Measure of the resilience to Spanish economic crisis: the role of specialization

Autores y e-mail de la persona de contacto: Ana Angulo (aangulo@unizar.es), Jesús Mur, Javier Trívez

Departamento: Departamento de Análisis Económico

Universidad: Universidad de Zaragoza

Área Temática: *Econometría Espacial y métodos del análisis regional*

Resumen: *Forecasting regional variables provides very important information for political, institutional and economic agents. In this paper, we use predictions from spatial panel data models to evaluate regional resilience to the present economic crisis in term of annual growth rate of employment. Furthermore, we evaluate whether specialization plays a significant role in the degree of resilience to the economic crisis suffered in Spain from 2007. Results show that while specialization on construction and non-market services declines resilience to the crisis, specialization on energy and manufacturing or distribution, transport and common services enlarges the availability of returning to his pre-shock growth path.*

Palabras Clave: *Forecasting regional data, resilience to the Spanish economic crisis, role of specialization, spatial panel data model.*

Clasificación JEL: C21; C22; C23; C53; R15.

1. Introduction

The field of panel data models has received considerable attention during the last decade. Panel data literature offers the opportunity of allowing for unobservable cross-sectional and time-period specific effects. Other advantages of panel data are that they are generally more informative and contain more variation and less collinearity between variables. The use of panel data leads to a greater availability of degrees of freedom and, hence, increases the efficiency of the estimation. Panel data also allow for the specification of more complicated behavioural hypotheses, including effects that cannot be addressed using pure cross-sectional or time-series data (Wooldridge, 2002; Arellano, 2003; Hsiao, 2003; Baltagi, 2005).

When cross-sectional data refers to spatial units (municipalities, provinces, regions or countries) the spatial dependence between cross-sectional units at each point in time is also important. Spatial dependence implies that, due to spillover effects (e.g., commuter labour and trade flows), neighbouring regions may have similar economic performance. Hence, we expect to improve traditional panel data models by paying attention to the location of the spatial units. There has been growing interest in the estimation of panel data models with spatial dependence: see Kelejian and Prucha (2002), Elhorst (2003, 2010), Yang et al. (2006), Baltagi et al. (2006), Kapoor et al. (2007), Kelejian et al. (2006) or Pesaran (2006). Prediction with these types of models is analysed in Baltagi and Li (2004, 2006) for predicting per-capita cigarette and liquor consumption in the United States, respectively, in Longhi and Nijkamp (2007) for forecasting the regional labour market in West German regions, while Baltagi et al. (2012) make performance comparison of different spatial panel data models.

Since there is a consensus on the good performance of spatial panel data model for forecasting purpose, the main purpose of this paper is to use forecasts from a spatial panel data model to evaluate the impact of the actual economic crisis on annual growth rate of employment in Spain, following work by Fingleton and Palombi (2013). Since the economic crisis started in Spain at the end of 2007, firstly, we estimate and check several panel data models estimated for the period 1980-2006. Secondly, estimation results are used to forecast the annual growth rate of employment by Spanish provinces for the period 2007-2010. The predicted values for each region and time represent the counterfactual (or projected) annual growth rate of employment expected in absent of the economic crisis. That is, forecast values purge of the effect of crisis. Finally, we compare forecast values with actual one as a measure of the crisis effects on annual growth rate of employment. Three cases can be distinguished: i) a negative difference (actual values below its counterfactual) suggests that lack of resilience or region's failure to recover from the shock; ii) a small or zero difference (actual values similar its counterfactual) suggests (long-run) regional resilience, since the region is able to return to his pre-shock growth path; and iii) a positive difference would indicate super-resilience since the region is able to more than rebound.

Since the economic crisis has not equally affected to all economic sectors, our conclusions will refer to the performance of the different specialised regions distinguishing the following sectors: i) agriculture; ii) energy and manufacturing; iii) construction; iv) distribution, transport and common services; v) finance and other services; and vi) non-market services. We measure the degree of specialization through the localization quotient.

The structure of the present paper is as follows. In Section 2, we provide a description of the spatial panel data model we consider in our application. Section 3 is devoted to the presentation of the data. In Section 4, we present the main estimation results. Finally, the paper finishes with a section of concluding remarks.

2. Methods

Our base model is the pool data model, assuming a Keynesian approach of economy performance as well as an econometric strategy from the specific to general:

$$y_t = x_t\beta + \varepsilon_t \qquad t = 1,\dots,T$$

$$y_t = \begin{bmatrix} y_{1t} \\ y_{2t} \\ \vdots \\ y_{Rt} \end{bmatrix}; x_t = \begin{bmatrix} 1 & x_{1,1t} & \vdots & x_{k,1t} \\ 1 & x_{1,2t} & \vdots & x_{k,2t} \\ \vdots & \vdots & \vdots & \vdots \\ 1 & x_{1,Rt} & \vdots & x_{k,Rt} \end{bmatrix}; \varepsilon_t = \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \\ \vdots \\ \varepsilon_{Rt} \end{bmatrix} \tag{1}$$

where y_t is the annual growth rate of employment at time t in all regions (r=1,…,R); x_t represent the matrix of explanatory variables in t, which included the growth rate of gross value added and a set of dummy variables referred to whether or not region r is specialised in an specific sector in period t; β represent a (kx1) vector of parameters to be estimated.

Next, the pool model (1) is extended by the consideration of the vector $\mu = \left[\mu_1, \mu_2, ..., \mu_R\right]'$ that captures the individual heterogeneity or, in other terms, controls for the effects of omitted variables, as follows:

$$y_t = x_t\beta + \mu + \varepsilon_t \qquad \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \\ \vdots \\ \mu_R \end{bmatrix}; \quad t = 1, 2, \ldots T \tag{2}$$

The individual heterogeneity μ can be considered a fixed vector of parameters to be estimated or a random vector with a normal distribution, $\mu \sim N\left[0, \sigma_\mu^2 I_R\right]$. In the first case, we obtain the so-called fixed effects model while the second is the random effects model. Finally, ε_t is a (Rx1) vector of random terms.

Discussion about random or fixed effects models appears routinely in all panel estimations (Hsiao, 2003). The key issue in this selection concern whether or not the omitted variables (represented with μ) are correlated with the explanatory variables included in the model (x_t). As it is well-known, if this is the case, the fixed effects models are consistent, since they provide a means for controlling for omitted variable bias, while the random effect estimators are inconsistent. Due to this fact, in or case, we propose the Fixed Effect (FE) model as the most compelling specification since we assume that the omitted variables in our model are probably correlated with the included ones. Furthermore, as Elhorst (2003) indicates, in the context of a spatial data set, the FE model is compelling because the spatial units of observation are neither representative of a larger population nor are potentially able to go to infinity in a regular fashion. Nevertheless, the Hausman (1978) test will also be applied to confirm our decision.

Next, in order to include the spatial dependence, the start with the so-called FE-SLX model which is expressed as follows:

$$y_t = x_t\beta + Wx_t\theta + \mu + \varepsilon_t \quad (3)$$

Where the weights matrix, *W*, is a square R by R matrix for R regions with cell values denoting the strength of interregional interaction, and zeros on the main diagonal. Furthermore, the following spatial panel data models could also adjust properly our data:

- The FE-General nesting model (GM): $\begin{array}{l} y_t = \rho W y_t + x_t\beta + Wx_t\theta + \mu + u_t \\ u_t = \lambda W u_t + \varepsilon_t \end{array}$ (4)

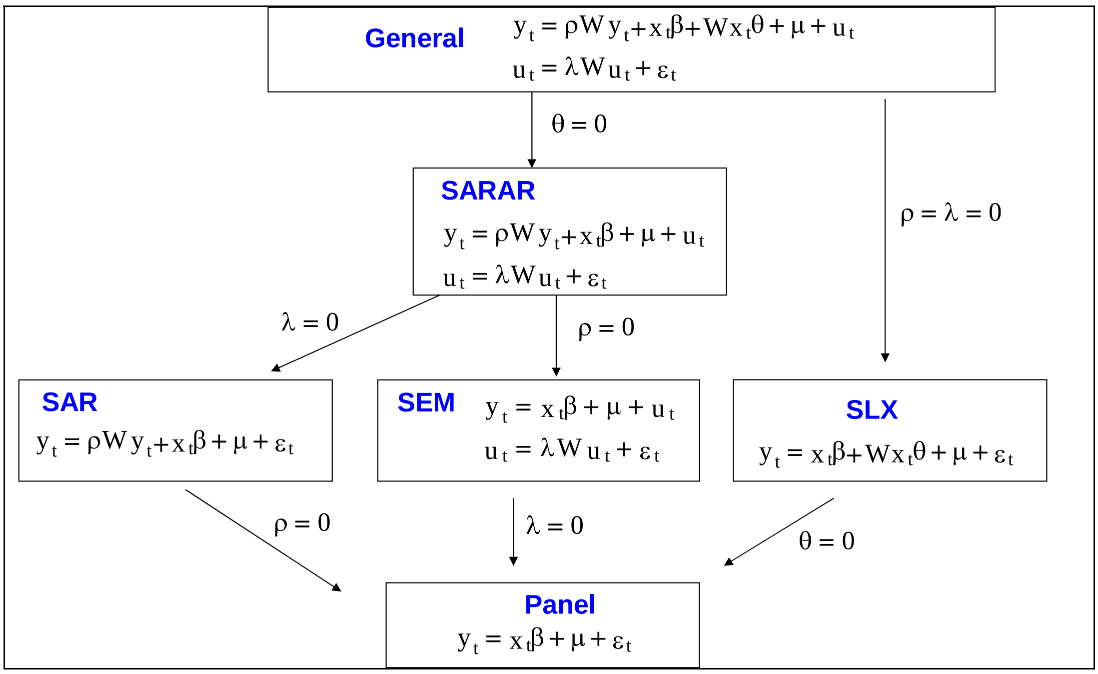
- The FE-SARAR model: $\begin{array}{l} y_t = \rho W y_t + x_t\beta + \mu + u_t \\ u_t = \lambda W u_t + \varepsilon_t \end{array}$ (5)

- The FE-SAR model: $y_t = \rho W y_t + x_t\beta + \mu + \varepsilon_t$ (6)

- The FE-SEM model: $\begin{array}{l} y_t = x_t\beta + \mu + u_t \\ u_t = \lambda W u_t + \varepsilon_t \end{array}$ (7)

The nesting structure among previous panel data models is shown in Figure 1.

Figure 1. The nesting structure among the proposed spatial panel data models



To cope with our objective, we proceed as follows:

i) First, we estimate alternative models for the period 1980-2006, and we select the specification that better adjusts our data.

ii) Secondly, estimation results are used to forecast the annual growth rate of employment by provinces for the period 2007-2010. The obtained forecasts are considered the counterfactual (or projected) annual growth rate of employment in absence of the economic crisis.

iii) Finally, we compare forecast values with actual one as a measure of impact of the crisis.

Regarding forecasting, the best linear unbiased predictor (BLUP) for the R cross-sectional units in a period T+C is defined as follows:

- For the FE-General nesting model (GM):

$$y_{T+C}=\left(I_R-\hat{\rho}_{FE-GM}W\right)^{-1}\left(x_{T+C}\hat{\beta}_{FE-GM}+Wx_{T+C}\hat{\theta}_{FE-GM}+\hat{\mu}_{FE-GM}\right) \tag{8}$$

- For the FE-SARAR model:

$$y_{T+C}=\left(I_R-\hat{\rho}_{FE-SARAR}W\right)^{-1}\left(x_{T+C}\hat{\beta}_{FE-SARAR}+\hat{\mu}_{FE-SARAR}\right) \tag{9}$$

- For the FE-SAR model:

$$y_{T+C}=\left(I_R-\hat{\rho}_{FE-SAR}W\right)^{-1}\left(x_{T+C}\hat{\beta}_{FE-SAR}+\hat{\mu}_{FE-SAR}\right) \tag{10}$$

- The FE-SEM model:

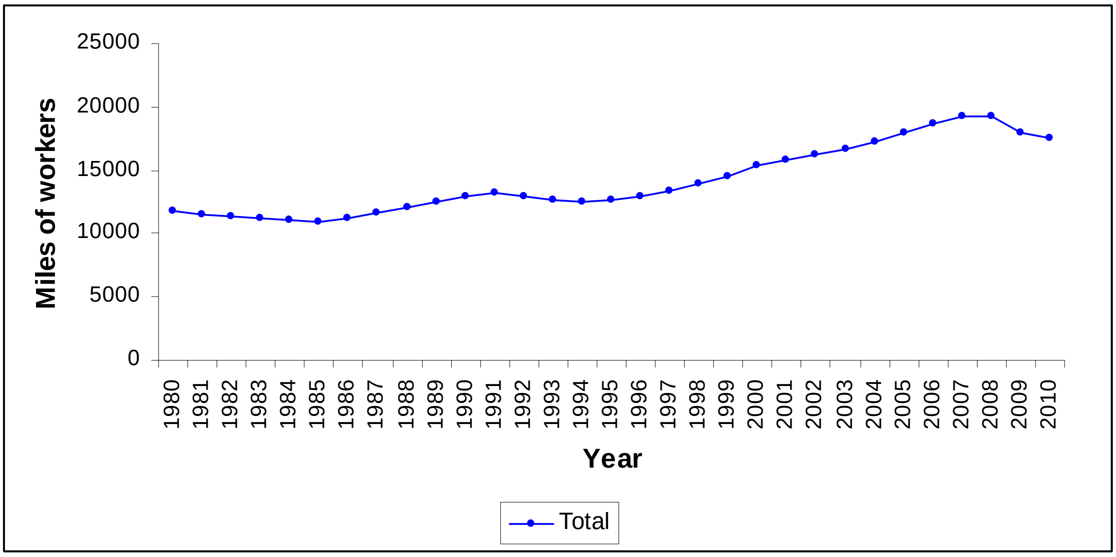
$$y_{T+C}=\left(x_{T+C}\hat{\beta}_{FE-SEM}+\hat{\mu}_{FE-SEM}\right) \tag{11}$$

3. Data

In the application that follows, we use data on total employment of 47 Spanish regions (NUTS III administrative spatial unit in terms of Eurostat). As said before, annual growth rate of employment will be explained by annual growth rate of gross value added. The model also included six dummies variables, which capture the effect on employment growth rate of regional specialization on the following sectors: i) agriculture; ii) energy and manufacturing; iii) construction; iv) distribution, transport and common services; v) finance and other services; and vi) non-market services. The data for all the variables are gathered, for the period 1980 to 2010, from the Cambridge Database.

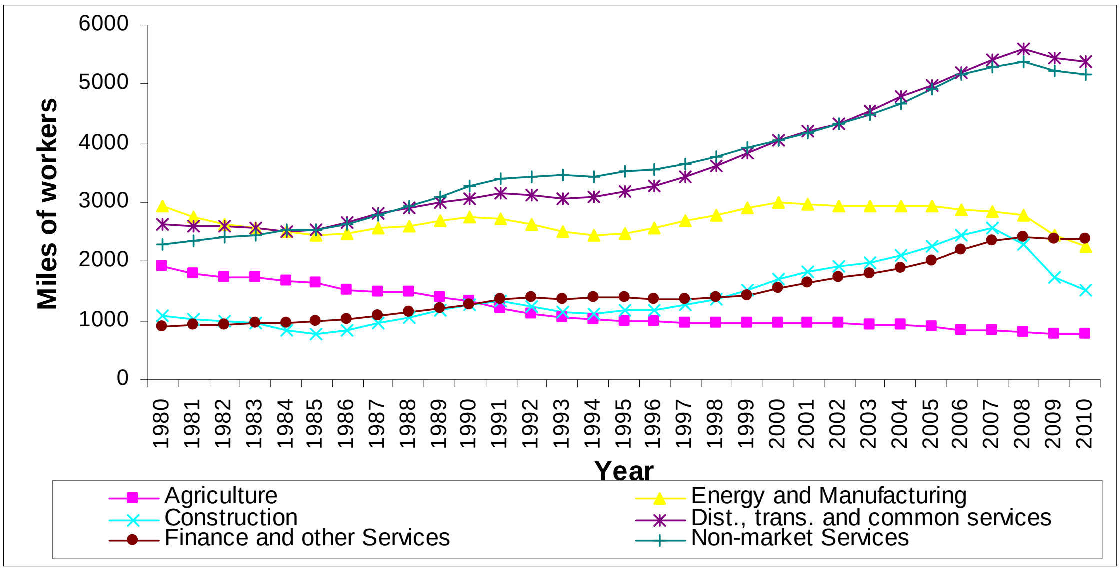
Firstly, we show the evolution of total employment along the analysed period (Figure 2). As observed in the graph, there is a clear decrease in employment around years 2007 and 2008 due to the important Spanish economic crisis.

Figure 2. Evolution of total employment in Spain



If we pay attention to the evolution of employment by the different economic activity sectors (Figure 3) we observe similar pattern. However, important differences seem to exist among sectors. For instance, in the finance and other services sector the level of employment in such years has even increased, while a strong decrease takes place in the cases of construction, energy and manufacturing or non-market services.

Figure 3. Evolution of employment in the different economic sectors in Spain



As indicated before, we want to analyse the role of specialization on employment growth rate. To cope with this objective, we calculate the localization quotient for region *r* and sector *i* in period t, $QL_{ir,t}$, as follows:

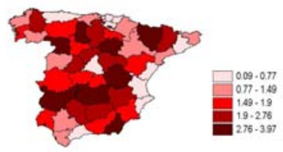
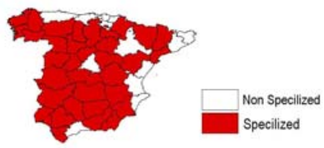
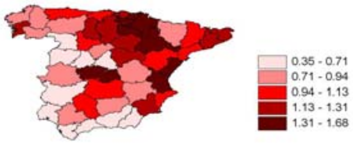
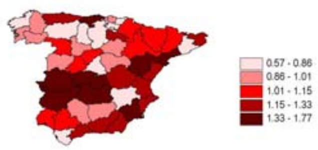
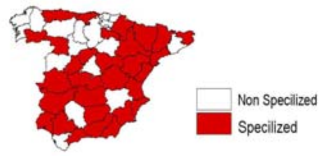
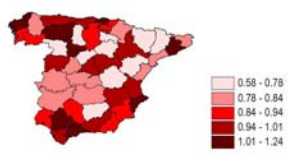
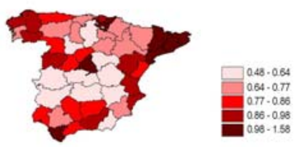
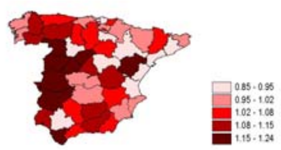
$$QL_{ir,t} = \frac{E^{r}_{i,t} \big/ E^{r}_{\bullet,t}}{E^{\bullet}_{i,t} \big/ E^{\bullet}_{\bullet,t}} \qquad (12)$$

where $E^{\bullet}_{i,t}$ measures the number of employees in sector *i* in period t; $E^{\bullet}_{\bullet,t}$, the total number of employees in Spain (the 47 regions as a whole) in period t; $E^{r}_{i,t}$, the number of employees in sector *i* and region *r* in period t; and $E^{r}_{\bullet,t}$, the total number of employees in region *r* in period t.

The localization quotient is a relative measure as it measures the regional share of workers in a specific sector relative to the national share of workers in that sector. If the localization quotient is larger than one the interpretation is that the sector has a larger share of the employees in a region than the country as a whole, implying that the region is more specialized than average in such specific sector.

The localization quotients are calculated along the considered period 1980-2010. From them, we have generated the corresponding dummy variables *Dsp_i*, that take a value of one if the corresponding region is specialized in sector *i* (its localization quotient has a value greater than one), (i= agriculture; energy and manufacturing; construction; distribution, transport and common services; finance and other services; and non-market services. An example on the information generated is shown in Figure 4.

Figure 4. Location quotes by economic sectors in 2010. Specialized regions in the different economic sector in 2010.

Agriculture 2010	Specialized agriculture 2010
	
Energy and M. 2010	Specialized Energy and M 2010
	
Construction 2010	Specialized Construction 2010
	
Dist., trans, c. S. 2010	Specialized Dist., t., c. S. 2010
	
Finance and o. Services 2010	Specialized Finance and o.S 2010
	
Non- market services, 2010	Specialized Non market s. 2010
	

4. Results

We start by estimating the pool panel data model expressed in (1). Results are shown in the first column of Table 1. Next, we estimate the assumed Fixed Effect (FE) model (second column). The Hausman test confirms that this model outperforms the random effect one.

Next, we enlarge model to take into account the spatial nature of the data through the estimation of the FE-SLX model (third column of the table), which is estimated defining the spatial weight matrix (W) as the row-normalization of the four-nearest neighbor binary matrix. However, specification tests do not support this model, since the null of no spatial autocorrelation in the form of SAR or SEM structure is rejected by the data. Consequently, at this stage, we estimate the general nesting model defined in (4), which nests the FE-SARAR model, which also nest all the other mentioned ones: FE-SAR, FE-SEM and FE-SLX. Results for the corresponding Likelihood Ratio (LR) tests indicate that the FE-SARAR specification is the one that better adjust our data.

Table 1. Estimated parameters for alternative models and specification tests (1980-2006)

Dependent Variable: Δ ln (total employment)					
	Pool (OLS)	**Fixed-Effect (FE)**	**FE- SLX**	**FE-General Nesting (GM)**	**FE-SARAR**
Constant	-0.003 (-0.69)	-0.002 (-0.43)	-0.006 (-1.17)		
Δ Ln (gross value added)	0.553* (18.62)	0.527* (17.51)	0.457* (14.41)	0.333* (10.81)	0.333* (10.87)
W Δ Ln (gross value added)			0.294* (6.14)	-0.009 (-0.19)	
Dsp_agriculture	-0.007* (-2.52)	0.003 (0.50)	0.001 (0.17)	-0.003 (0.71)	-0.003 (0.71)
Dsp_ Energy and Manufact.	0.006* (2.42)	0.001 (0.12)	-0.001 (-0.13)	-0.003 (-0.75)	-0.003 (-0.75)
Dsp_ Construction	0.006* (3.12)	0.006* (2.58)	0.006* (2.61)	0.005* (2.93)	0.005* (2.95)
Dsp_ Dist., trans, c. services	-0.005* (-2.13)	-0.012* (-3.81)	-0.012* (-3.90)	-0.009* (-3.93)	-0.009* (-3.93)
Dsp_Finance and o. services	-0.002 (-0.54)	-0.017* (-2.96)	-0.015* (-2.58)	-0.009* (-2.00)	-0.009* (-2.01)
Dsp_Non-market services	0.008 (3.72)	0.009* (3.13)	0.007* (2.65)	0.005* (2.37)	0.005* (2.37)
$\hat{\rho}$				0.603* (16.83)	0.602* (16.83)
$\hat{\lambda}$				-0.659 (-6.66)	-0.659 (-6.65)
$\hat{\sigma}$	0.034	0.034	0.033	0.031	0.029
Testing for panel specification					
Hausman Test H_0: Random Effect (RE) H_0: Fixed Effect (FE)		39.01*			
Testing for spatial panel autocorrelation					
LM test no spatial lag			87.01*		
Robust LM test no spatial lag			22.70*		
LM test no spatial error			71.08*		
Robust LM test no spatial error			6.77*		
Testing for spatial panel specification					
F test, General Model vs. SARAR H_0: SARAR; H_1: GM				0.04	
LR test, SARAR vs. SEM H_0: SEM; H_1: SARAR					63.42*
LR test, SARAR vs. SLM H_0: SLM; H_1: SARAR					34.63*

(a) T-ratios in parenthesis

From the selected FE-SARAR model, we calculate the effects of explicative variables on annual growth rate of employment, distinguishing between direct and indirect effects. Results are gathered in Table 2. As shown in the table, a 1% annual growth rate in value added in a region provokes an annual growth rate in employment of 0.382% in the same region, but also a 0.458% in the neighboring regions. Hence, total effect accounts for 0.84%. Regarding significant effect of specialization, table 2 shows that those regions specialized in construction present an annual growth rate of own-employment of, approximately, 0.6% higher than the non-specialized ones; moreover, if we also consider the indirect effect of 0.8%, the total effect reaches a 1.4%. That is, a region specialized in construction generates an annual growth rate of employment of 1.4% higher than the non-construction specialized regions in the estimation period (pre-crisis). Similarly, a region specialized in non-market services generates an annual growth of employment of, 1.3% higher than the non-specialized regions. On the contrary, a region specialized in distribution, transport and communications or finance and other services presents an annual growth of employment of, approximately, 2.0% lower than the non-specialized regions.

Table 2. Effects of explicative variables on employment growth from the FE-SARAR model.

	Direct Effects	**Indirect Effects**	**Total Effects**
Δ Ln (gross value added)	0.382* (15.18)	0.458* (10.96)	0.840* (16.15)
Dsp_agriculture	-0.003 (-0.57)	-0.004 (-0.56)	-0.007 (-0.56)
Dsp_ Energy and manufacturing	-0.003 (-0.65)	-0.003 (-0.64)	-0.006 (-0.65)
Dsp_ Construction	0.006* (3.07)	0.008* (2.86)	0.014* (2.99)
Dsp_ Dist., trans, common services	-0.010* (-3.9)	-0.012* (-3.59)	-0.022* (-3.8)
Dsp_Finance and other services	-0.009 (-1.77)	-0.011 (-1.74)	-0.020 (-1.76)
Dsp_Non-market services	0.006* (2.27)	0.007* (2.24)	0.013* (2.27)

Next, estimation results are used to forecast the annual growth rate of employment by provinces for the period 2007-2010. However, as our main objective is to obtain the employment growth rate purging of the effect of crisis, we derive the future values of explicative variables as a seven-year moving average method in order to smooth the original data obtaining series that approximate the long term underlying trend, as in Fingleton and Palombi (2013). The predicted values for each region and time represent the counterfactual (or projected) employment growth rates in absence of the economic crisis.

Finally, we compare actual values with forecast one as a measure of crisis effects; that is, we calculate the forecast error for each region and time. Three cases can be distinguished: i) a negative difference (actual values below its counterfactual) suggests a lack of resilience or failure to recover from the shock; ii) a small or zero difference (actual values similar its counterfactual) suggests (long-run) resilience, since the economy is able to return to his pre-shock growth path; and iii) a positive difference would indicate super-resilience since the economy is able to more than rebound.

Table 3 shows the mean forecast error for the post-crisis period (2007-2010) for all the regions which, as expected, is negative (-0.0213) and significant. Hence, on average, there is a lack of resilience or failure to recover from the shock.

Table 3. Mean forecast error from FE-SARAR model in post-estimation sample (post-crisis: 2007-2009).

Mean forecast error by FE-SARAR model, Post-crisis: 2007-2010	
ALL REGIONS	-0.0213
H_0: E[Mean forecast error]=0	8.8166*

Finally, to cope with our objective, we disaggregate results by specialization in order to capture possible differences in sectorial resilience to the economic crisis suffered in Spain. Results are gathered in Table 4. As previously, for comparison purpose, we include mean forecast error in different time periods: pre-crisis period (first column), post-crisis period (second column) and last year (2010). Furthermore, we disaggregate results by sectors, distinguishing within sectors, between specialized and non-specialized regions. Finally, in each case, a test of non-significant differences is carried out.

Table 4. Differences in forecast error by specialization.

	Mean forecast error in pre-crisis (1980-2006)	Mean forecast error in post-crisis (2007-2010)	Forecast error in 2010
Agriculture			
Non-Specialized	-0.0004	-0.0222	-0.0241
Specialized	0.0002	-0.0208	-0.0236
Differences	-0.0006	-0.0013	-0.0005
H_0: Differences=0	-0.2791	-0.3231	-0.1545
Energy and manufacturing			
Non-Specialized	0.0000	-0.0249	-0.0281
Specialized	-0.0000	-0.0178	-0.0192
Differences	0.0000	-0.0070	-0.0090
H_0: Differences=0	0.016	-2.040*	-3.3841*
Construction			
Non-Specialized	0.0003	-0.0150	-0.0171
Specialized	-0.0003	-0.0242	-0.0275
Differences	0.0006	0.0092	0.0105
H_0: Differences=0	0.3408	2.502*	3.9147*
Distribution, transport and common services			
Non-Specialized	0.0001	-0.0234	-0.0254
Specialized	-0.0002	-0.0136	-0.0174
Differences	0.0003	-0.0098	-0.0080
H_0: Differences=0	0.1586	-2.3929*	-2.3443*
Finance and other services			
Non-Specialized	0.0000	-0.0205	-0.0235
Specialized	-0.0001	-0.0253	-0.0247
Differences	0.0002	0.0048	0.0012
H_0: Differences=0	0.0673	0.9564	0.3070
Non- market services			
Non-Specialized	0.0002	-0.0173	-0.0180
Specialized	-0.0003	-0.0238	-0.0273
Differences	0.0005	0.0066	0.0093
H_0: Differences=0	0.2479	1.8646	3.3960*

As expected, mean forecast error in pre-crisis period (residuals) are homogeneous among regions which, in other terms, it is supporting our selected model. However, this is not the case for the post-crisis or last period (second and third column, respectively). These results indicate that specialization makes some differences in resilience to the economic crisis suffered in Spain.

As shown in the table, specialization in agriculture or finance and other services sectors does not make a significant difference in the degree of resilience to the crisis, although, as in general, the crisis has reduced the employment growth of the sectors. On the contrary, the specialization in construction or non-market services makes a significant difference in economic resilience, since the specialisation in these sectors has provoked stronger shocks. In other words, regions specialised in those sectors specially fails to recover from the crisis shock. Finally, specialisation in energy and manufacturing sector, on one hand, or in distribution, transport and common services, on the other, also makes a significant difference as regards resilience. However, in these cases, specialization has reduced the impact of crisis or, in other word, has made easier the recovery from the crisis.

5. Concluding remarks and references

Econometric literature clearly accepts the good performance of panel data models, in general, and spatial panel data models, in particular, for capturing the unobservable heterogeneity of data. Obtained results can be used for analyzing or predicting an economic variable. In this paper, we show the potential of these models as a measure of the effect of Spanish economic crisis on employment growth rate. Moreover, we focus on the role of specialization on the economic reliance to the crisis. A FE-SARAR spatial panel model is selected as the best specification for explaining the annual growth of employment rate in Spain for the period 1980-2006. Forecasts have been generated for the period 2007-2010, representing the counterfactual (or projected) employment growth rates in absence of the economic crisis. Finally, we compare actual values with forecast one as a measure of the crisis effects.

Main results are the following. Firstly, as expected, the economic crisis provokes a significant decrease in employment growth rate in all the sectors. However, specialisation makes a difference in the regional resilience. While specialization in construction or in non-market services declines resilience to the crisis, specialization in energy and manufacturing or in distribution, transport and common services enlarges availability of returning to the pre-shock growth path.

Acknowledgments

The authors are grateful for the financial support of the Spanish Government's Ministry of Economy and Competitiveness (ECO2012-36032-C03-01).

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