non-significant estimates, all the impact elasticities are positive and most of them are statistically significant at least at the 90% confidence level (53 of 68), pointing to strong interregional linkages among the Spanish regions. Moreover, most of the overreactions (elasticities greater than one) occur in the output and employment variables. This result suggests that output and employment in the Spanish regions are much affected in the short-run by changes in the economic conditions of the regions with which they maintain trade linkages. Thus, as expected, trade acts as a mechanism of interregional transmission of business cycles, ‘synchronizing’ the dynamics of the main macroeconomic variables across regions.

<<insert table 6 about here>>

Push-out spillover effects

The dynamic analysis that we present in this section follows the Generalized Impulse Response (GIR) approach proposed by Koop *et al.* (1996) and Pesaran and Shin (1998). This approach generalizes the traditional Orthogonalized Impulse Response method of Sims (1980); further, it is invariant to the ordering of the variables in the SpVAR models and does not require the identification of shocks. Although it is not possible to interpret the economic shocks in a structural sense, the GIR functions are a very useful tool to analyze the mechanism of the propagation of shocks among the regions of a country, as is the case in this analysis.

Starting from the system given by (3), obtained during the solution of the multiregional model, the GIR function of a unit shock (one standard error) at time t to

¹² Because all the variables are in log-differences form, the \mathbf{Y}_i^* vector contains spatially-lagged variables that are linear combinations of (approximately) growth rates of state variables from related regions. Then, the parameters contained in Φ_{0i} provide in each case a measure of influence for related region’s growth rates on the growth rate of region i . If positive, these parameters indicate that regional growth rates are positively related to a linear combination of those from related regions.

the l^{th} equation in the system on the j^{th} variable at time $t+s$ ($s=0,1,2,\dots$) is defined as the j^{th} element of the vector

$$GIR(\mathbf{Y}_t; u_{it}, s) = \frac{\mathbf{v}_j' \mathbf{M}_s \mathbf{G}_0^{-1} \boldsymbol{\Sigma}_u \mathbf{v}_l}{\sqrt{\mathbf{v}_l' \boldsymbol{\Sigma}_u \mathbf{v}_l}}$$

where $\mathbf{v}_l = (0, 0, \dots, 0, 1, 0, \dots, 0)'$ is a selection vector with unity as the l^{th} element and zeros otherwise, and the \mathbf{M}_s moving-average matrices can be derived recursively as $\mathbf{M}_l = \boldsymbol{\Pi}_1 \mathbf{M}_{l-1} + \boldsymbol{\Pi}_2 \mathbf{M}_{l-2} + \dots + \boldsymbol{\Pi}_r \mathbf{M}_{l-r}$ for $l=1, 2, \dots$ with $\mathbf{M}_0 = \mathbf{I}$.

In our application, when we simulate the response of the system to a temporary shock in an internal variable in one specific region of Spain, due to the existence of trade links between regions, other regions in the system will be affected from the disturbance. The results of this impact analysis provide relevant information about the degree of interregional spillovers in the Spanish regional system.

Essentially, the empirical analysis is carried out by simulating the space-time output effects of a temporary unit increase (one standard error positive shock) in the output of the different regions of Spain. These simulations will determine the degree of importance of each region in terms of the generation of outward output spillovers, serving to identify the ‘growth spillover leaders’ in the Spanish regional system.

The impact (zero-year) and medium-term (three-years) median bootstrap estimates¹³ in each case are presented in table 7, each number measuring the impact from region i 's growth shock to region j 's output growth rate (push-out output spillover effect).¹⁴

<<insert table 7 about here>>

The results presented in table 7 reveal that six regions can be identified as key sources of outward growth spatial spillovers: Andalusia, Aragón, Catalonia, Madrid, the Basque Country and the Valencian Community, and especially the role of Madrid as a source of transmission of positive growth impulses. This result should not be surprising since these regions account for about 70% of total Spanish output and, further, these are

¹³ The sieve bootstrap technique with 1000 replications was applied in the calculations. Details about the bootstrapping method used are exposed in the Supplement A of Dees et al. (2007).

¹⁴ As a complement, the GIR functions showing the dynamic response of the output over a time horizon of 25 years were plotted. All the GIRF's settle down in the long-run, providing confidence that the estimated MultiREG-SpVAR model is stable. Results are available upon requests.

the most important regions in terms of interregional trade-volume and trade-connectivity (see panel two of table 2).

The key regions identified using our multiregional spatial VAR approach are, except in the case of Aragón, the same key regions found by Llano (2009) using the hypothetical regional extraction (HRE) method over a Spanish interregional input-output model in order to compute the interregional backward and feedback effects of every region in Spain. Similarly, these regions have also been identified as strategic regions (Catalonia being the most relevant) by Pavía *et al.* (2006) when they analyzed the Spanish interregional commercial flows by means of an input-output scheme, computing the corresponding Rasmussen (1963) key sector identification methodology.

4. Final remarks and conclusions

In this paper, a MultiREG-SpVAR approach is developed to address the problem of investigating the spatio-temporal transmission of macroeconomic shocks across regional economies. In contrast to previous work in regional science, the approach allows the joint modeling of dynamic interdependencies of business cycles within a regional system, analyzing the spatial and temporal response of all regions to a temporary shock in a state variable of one specific region. A key feature of the multivariate specification is that it allows consideration of the cross-unit interdependencies and heterogeneity in the underlying dynamic process.

We illustrate the use of our approach in a study of the extent to which a Spanish region's economic output growth is influenced by the growth of its neighbors (push-in or inward growth effect); we also investigate the relevance of spillovers derived from temporary region specific output growth shocks (push-out or outward growth effect).

Overall, we find significant spatial dependence across Spanish regions. In particular, estimation results identify some regions that perform as 'growth generating' within the Spanish regional system because growth shocks from these regions spill over to a large number of regions of the country, playing a key role in transmitting regional business cycles. These regions are Andalusia, Aragón, Catalonia, Madrid, the Basque Country and the Valencian Community. The policy implications of our results suggest that national and/or regional governments should stimulate economic activity in these

leading regions in order to favor the economic recovery process of the whole Spanish economy.

In the future work, we will study how to extend our approach to quantify the relevance of different channels of transmission of spillovers, how to obtain sectoral data and so, sectoral results. Other pending tasks are the analysis of both the determinants of the size of growth spillovers and the sources of growth in the 'growth leaders'. From a technical point of view, it is an open question as to whether features of our approach could be extended to more complex dynamic panel data models (prior knowledge of some parameters; non-linear relationships; error correction, time varying or factor-augmented SpVARs, etc.).

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TABLES AND FIGURES

Table 1. Summary statistics of the database (year base 2003)

	<i>GVA</i> (share)	<i>E</i> (share)	<i>KPR</i> (share)	<i>KPU</i> (share)	<i>POP</i> (share)	<i>GVAp_c</i> (relative)
AND	13.8	15.0	13.6	14.9	17.9	77.2
ARA	3.1	3.2	3.5	4.4	2.9	106.4
AST	2.2	2.2	2.5	3.1	2.6	85.7
BAL	2.4	2.4	2.7	1.7	2.2	111.8
CAN	4.1	4.1	4.5	4.3	4.4	93.1
CANT	1.3	1.3	1.3	1.5	1.3	96.3
CAT	18.8	17.8	18.4	14.0	15.6	120.1
CLM	3.4	4.0	3.8	4.9	4.3	79.3
CYL	5.5	5.7	6.2	8.1	5.9	93.4
EXT	1.7	2.0	2.0	2.5	2.6	66.1
GAL	5.1	5.7	5.2	6.4	6.5	78.2
MAD	17.7	15.8	15.6	13.7	13.4	131.6
MUR	2.5	2.8	2.3	2.3	3.0	83.8
NAV	1.7	1.7	1.8	1.9	1.4	126.9
PV	6.2	5.5	6.4	6.0	5.0	124.2
RIO	0.8	0.8	0.8	0.9	0.7	111.2
VAL	9.7	10.3	9.4	9.3	10.3	94.0
SPAIN	100	100	100	100	100	100

SOURCE: Own elaboration from *BD.MORES* and *Fundación BBVA-Ivie* databases.

REGIONAL ABBREVIATIONS: Andalusia (AND), Aragón (ARA), Asturias (AST), Balearic Islands (BAL), Canary Islands (CAN), Cantabria (CANT), Catalonia (CAT), Castile-La Mancha (CLM), Castile and León (CYL), Extremadura (EXT), Galicia (GAL), Madrid (MAD), Murcia (MUR), Navarre (NAV), Basque Country (PV), La Rioja (RIO) and the Valencian Community (VAL).

Table 2. Spatial weights matrices used in the empirical application

a) Weights based on first-order contiguity geographical neighbors (W_{geog})

	AND	ARA	AST	BAL	CAN	CANT	CAT	CLM	CYL	EXT	GAL	MAD	MUR	NAV	PV	RIO	VAL
AND	0	0	0	0	0	0	0	0.33	0	0.33	0	0	0.33	0	0	0	0
ARA	0	0	0	0	0	0	0.17	0.17	0.17	0	0	0	0	0.17	0	0.17	0.17
AST	0	0	0	0	0	0.33	0	0	0.33	0	0.33	0	0	0	0	0	0
BAL	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CAN	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CANT	0	0	0.33	0	0	0	0	0	0.33	0	0	0	0	0	0.33	0	0
CAT	0	0.50	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.50
CLM	0.14	0.14	0	0	0	0	0	0	0.14	0.14	0	0.14	0.14	0	0	0	0.14
CYL	0	0.11	0.11	0	0	0.11	0	0.11	0	0.11	0.11	0.11	0	0	0.11	0.11	0
EXT	0.33	0	0	0	0	0	0	0.33	0.33	0	0	0	0	0	0	0	0
GAL	0	0	0.50	0	0	0	0	0	0.50	0	0	0	0	0	0	0	0
MAD	0	0	0	0	0	0	0	0.50	0.50	0	0	0	0	0	0	0	0
MUR	0.33	0	0	0	0	0	0	0.33	0	0	0	0	0	0	0	0	0.33
NAV	0	0.33	0	0	0	0	0	0	0	0	0	0	0	0	0.33	0.33	0
PV	0	0	0	0	0	0.25	0	0	0.25	0	0	0	0	0.25	0	0.25	0
RIO	0	0.25	0	0	0	0	0	0	0.25	0	0	0	0	0.25	0.25	0	0
VAL	0	0.25	0	0	0	0	0.25	0.25	0	0	0	0	0.25	0	0	0	0

b) Weights based on regional trade flows (W_{econ})

	AND	ARA	AST	BAL	CAN	CANT	CAT	CLM	CYL	EXT	GAL	MAD	MUR	NAV	PV	RIO	VAL
AND	0	0	0	0	0	0	0.33	0	0	0	0	0.33	0	0	0	0	0.33
ARA	0	0	0	0	0	0	0.33	0	0	0	0	0	0	0	0.33	0	0.33
AST	0	0	0	0	0	0	0	0	0.25	0	0.25	0.25	0	0	0.25	0	0
BAL	0.33	0	0	0	0	0	0.33	0	0	0	0	0	0	0	0	0	0.33
CAN	0.33	0	0	0	0	0	0.33	0	0	0	0	0.33	0	0	0	0	0
CANT	0	0	0	0	0	0	0.33	0	0.33	0	0	0	0	0	0.33	0	0
CAT	0.25	0.25	0	0	0	0	0	0	0	0	0	0.25	0	0	0	0	0.25
CLM	0.25	0	0	0	0	0	0.25	0	0	0	0	0.25	0	0	0	0	0.25
CYL	0	0	0	0	0	0	0.25	0	0	0	0.25	0.25	0	0	0.25	0	0
EXT	0.25	0	0	0	0	0	0	0.25	0.25	0	0	0.25	0	0	0	0	0
GAL	0	0	0.20	0	0	0	0.20	0	0.20	0	0	0.20	0	0	0.20	0	0
MAD	0.20	0	0	0	0	0	0.20	0.20	0.20	0	0	0	0	0	0	0	0.20
MUR	0.33	0	0	0	0	0	0.33	0	0	0	0	0	0	0	0	0	0.33
NAV	0	0.33	0	0	0	0	0.33	0	0	0	0	0	0	0	0.33	0	0
PV	0	0	0	0	0	0	0.25	0	0.25	0	0	0.25	0	0.25	0	0	0
RIO	0	0	0	0	0	0	0.25	0	0.25	0	0	0	0	0	0.25	0	0.25
VAL	0.25	0	0	0	0	0	0.25	0	0	0	0	0.25	0.25	0	0	0	0

NOTE: Regional abbreviations: Andalusia (AND), Aragón (ARA), Asturias (AST), Balearic Islands (BAL), Canary Islands (CAN), Cantabria (CANT), Catalonia (CAT), Castile-La Mancha (CLM), Castile and León (CYL), Extremadura (EXT), Galicia (GAL), Madrid (MAD), Murcia (MUR), Navarre (NAV), Basque Country (PV), La Rioja (RIO) and the Valencian Community (VAL).

Table 3. Information criterion for alternative specifications of the spatial weights matrix: AIC statistics for each regional SpVAR model

	Geographical weights matrix (W_{geog})	Economic weights matrix (W_{econ})
AND	511.45	516.45
ARA	489.27	494.28
AST	453.32	452.34
BAL	-	463.76
CAN	-	446.39
CANT	436.34	441.26
CAT	484.12	503.49
CLM	471.31	467.60
CYL	513.98	492.63
EXT	459.44	461.55
GAL	501.15	509.50
MAD	417.63	442.29
MUR	438.64	445.14
NAV	412.84	421.44
PV	462.22	467.88
RIO	389.99	370.13
VAL	503.84	518.20

NOTE: Regional abbreviations: Andalusia (AND), Aragón (ARA), Asturias (AST), Balearic Islands (BAL), Canary Islands (CAN), Cantabria (CANT), Catalonia (CAT), Castile-La Mancha (CLM), Castile and León (CYL), Extremadura (EXT), Galicia (GAL), Madrid (MAD), Murcia (MUR), Navarre (NAV), Basque Country (PV), La Rioja (RIO) and the Valencian Community (VAL).

Table 4: Correlation of real GVA growth rates (year-on-year) and filtered real GVA growth rates between Spain and regional economies, 1965-2003

	Real GVA growth rates				Filtered Real GVA growth rates			
	1965-1975	1976-1985	1986-1995	1996-2003	1965-1975	1976-1985	1986-1995	1996-2003
AND	0.97	0.98	0.94	0.72	0.97	0.98	0.99	0.78
ARA	0.95	0.95	0.97	0.13	0.90	0.93	0.99	0.69
AST	0.87	0.18	0.82	0.37	0.95	0.45	0.96	0.82
BAL	0.91	0.72	0.95	0.50	0.73	0.34	0.98	0.76
CAN	0.82	0.73	0.75	0.61	0.69	0.35	0.97	0.91
CANT	0.85	0.92	0.84	0.83	0.88	0.81	0.99	0.89
CAT	0.99	0.97	0.98	0.67	0.99	0.98	0.99	0.92
CLM	0.96	0.94	0.94	0.05	0.95	0.86	0.99	0.92
CYL	0.99	0.98	0.74	0.26	0.92	0.96	0.97	-0.05
EXT	0.96	0.81	0.79	0.57	0.96	0.68	0.99	0.71
GAL	0.99	0.94	0.87	0.72	0.99	0.84	0.99	0.75
MAD	0.93	0.89	0.98	0.88	0.90	0.96	0.99	0.97
MUR	0.96	0.88	0.93	0.77	0.96	0.77	0.99	0.95
NAV	0.89	0.83	0.90	0.74	0.93	0.69	0.96	0.95
PV	0.80	0.80	0.99	0.92	0.91	0.78	0.99	0.97
RIO	0.98	0.89	0.86	0.53	0.94	0.20	0.96	0.80
VAL	0.98	0.97	0.99	0.93	0.96	0.95	0.99	0.93

NOTE: Regional abbreviations: Andalusia (AND), Aragón (ARA), Asturias (AST), Balearic Islands (BAL), Canary Islands (CAN), Cantabria (CANT), Catalonia (CAT), Castile-La Mancha (CLM), Castile and León (CYL), Extremadura (EXT), Galicia (GAL), Madrid (MAD), Murcia (MUR), Navarre (NAV), Basque Country (PV), La Rioja (RIO) and the Valencian Community (VAL).

Table 5. SpVAR order of individual models

	p_i	q_i
AND	2	1
ARA	2	1
AST	2	1
BAL	2	1
CAN	1	1
CANT	2	1
CAT	2	1
CLM	2	1
CYL	2	1
EXT	2	1
GAL	2	1
MAD	1	1
MUR	2	1
NAV	2	1
PV	2	1
RIO	2	1
VAL	2	1

NOTE: 1) p_i : lag order of domestic variables; q_i : lag order of external variables. 2) Regional abbreviations: Andalusia (AND), Aragón (ARA), Asturias (AST), Balearic Islands (BAL), Canary Islands (CAN), Cantabria (CANT), Catalonia (CAT), Castile-La Mancha (CLM), Castile and León (CYL), Extremadura (EXT), Galicia (GAL), Madrid (MAD), Murcia (MUR), Navarre (NAV), Basque Country (PV), La Rioja (RIO) and the Valencian Community (VAL).

Table 6. Push-in spillovers effects: estimated contemporaneous responses of region-specific variables to a unitary shock to their external counterpart (by rows)

Region	y	e	kpr	kpu
AND	0.71 [*] [3.90]	0.82 [*] [3.45]	0.17 [*] [1.95]	0.22 [1.43]
ARA	0.72 [*] [2.35]	1.07 [*] [4.69]	0.42 [*] [2.61]	-0.02 [-0.15]
AST	1.08 [*] [5.06]	0.91 [*] [8.79]	0.38 [1.28]	0.65 [*] [4.49]
BAL	1.19 [*] [5.10]	1.40 [*] [3.43]	0.37 [*] [2.44]	0.74 [*] [4.79]
CAN	0.61 [*] [2.09]	1.08 [*] [4.43]	0.48 [*] [3.26]	0.63 [*] [5.58]
CANT	0.42 [1.30]	1.46 [*] [6.34]	0.73 [*] [3.40]	0.38 [*] [1.81]
CAT	1.03 [*] [5.94]	0.94 [*] [4.92]	0.70 [*] [4.30]	1.28 [*] [7.06]
CLM	0.81 [*] [2.25]	0.91 [*] [3.67]	0.07 [0.59]	0.78 [*] [6.78]
CYL	0.83 [*] [3.17]	0.81 [*] [3.66]	0.34 [1.59]	0.42 [*] [3.53]
EXT	1.46 [*] [5.29]	0.59 [*] [2.57]	0.69 [*] [4.60]	0.69 [*] [6.29]
GAL	0.70 [*] [3.57]	0.12 [0.94]	0.11 [0.94]	0.42 [*] [2.62]
MAD	0.52 [1.46]	1.21 [*] [5.59]	1.29 [*] [6.75]	0.92 [*] [4.16]
MUR	1.42 [*] [4.68]	0.46 [*] [1.76]	0.42 [*] [3.01]	0.42 [*] [2.23]
NAV	0.48 [*] [2.46]	1.45 [*] [6.89]	-0.05 [-0.59]	0.50 [1.50]
PV	0.86 [*] [2.65]	0.58 [*] [3.68]	0.44 [1.17]	0.60 [*] [3.45]
RIO	0.29 [0.96]	1.35 [*] [5.86]	0.52 [*] [2.13]	0.63 [1.05]
VAL	0.83 [*] [4.44]	0.43 [1.10]	0.93 [*] [11.41]	0.56 [*] [3.91]

NOTE: 1) t -ratios are reported in square brackets below the corresponding elasticities, calculated using autocorrelation and heteroscedasticity consistent Newey-West standard errors. 2) Superscript (*) denotes that the corresponding 90% percentile confidence interval does not include zero. 3) Regional abbreviations: Andalusia (AND), Aragón (ARA), Asturias (AST), Balearic Islands (BAL), Canary Islands (CAN), Cantabria (CANT), Catalonia (CAT), Castile-La Mancha (CLM), Castile and León (CYL), Extremadura (EXT), Galicia (GAL), Madrid (MAD), Murcia (MUR), Navarre (NAV), Basque Country (PV), La Rioja (RIO) and the Valencian Community (VAL).

Table 7. Push-out spillover effects: estimated bilateral responses of output to a unitary shock to GVA in each region of Spain (by rows)

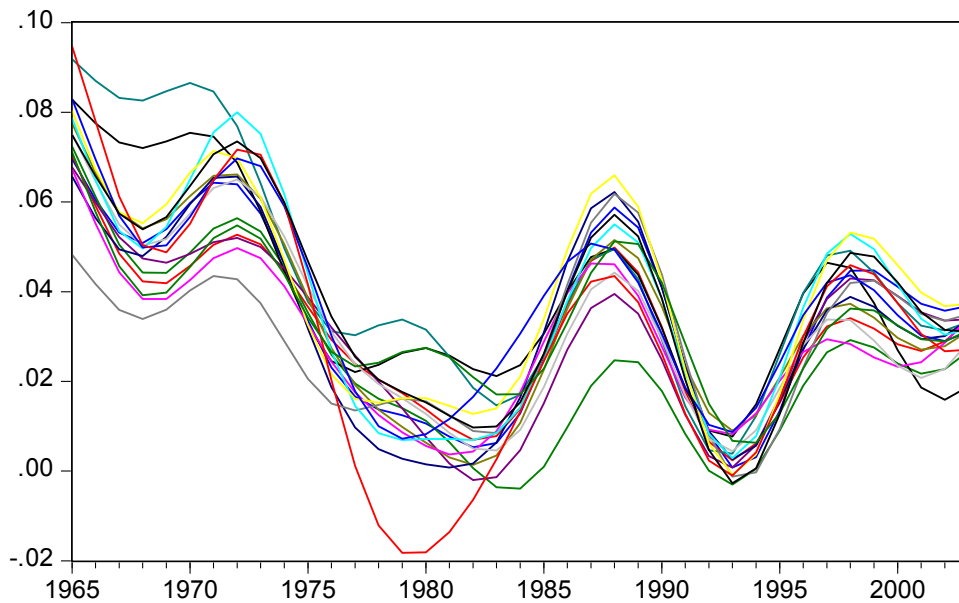
Response (%) in:	AND		ARA		AST		BAL		CAN		CANT		CAT		CLM		CYL		EXT		GAL		MAD		MUR		NAV		PV		RIO		VAL		
	0	3	0	3	0	3	0	3	0	3	0	3	0	3	0	3	0	3	0	3	0	3	0	3	0	3	0	3	0	3	0	3			
After (years)																																			
AND	0.65*	0.35	0.30*	0.04	0.21	0.12	0.62*	0.53	-0.17	-0.39	-0.12	-0.46	-0.05	-0.40	0.62*	0.09	0.31*	0.17	0.31*	0.22	-0.13	-0.17	-0.15	-0.52	0.39	-0.08	0.06	-0.38	0.11	-0.16	0.27*	0.15	0.22	-0.16	
ARA	0.21	-0.02	0.83*	0.64	0.26*	0.15	0.07	-0.25	0.18	0.03	0.30*	0.34	0.31*	0.02	0.25	0.03	0.42*	0.18	0.42*	0.16	0.16*	0.12	-0.05	-0.22	0.33	0.01	-0.14	-0.23	-0.25	-0.41	0.03	0.11	0.00	-0.09	
AST	0.00	0.11	0.11	0.07	0.89*	0.82*	0.25	0.47	-0.43	-0.42	0.04	-0.20	-0.23	-0.21	0.33	0.29	0.22*	0.23	0.27	0.08	-0.08	0.00	-0.24	-0.26	-0.16	-0.09	-0.32	-0.35	0.14	0.16	0.16	0.04	-0.26	-0.35	
BAL	0.03	-0.32	-0.13	-0.57	0.32*	-0.11	0.98*	0.85*	-0.13	-0.51	-0.08	-0.72	-0.41	-0.88	0.20	-0.50	0.10	-0.17	0.27	-0.47	0.10	-0.35	-0.39	-1.02	-0.38	-0.83	-0.14	-0.79	0.13	-0.43	0.35*	-0.05	0.03	-0.64	
CAN	0.00	-0.06	0.09	0.13	-0.15	-0.12	0.08	-0.08	1.42*	1.53*	0.34*	0.59	0.09	0.10	-0.14	-0.10	-0.11	-0.17	-0.01	-0.13	0.28*	0.25	0.18	0.28	0.28	0.28	0.12	0.21	-0.08	-0.09	-0.01	0.13	0.20	0.30	
CANT	-0.05	0.25	0.21	0.44	0.09	0.27	0.08	0.27	0.47*	0.83	0.90*	1.36*	0.19	0.56	-0.10	0.39	-0.14	0.05	0.07	0.07	0.32*	0.49	-0.10	0.30	-0.12	0.26	0.13	0.54	-0.11	0.37	0.28*	0.48*	0.11	0.48	
CAT	-0.08	0.01	0.25*	0.42	0.02	0.10	-0.27	-0.50	0.20	0.37	0.38*	0.82*	0.71*	0.92	-0.09	0.23	0.07	0.13	0.05	0.27	0.21*	0.37	0.33*	0.63	0.24	0.44	0.31*	0.54	0.17	0.31	-0.28	-0.03	-0.04	0.35	
CLM	0.06	-0.27	0.09	-0.26	0.58*	0.18	0.40*	0.29	-0.30	-0.62	0.00	-0.54	-0.26	-0.70	0.99*	0.22	0.39*	0.10	0.48*	0.04	0.14	-0.22	-0.36	-0.82	-0.35	-0.71	-0.03	-0.55	0.25	-0.20	0.18	-0.08	-0.05	-0.52	
CYL	0.22	-0.03	0.34*	0.07	0.39*	0.10	0.22	0.16	-0.22	-0.51	-0.17	-0.58	-0.01	-0.32	0.51*	0.13	0.84*	0.53*	0.44*	0.29	0.10	-0.06	-0.16	-0.51	0.07	-0.28	-0.25	-0.60	-0.07	-0.44	-0.14	-0.31	-0.07	-0.40	
EXT	0.00	-0.20	-0.13	-0.25	0.05	-0.14	0.04	-0.09	-0.08	-0.27	-0.14	-0.24	-0.13	-0.39	0.05	-0.27	-0.09	-0.22	0.94*	0.63*	-0.17	-0.32	-0.12	-0.33	0.39	0.06	-0.16	-0.33	-0.17	-0.40	-0.04	-0.15	-0.03	-0.22	
GAL	-0.09	0.07	0.05	0.19	-0.17	-0.12	0.04	0.11	0.48*	0.68	0.32*	0.52	0.09	0.27	-0.03	0.30	0.03	0.02	-0.04	-0.25	0.66*	0.58*	-0.05	0.16	-0.28	-0.04	0.26	0.41	-0.27	-0.06	0.22	0.35	0.19	0.41	
MAD	0.38*	0.68	0.30*	0.74	0.20	0.68	0.07	-0.01	0.75*	1.41*	0.20	1.02*	0.75*	1.24*	0.09	0.62	0.03	0.30	-0.07	0.41	0.19	0.79*	1.31*	2.03*	1.05*	1.32*	0.71*	1.18*	0.98*	1.40*	-0.10	0.32	0.51*	1.21*	
MUR	0.11	0.08	0.08	0.09	-0.01	0.06	-0.20	-0.31	0.29	0.26	-0.18	-0.08	0.12	0.13	-0.12	-0.07	-0.07	-0.05	0.30*	0.48	-0.34	-0.24	0.26	0.31	1.04*	0.82	-0.06	0.03	0.06	-0.09	-0.37	-0.33	-0.03	0.00	
NAV	-0.03	-0.15	-0.28	-0.38	-0.06	-0.21	0.23	0.17	0.11	0.01	0.23*	0.15	-0.04	-0.21	0.26	0.07	-0.19	-0.23	-0.01	-0.02	0.26*	0.05	-0.09	-0.25	-0.20	-0.29	0.67*	0.32	0.08	-0.05	0.17	0.05	0.33*	0.18	
PV	0.18	0.06	0.01	-0.23	0.57*	0.38	0.49*	0.58	-0.07	-0.14	-0.03	-0.39	0.02	-0.19	0.42*	0.13	0.15	0.09	0.09	-0.10	0.08	0.02	0.33*	0.11	0.16	-0.15	0.21	-0.17	1.13*	0.81	0.29*	0.07	0.13	-0.19	
RIO	0.01	0.04	-0.05	-0.04	0.15	0.14	0.33	0.55	-0.11	-0.01	0.21*	0.10	-0.30	-0.27	0.06	-0.02	-0.17	-0.13	-0.13	-0.47	0.14	0.09	-0.29	-0.28	-0.49	-0.39	-0.01	-0.04	0.06	0.20	1.00*	1.04*	0.03	0.02	
VAL	0.32*	0.68	-0.01	0.23	-0.02	0.26	0.61*	0.91*	0.15	0.56	0.20*	0.41	0.00	0.45	0.42*	0.75	0.01	0.17	0.17	0.27	0.30*	0.45	0.02	0.37	0.07	0.43	0.53*	0.70	0.16	0.58	0.42*	0.52	0.70*	0.97*	

NOTE: Numbers reported are median estimates of responses of regional GVA to one standard error positive shock to GVA in the row region. Superscript (*) denotes that the corresponding 90% percentile confidence interval does not include zero. Numbers in black indicate statistically significant effects at the 90% confidence level.

Figure 1: Spanish regions



Figure 2: Regional cycles (band-pass filtered)



NOTE: Regional abbreviations: Andalusia (AND), Aragón (ARA), Asturias (AST), Balearic Islands (BAL), Canary Islands (CAN), Cantabria (CANT), Catalonia (CAT), Castile-La Mancha (CLM), Castile and León (CYL), Extremadura (EXT), Galicia (GAL), Madrid (MAD), Murcia (MUR), Navarre (NAV), Basque Country (PV), La Rioja (RIO) and the Valencian Community (VAL).