Essays in Spatial Econometrics

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Introduction

This thesis is an attempt to obtain further insight into the role of spatial and dynamic linkages in the field of Economics given the crucial need for a better understanding of the fundamental processes behind the spatial and temporal correlation patterns observable in the economic data.

To date, most theoretical economic models and econometric studies have treated units of analysis as isolated entities, ignoring the spatial characteristics of the data and the potential role of space in modulating the economic evolution of countries, regions, municipalities, etc. Typically, the regression models used to analyze cross-section and panel data have assumed that observations are independent of one another. As an example, a conventional regression model that relates economic and social factors in country i to the growth rate of country i, assumes that the growth rate in a neighboring country j has no influence on the growth rate of country i (Barro, 1996). However, the existence of physical and human capital externalities as well as technological interdependence between economies, suggests that the growth rate of country i may depend on the growth rates of neighboring economies other than i (Ertur and Koch, 2007).

In this regard, the essence of spatial economic analysis is that *space matters*. This implies that what happens in one economic unit of analysis is linked to what happens in neighboring economic units. In a spatial economic modeling framework, the spatial dimension and geographical arrangement of interacting economic agents are key drivers of economic processes and their final outcomes. As a matter of fact, there are three distinct and distinguishable types of interaction effects operating through space that can be distinguished: (i) endogenous interaction effects among the dependent variable, (ii) exogenous interaction effects among the independent variables and (iii) interaction effects among the disturbance terms (Elhorst, 2014). Thus, recognition of the wide range of interconnections between the interacting agents within any economic system requires to accommodate such interdependence in the modeling process and in order to verify models of social and spatial interaction, these spatial effects need to be explicitly accounted for.

Models that do not take into account spatial interaction in an economic setting should not suffer from major problems in the strength and validity of their conclusions as long as each economy evolves independently from the rest. However, this does not seem a realistic assumption in the context of European integration or in the current process of economic globalization. Indeed, in the context of the interconnected and globalized economy of the early twenty first century, trade flows, migratory processes, capital movements, technology and knowledge transfers from one country to another are of major importance (Mountford, 1997; Cheng and Yang, 1998; Fingleton and López-Bazo, 2006; Pesaran and Smith, 2011).

In response to this new scenario, theoretical models of interacting agents and social interaction have started in recent years to switch the emphasis from the individual behavior of traditional atomistic agents to the interaction among them (Glaeser *et al.*, 1996; Akerlof, 1997; Ertur and Koch, 2007). This has provided new theoretical perspectives from which to analyze phenomena such as peer effects, neighborhood effects, spatial spillovers and network effects (Manski, 2000). Through this research, therefore, an effort has been made to (i) extend traditional theoretical frameworks of growth, labor markets and fiscal policy in order to include spatial interactions in the modeling exercise and to (ii) provide a link between the theoretical models developed and the empirical analysis carried out.

However, two important problems arise in empirical modeling exercises if the sample data has a spatial or a locational component: (i) spatial dependence between the observations and (ii) spatial heterogeneity in the modeled relationships (Anselin, 2003, 2006).

Spatial dependence is a special case of cross-sectional dependence, in the sense that the structure of the correlation or covariance between random variables at different locations is derived from a specific ordering, determined by the relative position (distance, spatial arrangement) of the observations in geographic space or in network space. As explained by Lesage (2008), from a theoretical viewpoint, consumers in a neighborhood may emulate each other leading to spatial dependence. Local governments might engage in competition that could lead to local uniformity in taxes and services (Revelli, 2006). Labor demand shortages may foster migration flows to neighboring economies thereby reducing unemployment rate disparities across space (Möller, 2001). Pollution could create systematic spatial patterns (Madison, 2006), and clusters of consumers traveling to a more distant store to avoid a high crime zone might generate spatial dependence patterns in the data (Ackerman and Murray, 2004).

Spatial heterogeneity is a special case of unobserved heterogeneity similar to that of the time domain, where parameters are not spatially homogeneous, but varying over different geographical locations. There are abundant examples of spatial heterogeneity: one spatial unit could be located at high altitude in the mountains, the other on the border with a neighboring country; one spatial unit might be rural and located in the periphery, the other in a core urban area. Similarly, climatic characteristics and cultural elements such as social norms, trust and civic values, religious attitudes, etc, may differ considerably from one spatial unit to another. Failure to account for these features in the data, therefore, increases the risk of obtaining biased estimation results. In the context of panel data modeling, one way to remedy this problem is to introduce spatial specific fixed effects which control for all time-invariant variables whose omission could bias the estimates in a typical cross-sectional study. This solution is similar to that of the time-period specific effects in the time domain, as they control for all spatial-invariant variables whose omission could bias the estimates in a time-series study (Baltagi, 2001). A relevant issue in spatial panel data modeling is that spatial units are fixed and not sampled. Therefore, along this research, fixed effects models are used instead of random effect models given that the sample happens to be the population and each spatial unit represents itself (Beenstock and Felsenstein, 2007). Moreover, the consensus is that in spatial econometric modeling contexts, fixed effect models are generally more appropriate than random effect models since spatial econometricians tend to work with space-time data of adjacent spatial units located in unbroken study areas, such as regions, municipalities, etc (Elhorst, 2014).

Failure to take into account spatial dependence and spatial heterogeneity in econometric models leads to major estimation problems because the coefficient estimates will be biased, inconsistent and/or inefficient (Anselin and Bera, 1988; Anselin, 2003). Therefore, like correlation in the time domain, the distinct nature of spatial modeling requires a specialized set of techniques. However, it should be stressed here that spatial econometrics is not a straightforward extension of time-series econometrics to two dimensions. An obvious difference is that two geographical units can affect each other mutually while two time series observations in time-series data cannot. Moreover, as explained by Getis (2007), another complicating factor is the wide variety of potential forms for modeling spatial dependence (neighbors, distance, links, etc) as compared to those available for measuring temporal dependence.

In recent years, the spatial econometrics literature has shown a growing interest in the specification and estimation of econometric relationships and shifted its attention from cross-sectional spatial models to spatial panel data models (Anselin, 2010; Elhorst, 2010). This interest can be explained by the increased availability of panel data sets and by the fact that panel data offer researchers greater modeling possibilities than those provided by the single equation cross-sectional setting, which was, for a long time, the primary focus of spatial econometrics. This recent trend, has raised the need to develop new estimation approaches (Lee and Yu, 2010a,b; Elhorst, 2014).

According to Elhorst (2014) it is possible to differentiate between different generations of spatial econometric models. Early cross-sectional data models include key contributions such as Griffith (1988), Anselin and Bera (1998), Kelejian and Prucha (1999), Arbia (2006), and LeSage and Pace (2009). The second generation comprises non-dynamic models based on spatial panel data. These models might just pool time-series cross-sectional data, but the majority control for fixed or random spatial and/or time-period specific effects in order to deal with spatial and time heterogeneity. Relevant contributions to this literature are Elhorst (2014), Mur *et al.* (2010), Lee and Yu (2010a). The third generation of spatial econometric models encompasses dynamic spatial panel data models (Lee and Yu, 2010b,c; Yu *et al.*, 2008, 2012;). Until recently, there was no straightforward estimation method for this type of models. This is because methods developed for dynamic but non-spatial and for spatial but non-dynamic panel data models produce biased estimators when these methods/models are put together.

The structure of this thesis consists of four self-contained chapters. **Chapter 1** analyzes the volatility-regional growth nexus in a sample of European regions. **Chapter 2** explores the role of interaction effects shaping regional development gaps in Europe. **Chapter 3** examines the determinants of regional unemployment disparities in Europe. **Chapter 4** looks into the nature of fiscal policy interactions in local fiscal policy in Spain. A distinct and innovative feature of this research is the use of static and dynamic spatial panel data estimation techniques for the empirical testing and validation of the theoretical models developed in the successive chapters. This methodological approach is particularly appropriate for the analysis of economic phenomena from an integrated space-time perspective because it allows to model spillover, feedback and diffusion effects among the study units.

Chapter 1 examines the relationship between growth and volatility. There are many theoretical reasons to support either a positive or a negative relationship between growth and volatility (Aghion and Howitt, 1998). Following Ertur and Koch (2007), this study extends the neoclassical macroeconomic growth models of De Hek (1999) and Jones *et al.* (2005) to take into account technological externalities in the analysis of the volatility effect in European regional growth rates. Spatial externalities are used to model technological interdependence, which ultimately implies that the economic growth rate of a particular region is affected not only by its own degree of volatility but also by the output fluctuations experienced by the remaining regions.

In order to investigate the empirical validity of this result, the link between volatility and economic growth is examined in a sample of 272 European regions over the period 1991-2011 using a static spatial panel including spatial fixed effects. Estimates show the existence of a negative and statistically significant relationship between volatility and economic performance in the European regions. This is partly due to the role played by spatial spillovers induced by volatility in neighboring regions. The observed link is robust to the inclusion in the analysis of different explanatory variables that may affect both regional growth and business cycle fluctuations such as GDP per capita, the levels of investment and human capital, employment density or industry mix. Additionally, a number of checks to verify that the empirical results do not depend on the measure of volatility used in the analysis or the econometric specification employed to capture the nature of spatial spillovers are carried out. Therefore, the findings of this chapter suggest that policies aimed at reducing the variability of cyclical macroeconomic fluctuations at the regional level may have beneficial effects on long run growth rates.

In **Chapter 2**, regional economic development achievements in Europe are comprehensively analyzed by means of a composite index in a sample of 258 NUTS-2 level regions for the period 2000-2010. Nowadays, the widespread belief among academics and policy makers is that composite indexes provide a better characterization of the multidimensional nature of societal progress. To that end, a new multiplicative version of the Regional Lisbon Index (RLI) is proposed. This alternative index contains computational changes with respect the index developed by the regional policy directorate of the European Commission (Dijkstra, 2010). The Regional Lisbon Index includes employment, education and R&D indicators. Targets for these indicators are related to an action and economic development plan for the EU regions and have been incorporated into European Regional Policy programming to monitor the evolution towards a knowledge based economy (KBE). As to the various indicators in the composite indicator, labor market indicators are observed to improve substantially, while the targets set for RD, early school abandonment and life-long learning remained far from being achieved. The results obtained in this chapter show that the European Union failed to reach the original Lisbon Strategy targets by a 20%. These findings suggest that if policy makers aim to push Europe towards a KBE, renewed effort will be required to create an adequate innovation environment.

In a second step, following recent contributions in the literature linking knowledge, innovation and regional development (Rodríguez-Pose and Crescenzi, 2008; Capello *et al.*, 2011; Capello and Lenzi, 2013; 2014), this study analyzes the effect of a number of factors on the evolution of the RLI. In particular, regional development is analyzed by estimating different static spatial panel data model specifications including spatial and time-period fixed effects in which the dependent variable is the RLI growth rate. The empirical results of this modeling exercise highlight the role played by spillover effects in the context of regional development. The salient observation is that the main drivers of the RLI growth rate are technological capital, infrastructures and employment growth. Additionally, a convergence process among regions is observed, what implies that regions with lower levels of development are catching up with highly developed regions.

Chapter 3 of this research analyzes the evolution of regional unemployment rates and the sources of labor market disparities in a sample of 241 NUTS-2 European regions during the period 2000-2011. This chapter extends the theoretical framework developed by Blanchard and Katz (1992) and Zeilstra and Elhorst (2014) in order to accommodate regional labor market inter-connectivity. This is achieved by constructing a spatially augmented labor market model with interactions between labor supply, demand, wages and migration flows among regions. The theoretical model solution results in a *Dynamic Spatial Durbin Model* empirical specification including endogenous and exogenous interaction effects with regional level and national-level labor market institutional factors as explanatory variables. Important methodological issues such as the of choice spatial weight matrix, model specification and spatial co-integration are addressed. In conjunction with dynamic-spatial panel estimates, a set relative importance metrics are computed to determine the effect of regional level disequilibrium, equilibrium and national level factors in regional disparities in unemployment rates.

The empirical findings of this chapter suggest that unemployment disparities in the period 2000-2011 are explained by a mix of such factors with the equilibrium component dominating. The study furthermore detects slight overall convergence in the unemployment rate for the sample regions. However, the economic crisis that began in 2008 has virtually eliminated all progress on the convergence process observed since 2000. The two main reasons explaining the sharp increase in unemployment disparities experienced since 2008 are differences in regional labor demand and in the institutional frameworks. Thus, the results suggest that legislative changes and policies focused on nationwide labor market reforms should be implemented in addition to other policy interventions at the regional level in order to reduce unemployment gaps in Europe.

In **Chapter 4**, the nature of municipal fiscal policy interactions in Spain is explored. In the presence of spatial interdependence and spatial externalities, if a local entity makes significant expenditure in a particular spending category, neighboring local bodies may increase or reduce their spending in that particular category, which reflects complementarity or substitutability in local public good provision. This is because of public government spending of a juridisdiction may generate beneficial or negative effects that spread across boundaries, affecting the welfare of residents in neighboring jurisdictions (Kelejian and Robinson, 1992; Case *et al.*, 1993; Revelli, 2005). An important issue that has not been properly treated by previous spatial spillover models of government spending developed by Brueckner (2003) and Solé-Ollé (2006) is the existence of strong time correlations and persistence in local budgetary processes. In this chapter, spatial spillover models of government spending are extended by including serial dynamic effect, in order to overcome this problem. This extension allows for testing of two different hypothesis. First, it allows to analyze whether local public good provision behaves as a complementary or a substitutive good. Second, it helps to test the relevance of the incremental budget hypothesis stemming from political science research (Wildavsky, 1964). To that end, a dynamic spatial panel data model is estimated to quantify the relevance of spatial spillovers and diffusion effects over time.

Using annual data for a sample of 1,230 Spanish municipalities during the period 2000-2012, it is observed that there are significant simultaneous positive spatial spillovers in various government expenditure categories. This suggests that, overall, locally provided public goods in Spain behave as complements. However, the results obtained with relative importance metrics analysis show that the incremental hypothesis has greater explanatory power than that of spatial spillovers, which indicates that theoretical models of local government interactions should include time lags to capture behavioral frictions arising from complex political processes. The main result regarding the effects of exogenous explanatory variables is that municipal fiscal policy is mainly driven by economic and demographic factors, while local political factors, such as political power concentration, ideology or alignment with upper-tier level of government do not play a relevant role in determining government spending dynamics.

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Chapter 1

Volatility and Regional Growth in Europe: Does Space Matter?[1]

1.1 Introduction

Over the last two decades there have been numerous studies on spatial disparities in economic performance and development in Europe using a variety of different approaches and methods. This increasing interest has to do with the important advances that have taken place in economic growth theory, coinciding with the introduction of endogenous growth models in the mid 1980s (Barro and Sala-i-Martin, 1995). The assumptions underlying these models ultimately allow for the reversal of the neoclassical prediction of convergence, and lead to the conclusion that the faster growth of rich economies leads to an increase in regional disparities. In fact, the self-sustained and the selective nature of economic growth is also highlighted by many models of the "new economic geography" developed since the seminal contribution by Krugman (1991, 1998). According to these theories, increasing returns and agglomeration economies explain the accumulation of economic activity in the more dynamic areas, which causes ultimately spatial divergence. Academic debate aside, however, the increasing relevance of this topic in the European setting is closely related to the strong emphasis placed on achieving economic and social cohesion in the context of the process of integration currently underway (European Commission, 2007).

The literature has stressed the role played by various factors on regional growth in Europe, including the sectoral composition of economic activity (Paci and Pigliaru, 1999), structural change processes (Gil *et al.*, 2002), technology and innovation capacity (Fagerberg *et al.*, 1997), human capital stock (Rodríguez-Pose and Vilalta-Bufi, 2005), infrastructure endowment and investment (Crescenzi and Rodríguez-Pose, 2008), European regional policy (Rodríguez-Pose

[1]A version of this essay has been published in *Spatial Economic Analysis*.

and Fratesi, 2004), social capital (Beugelsdijk and Van Schaik, 2005), or income distribution (Ezcurra, 2009).[2] Nevertheless, the study of the possible relationship between volatility and regional growth has received hardly any attention in this context. Indeed, to date, only Martin and Rogers (2000) and Falk and Sinabell (2009) have examined this issue in a sample of European regions using aggregate data for the economy as a whole. Martin and Rogers (2000) identify a negative relationship between volatility and growth in a sample of 90 NUTS-1 and NUTS-2 regions during the period 1979-1992.[3] This finding contrasts with the positive correlation observed by Falk and Sinabell (2009) in 1,084 NUTS-3 regions between 1995 and 2004.[4]

The limited number of analysis on the volatility-growth connection in the European setting is especially remarkable in view of the abundant theoretical arguments supporting the existence of a link between short-term economic instability and economic performance (Ramey and Ramey, 1995; Aghion and Saint-Paul, 1998). Moreover, the issue poses potentially important implications for the design of policy (Norrbin and Pinar Yigit, 2005). In particular, the presence of a positive relationship suggests that public policies that endeavour to reduce the variability of cyclical macroeconomic fluctuations may restrict the possibilities of growth in the long-term. On the contrary, the existence of a negative link implies that government policies designed to stabilize the business cycle will help to rise the long-term growth rate of the economy.

Against this background, and in order to complement the results obtained so far in the existing literature, the aim of this chapter is to examine further the relationship between volatility and regional growth in Europe. In particular, this study pays special attention to the underlying geographical dimension of the processes of regional growth in the European setting. Accordingly, the sample regions are not treated as isolated units that evolve independently of the rest, and spatial effects are incorporated formally into the analysis. This approach allows to investigate the role played by spatial spillovers in explaining the impact of volatility on regional growth in Europe. In particular, the present analysis takes explicitly into account the possibility that the economic performance of any given region is influenced by the degree of volatility experienced

[2] This list of factors is not exhaustive. For further information, see the recent papers by Crespo Cuaresma and Feldkircher (2013) and Crespo Cuaresma *et al.* (2014), who consider other potential determinants of regional growth in Europe.

[3] NUTS is the French acronym for "Nomenclature of Territorial Units for Statistics", a hierarchical classification of subnational spatial units established by Eurostat according to administrative criteria. In this classification, NUTS-0 corresponds to the country level, while increasing numbers indicate increasing levels of territorial disaggregation.

[4] In addition to these contributions based on aggregate data, Ezcurra (2010) employs sectorally dissagregated data for six manufacturing activities to investigate the relationship between the fluctuations of the business cycle and output growth in the European regions between 1980 and 2006. Furthermore, Chandra (2003) tests the predictions of the portfolio model of the economy with European regional data. Using different frontier estimation methods, this author provides evidence of the existence of a convex growth-instability frontier.

by neighboring regions.

This study distinguishes itself from the earlier studies by Martin and Rogers (2000) and Falk and Sinabell (2009) mentioned above in three major aspects.

First, taking into account the process of economic integration currently underway in Europe, a theoretical framework to analyze the link between volatility and economic growth when regions are spatially interconnected is presented. To that end, a spatially augmented stochastic growth model with technological interdependence among economies is developed. Spatial externalities are used to model technological interdependence, which ultimately implies that the economic growth rate of a particular region is affected not only by its own degree of volatility, but also by the output fluctuations registered by the remaining regions.

Second, there are important differences from a methodological perspective between this paper and previous contributions. First, this is the first study investigating the link between regional growth and volatility in Europe using panel data. The employment of panel data leads usually to a greater availability of degrees of freedom, thus reducing the collinearity among explanatory variables and improving the efficiency of the estimates. Panel data techniques also allow to take into account unobserved heterogeneity (Islam, 2003). This is particularly useful in this context, since region-specific factors are likely to affect regional growth patterns.

Third, unlike this paper, Martin and Rogers (2000) and Falk and Sinabell (2009) do not add the investment level as a control variable when estimating the relationship between volatility and economic growth in the European regions. This omission may affect their findings, since there are numerous theoretical arguments that suggest the relevance of investment in this context (e.g. Ramey and Ramey, 1995; Imbs, 2007).

The paper is organized as follows. After this introduction, Section 2 reviews briefly the main results obtained so far in the empirical literature on the link between volatility and regional growth. Section 3 presents a theoretical growth model to investigate the effect of the fluctuations of the business cycle on economic performance when the regional economies are spatially interconnected. Section 4 describes the data and the econometric approach used in the analysis. The empirical findings of the paper are discussed in Section 5. The final section offers the main conclusions from this work and the policy implications of the research.

1.2 Literature Review

Business cycle fluctuations and long-run growth have traditionally been treated by economists as separate areas of research. According to this perspective, the long-term growth rate of the economy is considered as an exogenous trend that is not affected by short-term shocks. This point of view, however, has been questioned over the last three decades, coinciding with the publication of various contributions that link both phenomena in a common theoretical framework (e.g. Kydland and Prescott, 1982; Aghion and Saint-Paul, 1998).

From a theoretical perspective, however, the relationship between the variability of cyclical macroeconomic fluctuations and economic performance is ambiguous, as volatility can affect growth via several different mechanisms that often work in opposite directions (Aghion and Howitt, 1998; Jones *et al.*, 2005). Consequently, empirical research has attempted to shed light on the relationship between volatility and growth. In fact, numerous papers have explored this issue during the last years using cross-country data and different econometric techniques. Some authors find support for a positive link between volatility and growth (e.g. Kormendi and Meguire, 1985; Grier and Tullock, 1989; Caporale and McKiernan, 1996), while other researchers report a negative association (e.g. Ramey and Ramey, 1995; Martin and Rogers, 2000; Badinger, 2010). Finally, there are papers where the observed link is not statistically significant (e.g. Speight, 1999; Chatterjee and Shukayev, 2006).

In order to overcome the problems related to systematic data quality variations that affect many cross-country analyses, several scholars have investigated this issue using regional data from the US (Chatterjee and Shukayev, 2006; Dawson and Stephenson, 1997), Canada (Dejuan and Gurr, 2004), or the EU (Martin and Rogers, 2000; Falk and Sinabell, 2009). The regional approach is particularly appealing in this context, as the use of smaller geographical areas allows the researcher to increase the number of observations employed in the econometric analysis (Falk and Sinabell, 2009). Nevertheless, the empirical research on the relationship between volatility and economic growth based on regional data has been so far limited and, as occurs with cross-country studies, generally reaches diverging conclusions. In fact, as can be observed in Table (1.1), available empirical analyses at the regional level are not conclusive. The reasons for this diversity of results have to do with the fact that these contributions differ considerably in terms of the sample composition and the study period, the indicator used to measure the degree of volatility, and the econometric approach. Accordingly, further empirical research is required to clarify the nature of the link between volatility and economic growth at the regional level.

Table 1.1: The Empirical Relationship between Volatility and Regional Growth.

Authors (year)	Sample	Period	Methodology	Results
Chatterjee and Shukayev (2006)	48 US states	1963-1999	Cross-section	Negative but not significant
Dawson and Stephanson (1997)	48 US states	1970-1988	Panel data	Negative and significant at the 10% level
Dejuan and Gurr (2004)	10 Canadian provinces	1961-2000	Cross-section and panel data	Positive and significant at the 10% level
Martin and Rogers (2000)	90 European regions (NUTS-1 and NUTS-2)	1979-1992	Cross-section	Negative and significant at the 5% level
Falk and Sinabell (2009)	1,084 European regions (NUTS-3)	1995-2004	Cross-section	Positive and significant at the 5% level
Ezcurra (2010)[a]	195 European regions (NUTS-2)	1980-2006	Cross-section	Positive and significant at the 5% level

Notes: [a] Sectorally disaggregated data only for manufacturing activities.

When considering the findings of the papers included in Table (1.1), it is important to recall that the literature on regional growth has emphasized repeatedly over the last decade the relevance of spatial effects on regional economic performance (e.g. López-Bazo *et al.*, 2004; Rey and Janikas, 2005; Le Gallo and Dall'erba, 2008). To date, however, with the only exception of Falk and Sinabell (2009), this issue has not been taken into account by the empirical literature on the volatility-growth connection at the regional level. This omission is particularly important from an econometric perspective and may lead to erroneous conclusions on the effect of volatility on regional growth. In view of this, this study pays particular attention to the possibility that spatial spillovers affect the relationship between the fluctuations of the business cycle and regional growth. In order to formalize this idea, the next section presents a theoretical growth model to analyze the link between volatility and economic growth when regional economies are spatially interconnected.

1.3 Theoretical Framework: A Spatial Stochastic Growth Model

In order to explain the relationship between volatility and regional growth, in this section a spatially augmented stochastic growth model is developed. Following Ertur and Koch (2007) and Fischer (2011), the model includes Arrow-Romer externalities and spatial externalities, which implies technological interdependence in a world of N regions denoted by $i = 1, \ldots, \mathrm{N}$. These regions have the same production possibilities, but they differ because of different resource endowments and spatial locations. Within a region all agents are identical. Consider an aggregate (Hicks-neutral) Cobb-Douglas production function for region i in period t with constant returns to scale in labor and reproducible physical capital:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{1-\alpha} \tag{1.1}$$

where Y_{it}, K_{it} and L_{it} are respectively the output, the level of reproducible physical capital and the level of labor. In turn, A_{it} stands for the aggregate level of technology, which can be expressed as:

$$A_{it} = \Omega_t k_{it}^{\phi} s_{it}^{\gamma} \prod_{j \neq i}^{N} A_{jt}^{\rho w_{ij}} \tag{1.2}$$

As can be observed in Equation (1.2), the aggregate level of technology depends on four terms. First, according to the traditional neoclassical growth model (Solow, 1956; Swan, 1956),

Ω_t denotes the proportion of technological progress that is exogenous and identical in all regions. In particular, $\Omega_t = \Omega_0 e^{gt}$ where g is its constant rate of growth. Second, it is assumed that region's i level of technology increases with the level of physical capital per worker, $k_{it} = \frac{K_{it}}{L_{it}}$. Note that Equation (1.2) implies that each unit of physical capital investment not only increases the stock of capital but also increases the level of technology available for all firms in the economy (Arrow, 1962; Romer, 1986). The parameter ϕ, with $0 \leq \phi \leq 1$, reflects the relevance of these externalities associated with physical capital. Third, the level of technology in region i is also affected by stochastic fluctuations resulting from random productivity shocks $s_{it} = e^{\epsilon_{it}}$, where ϵ_{it} is white noise. These productivity shocks have associated a certain degree of volatility which determines the output fluctuations experienced by the regional economy (De Hek, 1999; Jones *et al.*, 2005). In particular, it is assumed that the distribution of ϵ_{it} is given by the measure μ_θ, where θ is an index of riskiness. More specifically, $\theta' \geq \theta$ means that $\mu_{\theta'}$ is dominated in the sense of second order stochastic dominance by μ_θ, which implies that a higher θ corresponds to higher volatility of the innovation to the technology shock. In turn, $-1 < \gamma < 1$. Finally, the fourth term in Equation (1.2) is a geometrically weighted average of the aggregate level of technology of the neighboring regions. This term captures the idea that spillovers arising from capital investment and productivity shocks extend across regional borders but do so with decreasing intensity because of the existence of socio-economic and institutional differences captured by geographical distance (Ertur and Koch, 2007; Fischer, 2011). In order to formalize this argument, the so-called spatial weight terms w_{ij} that represent the spatial interdependence between regions i and j are introduced. As is usual in the literature, these terms are assumed to be non-negative, non-stochastic and finite, with $0 \leq w_{ij} \leq 1$ and $w_{ij} = 0$ if $i = j$. It is further assumed that $\sum_{j \neq i}^{N} w_{ij} = 1$ for $i = 1, \ldots,$ N, in order to avoid scale affects and ensuing explosive growth. The parameter ρ, with $0 \leq \rho < 1$, measures the relevance of spatial externalities in this context.

It should be noted that the presence of spatial technological interdependence in the model implies that regions cannot be treated as isolated units but must be considered as an interdependent system. Accordingly, rewriting the log-version of Equation (1.2) in matrix form yields:

$$A = \Omega + \phi k + \gamma s + \rho W A \tag{1.3}$$

where A is the $(N \times 1)$ vector of logarithms of the aggregate level of technology for the N regions, Ω is the $(N \times 1)$ vector of the logarithms of the exogenous part of technology, k is the

$(N \times 1)$ vector of the logarithms of per worker physical capital, and s is the $(N \times 1)$ vector of the logarithms of random productivity fluctuations. In turn, W denotes the $(N \times N)$ matrix of spatial weights representing the spatial connectivity structure between the N regions. Therefore, if $\rho \neq 0$ and if $\frac{1}{\rho}$ is not an eigenvalue of W, solving Equation (1.3) for A yields:

$$A = (I - \rho W)^{-1}\Omega + \phi(I - \rho W)^{-1}k + \gamma(I - \rho W)^{-1}s \tag{1.4}$$

Using the Sherman-Morrison formula to develop $(I - \rho W)^{-1}$ in its Taylor expansion form and regrouping terms for region i the evolution of technology is given by:

$$A_{it} = \Omega_t^{\frac{1}{1-\rho}} k_{it}^{\phi} s_{it}^{\gamma} \prod_{j \neq i}^{N} k_{jt}^{\phi \sum_{r=1}^{\infty} \rho^r w_{ij}^{(r)}} s_{jt}^{\gamma \sum_{r=1}^{\infty} \rho^r w_{ij}^{(r)}} \tag{1.5}$$

Replacing Equation (1.5) in the normalized per worker production function version of Equation (1.1) (i.e, dividing by L_{it}), it is possible to express output per worker as:

$$y_{it} = \Omega_t^{\frac{1}{1-\rho}} k_{it}^{v_{ii}} s_{it}^{u_{ii}} \prod_{j \neq i}^{N} k_{jt}^{v_{ij}} s_{jt}^{u_{ij}} \tag{1.6}$$

where:

$$v_{ii} = \alpha + \phi \left(1 + \sum_{r=1}^{\infty} \rho^r w_{ii}^{(r)}\right) \tag{1.7}$$

$$v_{ij} = \phi \left(\sum_{r=1}^{\infty} \rho^r w_{ij}^{(r)}\right) \forall i \neq j \tag{1.8}$$

$$u_{ii} = \gamma \left(1 + \sum_{r=1}^{\infty} \rho^r w_{ii}^{(r)}\right) \tag{1.9}$$

$$u_{ij} = \gamma \left(\sum_{r=1}^{\infty} \rho^r w_{ij}^{(r)}\right) \forall i \neq j \tag{1.10}$$

Given the production function of Equation (1.6), at each date t the representative agent of region i must choose how much to invest, x_{it}, and consume, c_{it}, in order to maximize her expected overall utility. Assuming that physical capital fully depreciates each period, the agent faces the following dynamic optimization problem (De Hek, 1999):

$$\text{Max} \quad \sum_{t=0}^{\infty} \delta^t EU\left(c_{it}\right) \tag{1.11}$$

subject to

$$c_{it} + k_{it+1} = y_{it}$$

$$y_{it} = \Omega_t^{\frac{1}{1-\rho}} k_{it}^{v_{ii}} s_{it}^{u_{ii}} \prod_{j \neq i}^{N} k_{jt}^{v_{ij}} s_{jt}^{u_{ij}}$$

$c_{it} \geq 0$, $x_{it} \geq 0$, k_{i0} given

where the parameter δ stands for the discount factor, with $0 < \delta < 1$. In turn, the preferences are represented by a constant elasticity of substitution utility function:

$$u(c_{it}) = \frac{c_{it}^{1-\sigma} - 1}{1-\sigma} \tag{1.12}$$

with $\sigma \neq 1$, $\sigma > 0$.

The first order conditions for consumption and investment are given by the following set of equations:

$$[c_{it}] : \delta^t c_{it}^{-\sigma} = \lambda_t \tag{1.13}$$

$$[k_{it+1}] : -\lambda_t + \lambda_{t+1} \left(v_{ii} \Omega_{t+1}^{\frac{1}{1-\rho}} s_{it+1}^{u_{ii}} k_{it+1}^{v_{ii}-1} \prod_{j \neq i}^{N} s_{jt}^{u_{ij}} k_{jt+1}^{v_{ij}} \right) = 0 \tag{1.14}$$

where λ_t is the Lagrange multiplier at time t. Combining Equations (1.13) and (1.14) the following Euler equation is obtained:

$$1 = \delta E \left[\left(\frac{c_{it}}{c_{it+1}} \right)^{\sigma} \left(v_{ii} \Omega_{t+1}^{\frac{1}{1-\rho}} s_{it+1}^{u_{ii}} k_{it+1}^{v_{ii}-1} \prod_{j \neq i}^{N} s_{jt}^{u_{ij}} k_{jt+1}^{v_{ij}} \right) \right] \tag{1.15}$$

Therefore the expected value of the growth rate of region i between t and $t+1$ is given by:

$$E\left[\frac{y_{it+1}}{y_{it}}\right] = \left[(\delta v_{ii})\, E \left(\Omega_{it+1}^{\frac{1-\sigma}{1-\rho}} k_{it+1}^{v_{ii}-1} s_{it+1}^{\eta} \prod_{j \neq i}^{N} k_{jt+1}^{(1-\sigma)v_{ij}} s_{jt+1}^{\zeta} \right) \right]^{\frac{1}{\sigma}} \left(\Omega^{\frac{1}{1-\rho}} s_{it+1}^{u_{ii}} \prod_{j \neq i}^{N} k_{jt+1}^{v_{ij}} s_{jt+1}^{u_{ij}} \right) \tag{1.16}$$

where $\eta = (1-\sigma)u_{ii}$ and $\zeta = (1-\sigma)u_{ij}$.

The interest relies in the effect of increasing volatility of the random productivity shocks on the decision variables of the model and the resulting expected growth rate. To explore this issue, consider the following function of η and ζ:

$$\Theta(\eta, \zeta) = \left[E\left(s_{it+1}^{u_{ii}}, s_{jt+1}^{u_{ij}}\right)\right]\left[E\left(s_{it+1}^{\eta}, s_{jt+1}^{\zeta}\right)\right]^{\frac{1}{\sigma}} \tag{1.17}$$

Note that the impact of a change in volatility on the expected growth rate is determined by the effect of a change in volatility on $\Theta(\eta, \zeta)$. According to Equation (1.17), there are two channels through which volatility can affect the expected growth rate. The first channel is related to the learning by doing effect given by the function $E\left(s_{it+1}^{u_{ii}}, s_{jt+1}^{u_{ij}}\right)$, while the second channel has to do with the optimal savings rate function $\left[E\left(s_{it+1}^{\eta}, s_{jt+1}^{\zeta}\right)\right]^{\frac{1}{\sigma}}$. In order to analyze the effect of a change in volatility on the expected growth rate, it is necessary to determine the shape of the functions associated with each channel. Focusing on the learning by doing channel, Equation (1.17) indicates that the impact on the expected growth rate of region i of an increase in the degree of volatility experienced by the own region is positive when $u_{ii} > 1$, null if $u_{ii} = 1$ and negative when $0 < u_{ii} < 1$. Furthermore, an increasing volatility in the neighboring regions exerts a positive effect on the expected growth rate of region i when $u_{ij} > 1$, null if $u_{ij} = 1$ and negative when $0 < u_{ij} < 1$. Regarding the channel related to the optimal saving rate, Equation (1.17), shows that the impact on the expected growth rate of region i of an increase in the degree of volatility experienced by the own region is positive when $\eta > 1$, null if $\eta = 1$ and negative when $0 < \eta < 1$. Additionally, an increasing volatility in the neighboring regions has a positive effect on the expected growth rate of region i when $\zeta > 1$, null if $\zeta = 1$ and negative when $\zeta < 1$.

As can be observed, the model shows that the final impact of volatility on regional growth rates is theoretically ambiguous. Empirical research is therefore key to shed further light on the relationship between business cycle fluctuations and regional economic growth. For this reason, the rest of the paper is devoted to studying empirically this issue using data for the European regions.

1.4 Empirical Framework

1.4.1 Data

The data for the empirical analysis are drawn from the Cambridge Econometrics regional database and Eurostat. In order to maximize the number of countries included in the analysis, the study period goes from 1991 to 2011. The sample covers a total of 272 NUTS-2 regions belonging to 27 EU member states, as well as Norway.[5] NUTS-2 regions are used in the analysis instead of other possible alternatives for various reasons. First, NUTS-2 is the territorial unit most commonly employed in the literature to investigate the determinants of regional growth in Europe, which facilitates the comparison of the results with those obtained in previous papers. Second, NUTS-2 regions are particularly relevant in terms of the EU regional policy since the 1989 reform of the European Structural Funds.

The key variables throughout the paper are the average and the standard deviation of the growth rates of real GDP per capita in the various regions between 1991 and 2010. The average annual growth rate for the European regions as a whole is 1.4%, while the standard deviation of growth across regions and time is 3.1% on average. Nevertheless, both variables exhibit a high degree of variation across the sample regions during the study period as can be observed in Figures (1.1) and (1.2) below. Figure (1.1) plots the spatial distribution of GDP per capita growth rates. The first quartile covers regions with growth rates below the 0.98%, the second quartile covers regions with intermediate growth rates between the 0.98 and 1.35%, the third quartile includes regions with growth rates between the 1.35% and 1.83% and the fourth quartile fast growing regions with average rates above the 1.83% threshold. Similarly, Figure (1.2) plots the spatial distribution of the output fluctuations. The first quartile covers regions with fluctuations of 1.88 points around its long run average growth rate, the second quartile includes regions with an average level of fluctuation between 1.88 and 2.55 points, the third covers fluctuation levels between 2.55 and 3.30 points while the fourth quartile covers highly-volatile regions where the average intensity of fluctuations is above 3.30 points its long run growth rate. As observed, there are fast growing regions with important fluctuations in economic activity, as in the cases of the Irish regions, Algarve in Portugal, or Aland in Finland. Likewise, high levels of volatility are also found in some regions with low growth rates, as occurs with Liguria or Calabria in Italy, Champagne-Ardenne in France. This is not particularly surprising given the heterogeneous behavior in terms of economic performance experienced by the sample regions during the study period, which gives a clear indication of the complexity of regional growth patterns in Europe (Rodríguez-Pose, 2002).

[5] The lack of data has obliged me to exclude from the study the French overseas departments and territories, and the Portuguese islands in the Atlantic.

Figure 1.1: GDP per capita Growth rates, 1991-2011.

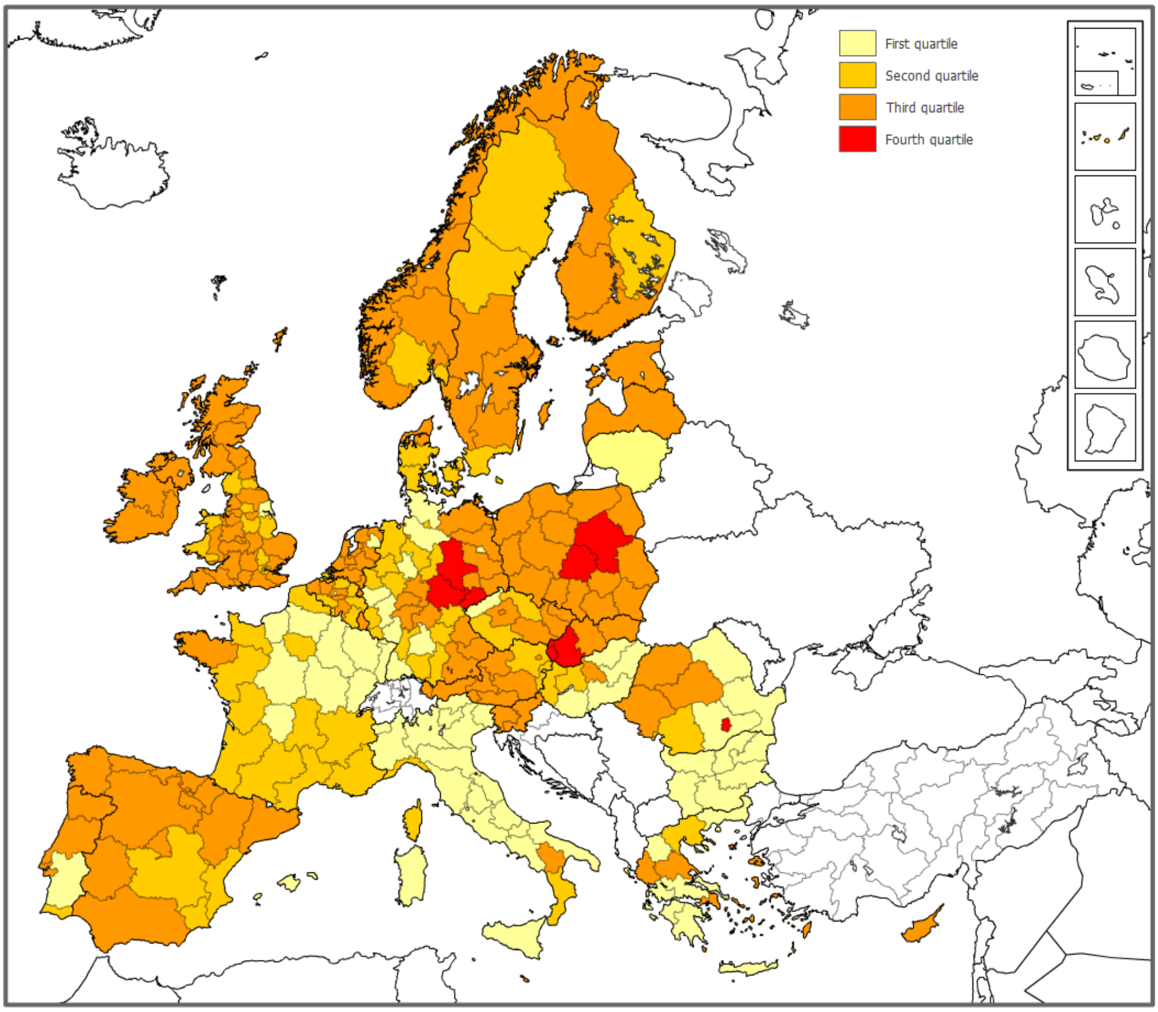
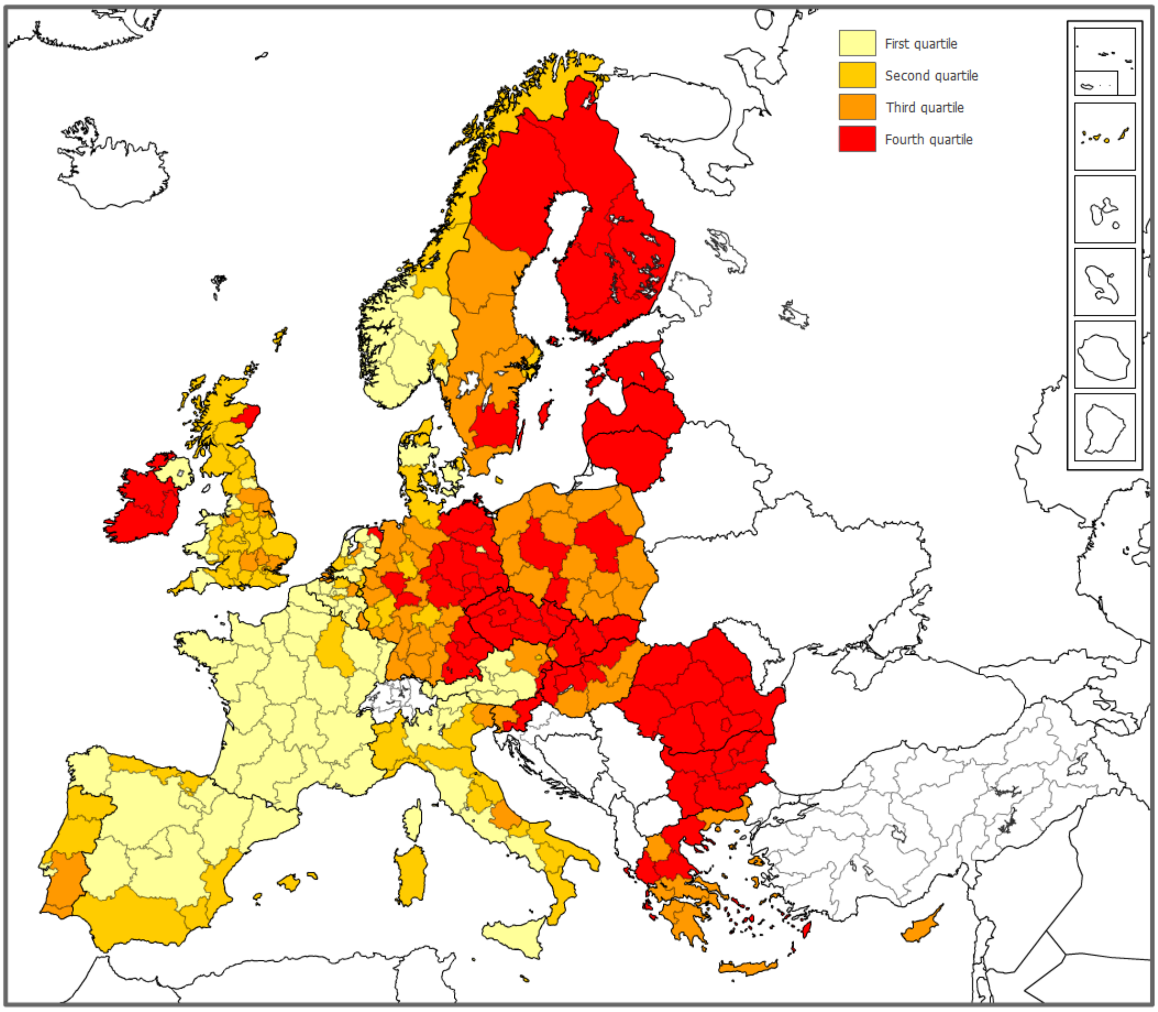


Figure 1.2: Output Growth Volatility, 1991-2011.



1.4.2 Econometric Model

As mentioned in the introduction, earlier studies on the volatility-growth connection in the European regions use a cross-sectional approach (Martin and Rogers, 2000; Falk and Sinabell, 2009). Nevertheless, the nature of the dataset allows to employ panel data techniques in this context, thus extending modeling possibilities as compared to the single equation cross-sectional setting employed so far (Baltagi, 2001; Hsiao, 2003). In view of this, the empirical analysis begins with the following fixed-effects model written in vector form for a cross-section of observations at time t:

$$\Delta Y_t = \mu + X_t\beta + \varepsilon_t \tag{1.18}$$

where ΔY_t denotes a $N \times 1$ vector including the average growth rate of GDP per capita for every region in the sample $(i = 1, \ldots, N)$ measured at a particular point in time $(t = 1, \ldots, T)$.[6] In this study, t denotes windows over five-year periods, X_t is a $N \times K$ matrix that includes the standard deviation of regional growth rates over each five-year period as a measure of volatility, as well as a set of additional variables that control for other factors that are assumed to influence regional growth.[7] In turn, $\mu = (\mu_1, \ldots, \mu_N)'$ is a $N \times 1$ vector that stands for unobservable region-specific effects, whereas $\varepsilon = (\varepsilon_{1t}, \ldots, \varepsilon_{Nt})'$ is a $N \times 1$ vector that represents the corresponding disturbance term.

The control variables included in X have been selected on the basis of the findings of existing studies on the determinants of regional growth in Europe. While the choice of these variables is theoretically well grounded, it ultimately depends on the availability of reliable statistical data for the geographical setting on which the study is focused. Thus, following the convention in the literature on economic growth, the initial level of GDP per capita is used to control for economic convergence across regions (Barro and Sala-i-Martin, 1992). The inclusion of this variable in the model helps to determine whether poor regions grew faster than richer ones during the study period, thus providing information on the dynamics of regional disparities. In addition, the level of investment and the population growth rate of the sample regions are included, two variables theoretically important when it comes to explaining capital accumulation and economic growth (Mankiw *et al.*, 1992; Barro and Sala-i-Martin, 1995). Furthermore, the share of the active population with tertiary education and/or an employment in science and

[6] In the remainder of the thesis it is assumed that the data are sorted first by time and then by spatial unit, whereas the classic panel data literature tends to sort the data first by spatial unit and then by time.

[7] The employment of five year periods to calculate the dependent variable in Equation (1.18) is consistent with the literature on the volatility-growth connection (e.g. Ramey and Ramey, 1995).

technology is employed as a human capital control.[8] This is particularly important, given the relevant role played by investment in human capital when explaining regional growth in Europe (Crespo Cuaresma and Feldkircher, 2013).

Additionally, regional growth patterns may be affected by the possible existence of agglomeration economies (Ciccone, 2002; Fujita and Thisse, 2002). Agglomeration economies result from market and non-market interactions, and imply that proximity to larger markets leads to productivity gains. In order to capture the degree of spatial concentration of economic activity in a given area, the employment density of the various regions is added to the list of regressors of the baseline specification (Ciccone, 2002). Furthermore, the economic performance of the sample regions may be related to the sectoral composition of economic activity. Indeed, several studies have found that industry mix affects regional growth in the EU (e.g. Paci and Pigliaru, 1999). Although the European economy has experienced a process of convergence in regional productive structures during the last decades, considerable differences persist in the patterns of regional specialization across Europe (Ezcurra *et al.*, 2006). Accordingly, X also includes the regional employment shares in agriculture, financial services and non-market services.

When examining the volatility-growth link, it is particularly important to control for regional size, as this factor may be related to the intensity of the output fluctuations experienced by the sample regions. Larger regions are often characterized by lower levels of specialization than smaller regions (Ezcurra *et al.*, 2006), which may imply a greater ability to face the adverse effects of economic shocks (Malizia and Ke, 1993; Trendle, 2006). It should be recalled that the region-specific effects included in the baseline specification allow to control for those time-invariant factors relevant in this context. This is the case of region's area. Nevertheless, a check on the correlation coefficient between these region-specific effects and total population (an alternative measure of regional size) reveals it is relatively low ($\rho = 0.06$). In view of this, region's population is included as an additional regressor in Equation (1.18).

With the only exception of the population growth rate, all the explanatory variables included in matrix X are measured at the beginning of each subperiod in order to minimize any potential endogeneity problem.

At this point it is important to note that, as is usual in the traditional convergence literature, Equation (1.18) considers the various regions as isolated units, thus ignoring the spatial characteristics of the data and the potential role of geography in shaping economic growth (Rey

[8]This specific measure was selected due to the lack of data for other alternative indicators. Nevertheless, it is worth noting that the nature of this variable implies that its use as a human capital control may be questionable, which should be taken into account when interpreting empirical findings.

and Janikas, 2005). This should raise no major problems, as long as each economy evolves independently of the rest. However, this does not seem a very realistic assumption in the context of the economic integration process currently underway in Europe. On the contrary, the importance of interregional trade, migratory movements and technology and knowledge transfer processes suggests that geographical location may play an important role in explaining regional growth patterns in the European setting (López-Bazo *et al.*, 2004; Creszenci, 2005; Fingleton and López-Bazo, 2006). In fact, the theoretical model developed in Section 3 shows that regional growth rates may be affected by the degree of volatility experienced by neighboring regions. The consequences of omitting these spatial effects from the specification of Equation (1.18) are potentially important from an econometric perspective (Anselin, 1988). Accordingly, this potential problem is taken into account in the empirical analysis. At this point it is important to note that the theoretical model does not provide a specific spatial specification to be estimated. In view of this, a fixed-effects *Spatial Durbin Model* (SDM), which is sufficiently general to allow for endogenous and exogenous spatial interactions between the sample regions is considered. This model can be written as follows:

$$\Delta Y_t = \mu + \rho W \Delta Y_t + X_t \beta + W X_t \theta + \upsilon_t \tag{1.19}$$

where W is the spatial weights matrix used to capture the degree of spatial interdependence between the various regions, and υ_t is the disturbance term. As can be observed, in this specification the regional growth rates depend on the spatial lag of the dependent variable, $W\Delta Y_t$, which captures the spatial effects working through the dependent variable. In addition, the model also includes the spatial lag of the measure of volatility and of the rest of control variables, WX_t.

The presence of spatial lags of the dependent and explanatory variables complicates the interpretation of the parameters in Equation (1.19) (Le Gallo *et al.*, 2003; Anselin and Le Gallo, 2006). Therefore, some caution is required when interpreting the estimated coefficients in the SDM. As shown by LeSage and Pace (2009, pp. 33-42), in a SDM a change in a particular explanatory variable in region i has a *direct effect* on that region, but also an *indirect effect* on the remaining regions. In this context, the direct effect captures the average change in the economic growth rate of a particular region caused by a one unit change in that region's explanatory variable. In turn, the indirect effect can be interpreted as the aggregate impact on the growth rate of a specific region of the change in an explanatory variable in all other regions, or alternatively as the impact of changing an explanatory variable in a particular region on the growth rates of the remaining regions. LeSage and Pace (2009) show that the numerical magnitudes of these two calculations of the indirect effect are identical due to symmetries in computation. Finally, the *total effect* is the sum of the direct and indirect impacts.

The specification in Equation (1.19) is particularly useful in this context, because the SDM allows one to estimate consistently the effect of volatility on regional growth when endogeneity is induced by the omission of a (spatially autoregressive) variable. Indeed, LeSage and Pace (2009) show that if an unobserved or unknown but relevant variable following a first-order autoregressive process is omitted from the model, the SDM produces unbiased coefficient estimates. Additionally, this model does not impose prior restrictions on the magnitude of potential spillovers effects. Furthermore, the SDM is an attractive starting point for spatial econometric modelling because it includes as special cases two alternative specifications widely used in the literature: the *Spatial Lag Model* (SLM) and the *Spatial Error Model* (SEM). As can be checked, the SDM can be simplified to the SLM when $\theta = 0$:

$$\Delta Y_t = \mu + \rho W \Delta Y_t + X_t \beta + \upsilon_t \tag{1.20}$$

and to the SEM if $\theta + \rho\beta = 0$:

$$\Delta Y_t = \mu + X_t \beta + \epsilon_t \tag{1.21}$$

where $\epsilon_t = \xi W \epsilon_t + \upsilon_t$ and $\upsilon_t \sim i.i.d.$ In fact, the SDM produces unbiased coefficient estimates even when the true data-generation process is a spatial lag or a spatial error model.

1.4.3 Spatial Weights Matrix Selection

The estimation of the various spatial models described above requires to define previously a spatial weights matrix. Given that this is a critical issue in spatial econometric modelling (Corrado and Fingleton, 2012), a broad range of alternative specifications of W are considered. The first spatial weights matrix is based on the concept of first order contiguity, according to which $w_{ij} = 1$ if regions i and j are physically adjacent and 0 otherwise. Secondly, several matrices based on the k-nearest neighbors ($k = 5, 10, 15, 20$) computed from the great circle distance between the centroids of the various regions (Le Gallo and Ertur, 2003). Additionally, various inverse distance matrices are constructed with different cut-off values above which spatial interactions are assumed negligible. As an alternative, inverse distance and exponential distance decay matrices are considered, whose off-diagonal elements are defined by $w_{ij} = \frac{1}{d_{ij}^{\alpha}}$ for $\alpha = 1.25, 1.50, \ldots, 3.00$ and $w_{ij} = exp(-\theta d_{ij})$ for $\theta = 0.005, \ldots, 0.030$, respectively (Keller and

Shiue, 2007; Elhorst *et al.*, 2013). As can be observed, the different matrices described above are based in all cases on the geographical distance between the sample regions, which in itself is strictly exogenous. This is consistent with the recommendation of Anselin and Bera (1998) and allows the researcher to avoid the identification problems raised by Manski (1993). Furthermore, as is common practice in applied research, all the matrices are row-standardized, so that it is relative, and not absolute, distance which matters.

In the literature there are different criteria to determine the spatial weights matrix that best describe the data. The most widely used approach is to compare the log-likelihood function values. Nevertheless, this approach has been criticized because it only finds a local maximum among competing models and it may be the case that the correctly specified W is not included (Harris *et al.*, 2011; Vega and Elhorst, 2013). As an alternative criterion, LeSage and Pace (2009) propose the employment of the Bayesian posterior model probability, while Elhorst *et al.* (2013) suggest to select the model with the lowest parameter estimate of the residual variance. In the Bayesian estimation exercise, non-informative diffuse priors for the model parameters (β, θ, σ) are used following the recommendation of LeSage (2014a). In particular, a normal-gamma conjugate prior is used for β, θ and σ while a beta prior for ρ is used. To that end, parameter c is set to zero and T to a very large number $(1e+12)$ which results in a diffuse prior for β, θ. Diffuse priors for σ are obtained setting $d = 0$ and $v = 0$. Finally, the parameterization of the prior for ρ is done by setting $a_0 = 1.01$:[9]

$$
\begin{aligned}
&\pi(\beta) \sim N\left(c, T\right) \\
&\pi\left(\frac{1}{\sigma^2}\right) \sim \Gamma\left(d, v\right) \\
&\pi\left(\rho\right) \sim \frac{1}{Beta\left(a_0, a_0\right)} \frac{\left(1+\rho\right)^{a_0-1}\left(1-\rho\right)^{a_0-1}}{2^{2a_0-1}}
\end{aligned}
\tag{1.22}
$$

Table (1.2) shows that, according to these criteria, the most appropriate matrix in this context is the exponential distance decay W with $\theta = 0.01$. Therefore, this is the spatial weights matrix used in the rest of the paper.[10]

[9]As noted by LeSage and Pace (2009), pp. 142, the $Beta\left(a_0, a_0\right)$ prior for ρ with $a_0 = 1.01$ is highly non-informative and diffuse as it takes the form of a relatively uniform distribution centered on a mean value of zero for the parameter ρ. For a graphical illustration on how ρ values map into densities see Figure 5.3 pp. 143. Also, notice that the expression of the Inverse Gamma distribution corresponds to that of Equation 5.13 pp.142.

[10]Posterior probabilities displayed in Table (1.2) are computed by scaling log-marginal values for each group of the geographical weights matrices. This is why the overall column-sum does not add up to one. However, when integrating and scaling over all the different W matrices together, the results are even more explicit pointing with a probability of 99% to the 1% exponential decay matrix as the most likely spatial scheme which suggests a peak-shape posterior density distribution.

Table 1.2: Spatial Weights Matrix Selection.

	Bayesian posterior model probability	Log-likelihood function value	Residual variance
First order contiguity	1.00	3509.84	1.18E-04
K-nearest neighbors ($K = 5$)	0.00	3552.87	1.09E-04
K-nearest neighbors ($K = 10$)	0.86	3551.59	1.09E-04
K-nearest neighbors ($K = 15$)	0.00	3512.16	1.17E-04
K-nearest neighbors($K = 20$)	0.00	3466.42	1.28E-04
Cut-off 500 km	1.00	3564.08	1.07E-04
Cut-off $1,000$ km	0.00	3491.27	1.22E-04
Cut-off $1,500$ km	0.00	3438.74	1.34E-04
Cut-off $2,000$ km	0.00	3401.29	1.44E-04
$1/d^{\alpha}$, $\alpha = 1.25$	0.00	3411.19	1.41E-04
$1/d^{\alpha}$, $\alpha = 1.50$	0.00	3447.64	1.32E-04
$1/d^{\alpha}$, $\alpha = 1.75$	0.00	3481.37	1.24E-04
$1/d^{\alpha}$, $\alpha = 2.00$	0.72	3526.97	1.14E-04
$1/d^{\alpha}$, $\alpha = 2.25$	0.27	3533.47	1.13E-04
$1/d^{\alpha}$, $\alpha = 2.50$	0.00	3535.66	1.12E-04
$1/d^{\alpha}$, $\alpha = 2.75$	0.00	3540.96	1.11E-04
$1/d^{\alpha}$, $\alpha = 3.00$	0.00	3532.95	1.13E-04
$exp - (\theta d)$, $\theta = 0.005$	0.00	3534.70	1.12E-04
$exp - (\theta d)$, $\theta = 0.010$	1.00	3580.55	1.03E-04
$exp - (\theta d)$, $\theta = 0.015$	0.00	3579.38	1.04E-04
$exp - (\theta d)$, $\theta = 0.020$	0.00	3564.39	1.06E-04
$exp - (\theta d)$, $\theta = 0.030$	0.00	3540.31	1.11E-04

Notes: Bayesian Markov Monte Carlo (MCMC) routines for spatial panels required to compute Bayesian posterior model probabilities do not exist yet. As an alternative, all cross-sectional arguments of James LeSage routines are replaced by their spatial panel counterparts, for example a block-diagonal $NT \times NT$ matrix, $diag(W, ..., W)$ as argument for W. All W's are row-normalized.

1.5 Results

1.5.1 Main Findings

The first column of Table (1.3) presents the results obtained when the fixed-effects model described in Equation (1.18) is estimated by OLS assuming that the disturbances are independent and identically distributed. As can be observed, the coefficient of the standard deviation of regional growth rates is negative and statistically significant at the 1% level. This seems to indicate the existence of a negative relationship between volatility and economic growth in the European regions. Furthermore, the results show that the coefficient of initial GDP per capita is negative and statistically significant, indicating the existence of a process of conditional convergence across the sample regions. Likewise, the remaining control variables included in matrix X are in general statistically significant and have the expected signs.

These results should be treated with caution. In particular it is important to recall that, as mentioned above, there are important reasons to believe that spatial effects play an important role in explaining regional growth patterns in the European setting, which may cause estimates of Equation (1.18) to become biased, inconsistent and/or inefficient. In order to investigate the relevance of this potential problem in the sample, the residuals of the OLS estimation of Equation (1.18) are used to calculate the Lagrange multiplier tests for the SLM (LM-SLM) and the SEM (LM-SEM), plus their robust versions.

Table (1.4) reveals that the results of these tests lead in all cases to the rejection of the null hypothesis of absence of residual spatial dependence. In view of this, the various spatial panel data models described in the previous section are estimated by maximum likelihood, using routines written by Elhorst (2014) and the bias correction method proposed by Lee and Yu (2010).

Column 2 of Table (1.3) presents the results from the SDM, whereas the SLM and the SEM are presented respectively in columns 3 and 4. Before continuing it is important to evaluate which is the best spatial specification in this context. To that end, likelihood-ratio tests (LR-SDM-SLM and LR-SDM-SEM) are calculated to find out if the SDM can be simplified respectively to the SLM ($H_0 : \theta = 0$) or the SEM ($H_0 : \theta + \rho\beta = 0$). As can be observed in Table (1.4), the null hypotheses of both tests are rejected. This implies that the SDM is the appropriate specification in this context (Elhorst, 2010). In fact, this conclusion is consistent with the information provided by the various measures of goodness-of-fit included in Table (1.3).

As mentioned in the previous section, correct interpretation of the parameter estimates in the

Table 1.3: Estimation Results: Volatility and Regional Growth.

Model	Non-spatial	Spatial Durbin	Spatial Lag	Spatial error
Volatility	-0.346***	-0.159***	-0.232***	-0.169***
	(-21.88)	(-8.68)	(-13.92)	(-9.35)
Initial GDP per capita (logs)	-0.092***	-0.133***	-0.085***	-0.129***
	(-19.29)	(-25.10)	(-17.86)	(-24.77)
Investment	0.038***	0.003	0.037***	0.006
	(3.19)	(0.29)	(3.20)	(0.52)
Population growth	-0.019	-0.096*	-0.035	-0.054
	(-0.30)	(-1.76)	(-0.58)	(-1.12)
Human capital	0.165***	-0.001	0.122***	0.000
	(9.63)	(-0.06)	(7.23)	(0.01)
Employment density (logs)	-0.067***	0.010	-0.006	0.006
	(-7.76)	(1.06)	(-0.66)	(0.66)
Agriculture	-0.014	-0.026	-0.044**	-0.032*
	(-0.79)	(-1.44)	(-2.46)	(-1.82)
Financial services	0.109***	0.100***	0.085***	0.103***
	(3.61)	(2.98)	(2.89)	(3.16)
Non market services	0.088***	0.001	0.078***	0.009
	(4.30)	(0.03)	(3.93)	(0.37)
Population (logs)	-0.020	-0.024	-0.046***	-0.019
	(-1.23)	(-1.64)	(-2.92)	(-1.32)
Neighbors' volatility		0.068**		
		(2.41)		
Neighbors' initial GDP per capita		0.118***		
		(13.72)		
Neighbors' investment		0.005		
		(0.24)		
Neighbors' population growth		-0.054		
		(-0.38)		
Neighbor's human capital		0.102***		
		(3.44)		
Neighbors' employment density		-0.034**		
		(-2.19)		
Neighbors' agriculture		0.029		
		(0.98)		
Neighbors' financial services		-0.192***		
		(-3.53)		
Neighbors' non market services		-0.012		
		(-0.29)		
Neighbors' population		-0.031		
		(-0.99)		
Neighbor's economic growth (ρ)		0.768***	0.455***	
		(28.93)	(17.91)	
Spatial autoregressive parameter (ξ)				0.897***
				(58.12)
Region-specific effects	Yes	Yes	Yes	Yes
Adjusted R-squared	0.72	0.79	0.71	0.54
Log-likelihood	3188.82	3580.55	3345.12	2467.25
Observations	1088	1088	1088	1088

Notes: The dependent variable is in all cases the average growth rate of GDP per capita of the various regions measured over five-year periods. t-statistics in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level.

Table 1.4: Model Specification Tests.

Test	Statistic	p-value
LM-SLM test	396.11	0.000
LM-SEM test	854.11	0.000
Robust LM-SLM test	37.80	0.000
Robust LM-SEM test	495.80	0.000
LR-SDM-SLM test	400.93	0.000
LR-SDM-SEM test	61.70	0.000

SDM requires to take into account the direct, indirect and total effects associated with changes in the regressors. Table (1.5) shows this information. Focusing on the main aim of the paper, results reveal that the relationship between volatility and economic performance is negative and statistically significant, thus confirming the empirical evidence provided by the previous analysis and by Martin and Rogers (2000). In particular, the estimates show that lowering the volatility measure by one standard deviation is associated with an increase in the average growth rate of around 1.6%. Nevertheless, this total effect is the sum of the direct and indirect impact of volatility on growth. The direct effect, Table (1.5) indicates that an increase in the degree of volatility registered by a specific region exerts a negative and statistically significant impact on its growth rate. In turn, the indirect effect shows that this increase also influences negative and significantly on the growth rates of neighboring regions. In fact, the indirect effect accounts for more than half of the overall impact caused by output fluctuations, thus corroborating the empirical relevance of spatial spillovers in this context. Accordingly, the economic performance of a particular region depends on the degree of volatility registered by the remaining regions, which is consistent with the conclusions of the theoretical model developed in Section 3.[11]

These findings are not affected by the inclusion of additional controls, confirming that the observed effect of the fluctuations of the business cycle on regional growth is not a spurious correlation due to the omission of relevant variables. In particular, volatility remains positive and significantly associated with economic growth even after controlling for the level of investment. This is especially important given that the literature and the theoretical model highlight the potential relevance of investment in explaining the volatility-growth connection (e.g. Ramey and Ramey, 1995; Imbs, 2007). However, the results do not provide empirical support for

[11]In order to investigate whether the observed relationship between volatility and economic growth is stable over time, the estimation of Equation (1.19) for the periods 1991-2006 and 1996-2011 is carried out using three subperiods of five years in each case. The results are very similar to those described in the text. In fact, the only noticeable difference has to do with the direct effect of volatility on economic growth for the period 1996-2011, which is negative but not statistically significant at conventional levels.

this transmission channel. In fact, the direct, indirect and total effects of volatility on economic growth continue to be negative and statistically significant when the investment level is excluded from the list of regressors.

Table 1.5: Spatial Durbin model: Direct, Indirect and Total effects.

Variable	Direct effects	Indirect effects	Total effects
Volatility	-0.168***	-0.224**	-0.392***
	(-9.30)	(-2.56)	(-4.32)
Initial GDP per capita (logs)	-0.130***	0.068**	-0.063**
	(-24.77)	(2.38)	(-2.13)
Investment	0.005	0.033	0.038
	(0.40)	(0.38)	(0.45)
Population growth	-0.120*	-0.545	-0.665
	(-1.75)	(-0.851)	(-0.96)
Human capital	0.016	0.423***	0.439***
	(0.75)	(3.86)	(3.80)
Employment density (logs)	0.005	-0.111**	-0.106*
	(0.53)	(-1.96)	(-1.72)
Agriculture	-0.024	0.038	0.014
	(-1.32)	(0.35)	(0.10)
Financial services	0.080**	-0.488***	-0.407**
	(2.53)	(-2.61)	(-2.16)
Non-market services	-0.002	-0.047	-0.049
	(-0.05)	(-0.32)	-0.32)
Population (logs)	-0.032**	-0.208	-0.240*
	(-2.08)	(-1.61)	(-1.77)

Notes: t-statistics in parentheses. *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 1000 simulated parameter combinations drawn from the variance-covariance matrix implied by the BCML estimates.

Table (1.5) also provides interesting information about the different control variables included in matrix X. Thus, it should be noted that the direct effect estimates are mostly statistically significant. In particular, the results obtained show that regions with relatively low levels of GDP per capita tend to grow faster, confirming the existence of a process of conditional convergence across the European regions during the study period. Furthermore, the population growth rate is negatively associated with the dependent variable. Likewise, empirical estimates also reveal that the employment share in financial services has a positive impact on regional growth, while the impact of total population is negative. These findings are in general consistent with the empirical evidence provided by the literature on regional growth in Europe. In turn, the investment level, human capital, employment density and the employment shares in agriculture and non-market services do not seem to exert a statistically significant direct effect on the dependent variable. In any case, it is important to observe that there are variables in which the direct effects displayed in Table (1.5) tend to be similar to the spatial Durbin model coefficient estimates of the non-spatial lagged variables reported in the second column of Table (1.3). The differences between these measures are due to feedback effects that arise from spatial spillovers induced by each region in the whole system. In those cases where these differences are not particularly relevant, it is possible to conclude that feedback effects do not play an important role in this context. Table (1.5) also reveals that the indirect impacts are statistically significant for the initial level of GDP per capita, the human capital control, employment density and the employment share in financial services. This means that the effect on the dependent variable of the remaining control variables tends to be confined to the region itself.

As mentioned above, the sum of direct and indirect effects allows one to quantify the total effect on regional growth of the different control variables. When direct and indirect effects are jointly taken into account, Table (1.5) indicates that the total effect is statistically significant exclusively in the case of the initial level of GDP per capita, the human capital control, employment density, the employment share in financial services and total population. The total effect of the initial level of GDP per capita implies a speed of convergence of 3.26%. When interpreting this result, it is interesting to note that the level of development of neighboring regions has a positive influence on the growth rate of any given region, thus reducing the speed of convergence provided by the estimate of the direct effect of the initial level of GDP per capita. In turn, the investment in human capital exerts a positive influence on the economic performance of the European regions, which has to do with the relevance of spatial spillovers associated with this variable. In the case of employment density and the employment share in financial services, the negative indirect effects outweigh the positive direct effects. As a result, the total effects of these variables show a negative correlation between them and the dependent variable. Furthermore, smaller regions are characterized by registering higher growth rates, confirming the information provided by the direct effect.

1.5.2 Robustness Checks

The analysis carried out so far suggests the existence of a negative and statistically significant link between the intensity of output fluctuations and regional growth in Europe. In particular, estimates seem to indicate that the observed relationship is in part due to the existence of spatial spillovers induced by volatility in neighboring regions. In the rest of this section the robustness of these findings is investigated.

As a first robustness test, it is examined to what extent the results may be sensitive to the choice of the measure used to quantify the incidence of volatility in the sample regions. To that end, an alternative measure of volatility used in the real business cycle literature that consists of the standard deviation of the GDP per capita gap (Hnatovska and Loayza, 2004) is considered. To calculate this measure, the trend of each region's GDP per capita series is estimated by applying the Hodrick-Prescott filter. The standard deviation of GDP per capita growth employed so far in the paper is based on the implicit assumption that the trend of GDP grows at a constant rate, whereas this measure allows the trend of GDP to follow a richer, time- and regional-dependent process. Table (1.6) shows the direct, indirect and total effects obtained when the SDM is estimated using the standard deviation of the GDP per capita gap to capture the relevance of the fluctuations of the business cycle in the sample regions. As can be seen, the different effects of volatility on regional growth continue to be negative and statistically significant in all cases, confirming previous results.

An additional issue is to examine until what extent previous findings are contingent on the specific spatial model used to investigate the link between volatility and economic growth in the European regions. In fact, the analysis performed so far is based on the estimation of a SDM. As discussed in Section 4, in this particular context there are important reasons to justify the employment of the SDM as the baseline specification. Nevertheless, it is important to note that the SDM is a global spillover specification (LeSage, 2014b). In view of this and in order to complement previous results, two local spatial spillover specifications are considered: the *Spatial Exogenous Lag Model* (SLX) and the *Spatial Durbin Error Model* (SDEM), which can be written respectively as follows:

$$\Delta Y_t = \alpha + X_t\beta + WX_t\theta + \upsilon_t \tag{1.23}$$

and

$$\Delta Y_t = \alpha + X_t\beta + WX_t\theta + \epsilon_t \tag{1.24}$$

where $\epsilon_t = \xi W\epsilon_t + \upsilon_t$ and $\upsilon_t \sim i.i.d.$. The results obtained when these alternative specifications are used instead of the SDM are shown in Table (1.7). As can be checked, the main findings remain unaltered. The direct, indirect and total effects of volatility on economic growth are

Table 1.6: Robustness Analysis (I): An Alternative Measure of Volatility.

Variable	Direct effects	Indirect effects	Total effects
Volatility	-0.241***	-0.250***	-0.492***
	(-14.52)	(-3.16)	(-5.99)
Initial GDP per capita (logs)	-0.116***	0.072***	-0.044
	(-23.84)	(2.69)	(-1.58)
Investment	0.012	-0.002	0.010
	(1.14)	(-0.03)	(0.14)
Population growth	-0.154***	-0.712	-0.866
	(-2.44)	(-1.23)	(-1.39)
Human capital	0.016	0.328***	0.345***
	(0.85)	(3.54)	(3.54)
Employment density (logs)	-0.001	-0.099*	-0.100*
	(-0.13)	(-1.92)	(-1.86)
Agriculture	-0.003	0.050	0.047
	(-0.16)	(0.53)	(0.48)
Financial services	0.074**	-0.488***	-0.414**
	(2.43)	(-2.94)	(-2.47)
Non-market services	0.011	-0.095	-0.084
	(0.52)	(-0.78)	(-0.68)
Population (logs)	-0.018	-0.139	-0.157
	(-1.29)	(-1.22)	(-1.32)

Notes: t-statistics in parentheses. *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 1000 simulated parameter combinations drawn from the variance-covariance matrix implied by the BCML estimates.

negative and statistically significant in all cases, regardless of the spatial model considered.

When interpreting previous results, it should be noted that the impact of volatility on economic growth may differ across regions, depending on their level of development. According to this hypothesis, the negative correlation observed between volatility and economic performance may be caused by the inclusion in the sample of regions with different levels of economic development. In order to test whether this is the case, the sample regions is divided into two groups: (i) regions with a GDP per capita below the 75% of the sample mean at the beginning of each five-year period, and (ii) remaining regions. This regional classification is used to estimate an alternative version of Equation (1.19) that allows the volatility-growth relationship to be different across groups (Ertur *et al.*, 2006).[12] The results of this additional analysis are summarized in Table (1.8). As can be observed, the negative association between volatility and economic performance still holds in the two groups of regions. Nevertheless, the different effects shown in Table (1.8) are statistically significant at conventional levels only in the case of the low-income regions. This result is potentially important from a policy perspective, as it suggests that output fluctuations are particularly harmful for economic growth in the Europe's poorest regions.

Finally, it is examined whether empirical results are affected by the fluctuations in the exchange rates of the various countries. As pointed out by Bivand and Brunstad (2006, p. 284), regions in countries with unusual exchange rate series can perform differently from regions in countries with typical exchange rate series. This is potentially important in this context, since the variations in the exchange rate series may have influence on the values of the regional growth rates and the measure of volatility used in the econometric analysis. In order to investigate this issue an approach similar to that used by Bivand and Brunstad (2006) is adopted here. In particular, a dummy variable that allows to identify regions in countries with high fluctuations in the exchange rate series over the study period is included. This dummy variable takes the value one if the region is in a country where the standard deviation of the variation of the exchange rate in each five-year period is above the third quartile of the distribution, zero otherwise. As can be observed in Table (1.9), the total effect on the dependent variable of this dummy variable is not statistically significant at conventional levels. However, previous findings on the relationship between volatility and economic growth remains unaffected.

[12] As an alternative, one may to consider the possibility of estimating Equation (1.19) separately for two groups of regions defined according to the level of development at the beginning of the study period. However, this would imply to use different spatial weights matrices in the two groups, thus ignoring the spatial interdependences between them.

Table 1.7: Robustnes Analysis (II): Alternative Spatial Specifications.

Model	SLX			SDEM		
Variable	Direct effects	Indirect effects	Total effects	Direct effects	Indirect effects	Total effects
Volatility	-0.167***	-0.237***	-0.403***	-0.177***	-0.153***	-0.330***
	(-7.91)	(-8.12)	(-17.31)	(-9.67)	(-2.96)	(-5.76)
Initial GDP per capita (logs)	-0.133***	0.056***	-0.077***	-0.129***	0.026*	-0.103***
	(-22.39)	(6.03)	(-10.18)	(-24.30)	(1.69)	(-6.17)
Investment	0.004	0.008	0.012	0.009	0.058	0.068
	(0.33)	(0.33)	(0.57)	(0.80)	(1.51)	(1.59)
Population growth	-0.142**	-0.167	-0.308*	-0.102	-0.141	-0.242
	(-2.27)	(-1.06)	(-1.74)	(-1.57)	(-0.61)	(-0.88)
Human capital	0.026	0.293***	0.319***	0.036*	0.209***	0.245***
	(1.14)	(8.93)	(11.93)	(1.77)	(4.69)	(4.45)
Employment density (logs)	0.07	-0.118***	-0.110***	0.006	-0.059**	-0.053*
	(0.72)	(-6.62)	(-6.91)	(0.59)	(-2.12)	(-1.72)
Agriculture	-0.022	-0.028	-0.050*	-0.021	0.021	0.000
	(-1.10)	(-0.84)	(-1.81)	(-1.11)	(0.36)	(0.00)
Financial services	0.088**	-0.233***	-0.145***	0.092***	-0.178*	-0.086
	(2.25)	(-3.71)	(-3.17)	(2.82)	(-1.75)	(-0.81)
Non-market services	0.013	-0.009	0.004	0.011	0.065	0.075
	(0.47)	(-0.20)	(0.10)	(0.50)	(0.93)	(1.07)
Population (logs)	-0.024	-0.091**	-0.115***	-0.031**	-0.053	-0.084
	(-1.45)	(-2.56)	(-3.45)	(-2.00)	(-1.07)	(-1.51)

Notes: t-statistics in parentheses. *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 1000 simulated parameter combinations drawn from the variance-covariance matrix implied by the BCML estimates.

Table 1.8: Robustness Analysis (III): The Effect of Regional Development Level.

Variable	Direct effects	Indirect effects	Total effects
Volatility of poorest regions	-0.172***	-0.221**	-0.393***
	(-9.33)	(-2.18)	(-3.74)
Volatility of remaining regions	-0.082*	-0.315	-0.397
	(-1.74)	(-0.87)	(-1.05)
Initial GDP per capita (logs)	-0.130***	0.067**	-0.063**
	(-24.67)	(2.23)	(-2.02)
Investment	0.006	0.033	0.039
	(0.49)	(0.38)	(0.43)
Population growth	-0.122*	-0.548	-0.669
	(-1.75)	(-0.81)	(-0.93)
Human capital	0.015	0.421***	0.436***
	(0.74)	(4.00)	(3.96)
Employment density (logs)	0.004	-0.106*	-0.101
	(0.46)	(-1.77)	(-1.63)
Agriculture	-0.023	0.037	0.015
	(-1.22)	(0.33)	(0.12)
Financial services	0.081**	-0.483**	-0.402**
	(2.49)	(-2.49)	(-2.05)
Non-market services	0.003	-0.051	-0.049
	(0.11)	(-0.37)	(-0.34)
Population (logs)	-0.031**	-0.215	-0.246*
	(-1.99)	(-1.64)	(-1.78)

Notes: t-statistics in parentheses. *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 1000 simulated parameter combinations drawn from the variance-covariance matrix implied by the BCML estimates.

Table 1.9: Robustness Analysis (IV): The Impact of Exchange Rate Fluctuations.

Variable	Direct effects	Indirect effects	Total effects
Volatility	-0.177***	-0.186**	-0.363***
	(-9.53)	(-1.96)	(-3.65)
Initial GDP per capita (logs)	-0.129***	0.066**	-0.063**
	(-24.58)	(2.19)	(-2.05)
Investment	0.006	0.033	0.039
	(0.57)	(0.38)	(0.44)
Population growth	-0.106	-0.584	-0.691
	(-1.53)	(-0.86)	(-0.95)
Human capital	0.014	0.454***	0.468***
	(0.68)	(4.15)	(4.11)
Employment density (logs)	0.006	-0.121**	-0.115*
	(0.69)	(-2.01)	(-1.83)
Agriculture	-0.023	0.055	0.032
	(-1.25)	(0.47)	(0.27)
Financial services	0.075**	-0.490**	-0.415**
	(2.26)	(-2.51)	(-2.10)
Non-market services	-0.006	-0.057	-0.063
	(-0.25)	(-0.38)	(-0.41)
Population (logs)	-0.036**	-0.199	-0.235*
	(-2.42)	(-1.48)	(-1.68)
Exchange rate factor	0.006***	-0.013*	-0.007
	(3.04)	(-1.86)	(-1.05)

Notes: t-statistics in parentheses. *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 1000 simulated parameter combinations drawn from the variance-covariance matrix implied by the BCML estimates.

1.6 Conclusions

This paper has examined the relationship between output volatility and regional growth in Europe. To that end, a spatially augmented stochastic growth model with technological interdependence among economies is developed. Spatial externalities are used to model technological interdependence, which ultimately implies that the economic growth rate of a particular region is affected not only by its own the degree of volatility but also by the output fluctuations registered by the remaining regions. The model shows that economic fluctuations generate effects on the growth rate of output through the channels of learning by doing and through the determination of the optimal savings rate, which ultimately depends on the attitudes towards risk. These effects are not confined to the region where the random innovation occurred and generate additional impacts in the production of other regions. In the theoretical model different parameter values characterizing the scaling of shocks, the impact on learning, attitudes to risk, the returns to scale of the different factors and the degree of regional interdependence shape the relationship between volatility and growth. Thus, highly volatile productivity paths in a given region could reduce its learning and knowledge formation affecting negatively not only its regional output but also the rest of the regions in the system. On the contrary, if individuals in a region are risk averse, volatile fluctuations will increase their savings through precautionary motives. The latter will tend to rise the output growth rate in the long run. However, in the proposed theoretical model, structural parameters take fairly general values and therefore, the question of whether volatility affects positively or negatively growth is left to the empirical analysis.

In order to investigate the empirical validity of this result, the volatility-growth connection in a sample of 272 European regions over the period 1991-2011 is examined. To do so, a spatial panel data model using spatial econometric techniques that allows one to take into account the relevance of spatial effects in the processes of regional growth is estimated. Empirical estimates show the existence of a negative and statistically significant relationship between volatility and economic growth in the European regions. This is partly due to the role played in this context by spatial spillovers induced by volatility in neighboring regions. The observed link is robust to the inclusion in the analysis of different explanatory variables that may affect regional growth such as the initial GDP per capita, the level of investment and human capital, employment density or industry mix. In addition, tests to check that the results do not depend on the measure of volatility used in the analysis are carried out. Likewise, the negative link detected between output fluctuations and economic growth still holds when alternative econometric specifications are employed to capture the nature of spatial spillovers in this context.

The results obtained in the paper have potentially interesting policy implications. At this point it needs to be recalled that the variability of cyclical macroeconomic fluctuations have typically been perceived as a negative phenomenon. The empirical evidence provided by the present analysis confirms this perception. In particular, the estimates show that short-term instability is negatively related to regional growth in the European context. This suggests that traditional public policies designed to promote regional growth should be complemented with initiatives to reduce the business cycle fluctuations experienced by the European regions. In this line, policy-makers could attempt to attract new industries to diversify the regional productive structure, thus reducing the risks faced by those regions with an excessive reliance on a small number of economic activities (Ezcurra, 2011). In any case, although further research is required to confirm definitely conclusions obtained here, the possible effect of short-term stability on economic growth should not be overlooked by policy-makers.

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Chapter 2

Development Differentials and Interaction Effects in the European Regions: A study based on the Regional Lisbon Index[1]

2.1 Introduction

Economists generally assume that regional economic development follows on from economic growth (Hirschman, 1958; Mynt, 1964). This classical view of the concept can be considered as economicist, given that it only deals with the material side of development. In fact, the GDP indicator is a basic one-dimensional measure of a country's overall output. It does not measure the development of a particular region as a whole, but rather summarizes the current state of market transactions within a society, regardless of qualitative or distributive issues (Herrero *et al.*, 2010). Moreover, the predictive power of GDP is further limited because it measures only present success, while giving no clue as to the probability of a long-term increase in regional welfare (Brookfield, 2001).

Nowadays, the widespread belief among academics and policy makers is that composite indexes provide a better characterization of the multidimensional nature of societal progress (Stiglitz *et al.*, 2010). Thus, recent years have seen a series of international initiatives to meet the demand for accurate social development indicators, incorporating more than purely economic perspectives. There are many alternative indicators that gradually incorporated as comprehensive, sustainable and all-embracing measurements as possible: the *Measure of Economic Welfare* and the *Sustainable Measure of Economic Welfare* (Nordhaus and Tobin, 1972), the *Index of Sustainable Economic Welfare* (Daly and Cobb, 1989), the *Genuine Progress Indicator* (Pearce and Atakinson, 1993; Pearce *et al.*, 1996; Everett and Wilks, 1999), the *Total Material Requirement Index* (Adriaanse *et al.*, 1997) or *The Happy Planet Index* (Marks *et al.*, 2006), etc.

[1]This essay has been published in *Tijdschrift voor Economische en Sociale Geografie.*

Nevertheless, the most relevant and widely-used composite indicator was published in the first Human Development Report (HDR) of the United Nations Development Programme (UNDP) has been the Human Development Index (HDI), designed by economist Mahbub ul Haq. However, HDI presents several problems in applied research if the focus of the study is related to advanced economies such as European Union. The most important problems are its components. The HDI components do not display an adequate portrayal of the broad concept of development given that in Europe development capabilities pivot around other issues. This failure was recognized by Anand and Sen (1994): "*Yet once we take of the high and similar levels of achievement in basic capabilities, it becomes relevant to asses performance using more refined capabilities*".[2]

In line with such policy making initiatives and in order to analyze development in European member states, Dijkstra (2010) proposes a new composite index to be used in regional level measurement: the Regional Lisbon Index (RLI). Remarkably, the RLI approach to the concept of development includes neither GDP per capita nor GDP per person employed and its correlation with GDP is 0.45, which suggests it provides new information that cannot be learned from GDP data. The specific purpose of the RLI indicator developed by Dijkstra (2010) was to serve as a measure of the achievement of objectives set out in the Lisbon Agenda or Lisbon Strategy (henceforth LS). The said objectives refer fundamentally to employment, education and research as the necessary means to achieve a knowledge-based economy (KBE) and social cohesion. In point of fact, LS goals trace an action and development plan for the EU regions, where the emphasis is laid on advancing towards a "*knowledge society*". Furthermore, the European Council, convened in Lisbon in March of 2000, announced its intention to "*turn the European Union into the most competitive knowledge-based economy in the world*" (European Council, 2000).

Originally, the aim of the RLI was to improve the methodology used in other Lisbon indicators, such as those published by ESPON3, the Lisbon Monitoring Platform, Lisbon Council and in the 4th Cohesion Report. Under the so-called Renewed LS (European Commission, 2005) Member States were urged to include its objectives in their regional programming for the period 2007-2013. However, at the end of the decade, the European Commission (2010a) performed an ambiguous, qualitative and optimistic evaluation of LS results, which has been criticized by Lundvall and Lorenz (2011) among others. In 2010, the European Commission (2010b) sets out new growth and employment strategy goals synthetized in "*Europe 2020*", which builds on the

[2] This is primarily because GDP per head; literacy, enrollment and life expectancy are all high in Europe, Bubbico and Dijkstra (2011).

LS and calls for a particular attention to the territorial dimension of innovation and knowledge creation (Paci and Marrocu, 2013). The two key differences between the *Europe 2020* and the LS are that (i) *Europe 2020* includes environmental and poverty indicators and (ii) there has been a shift from redistributive policies towards place-based policies aimed at sustaining specific regional capabilities (Barca, 2009). Nevertheless, the fact that "*Europe 2020*" strategy establishes new employment, education, research and social cohesion criteria to address economic development performance provides a motivation for empirical research based on the RLI, since it is this that will be guiding the assessment of European Regional Policy outcomes.

The objective of this paper is threefold. The first aim is to study the path of European regions towards a KBE as defined by RLI indicators and LS targets. To do so, a new version of the RLI containing changes with respect the index developed Dijkstra (2010) is proposed. Secondly, given that one of the main goals of the regional European development strategy has been to achieve social and territorial cohesion (European Commission, 2010c) the proposed alternative RLI indicator to analyze regional convergence dynamics among European regions is employed. Finally, it is explored how a variety of factors affect regional development growth rates. An innovative feature of the modeling exercise the role of geography and the existence of spatial interaction effects between regional units are taken into account. At this purpose, a spatial panel data econometrics approach is adopted. This empirical framework allows to analyze the magnitude and significance of spatial spillovers by means of recently developed econometric estimation techniques (LeSage and Pace, 2009; Lee and Yu 2010; 2010b; Elhrost, 2010; 2012; 2014). Important methodological issues such as region-specific and time-specific fixed effects, spatial estimation methods, specification and the selection of the spatial matrix are addressed.

The chapter is organized as follows. Section 2, which follows this introduction, reviews the construction and calculation of the composite Regional Lisbon Index. The shortcomings of the original RLI are discussed and a new computation of the RLI to address them is proposed. Section 3 describes the dataset used in the study and the empirical strategy used in this analysis. The main research findings are presented in Section 4 and the principal conclusions in the final section.

2.2 The Regional Lisbon Index

The development of a framework for the analysis of regional development based on composite indexes aimed at generating useful insights for policymaking poses a major theoretical and empirical challenge (Streeten, 1994). However, researchers appear to agree that knowledge plays a crucial role in helping, not only to stimulate and sustain long-term capabilities in firms and organizations, but also to enhance the success and well-being of individuals and communities (Howells, 2002). The "*learning economy*" (Lundvall and Johnson, 1994), "*knowledge economies*" (Cooke, 2002), the "*learning region*" (Florida, 1995) among others, posit the systemic nature of knowledge as the new paradigm for studying regional development.

The problem is that the KBE has not a unique interpretative paradigm and measuring the progress of the European regions towards a KBE could prove to be a daunting task (Sokol, 2004; Godin, 2006). Nevertheless, the adoption of the RLI as a policy evaluation tool by the European Comission and the European Central Bank[3] appears an appropriate first step towards efficient and quantitative monitoring of progress towards a KBE. At this regard, it is important to remark that the literature has identified a set of factors acting as structural forces of competitive disadvantage for the local economy. As Rodriguez-Pose (1999) points out, lagging regions in the EU share a common set of analogous social features. Consequently, it is possible to identify a set of structural conditions that are persistently associated with poor economic performance. These factors concern, to different extents, to the features of the labor force, the employment of local resources, the demographic structure and the accumulation and quality of human capital (Malecki, 1997; Fargeberg *et al.*, 1997; Rodriguez-Pose and Crescenzi, 2008).

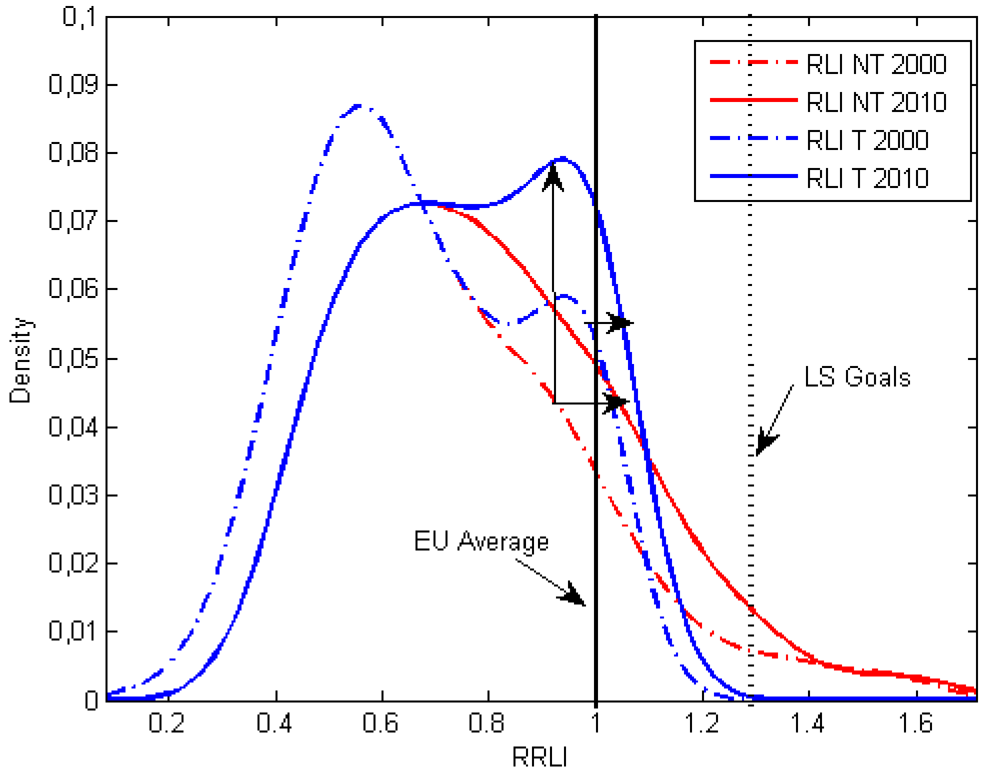
The virtue of the RLI is that it captures the set of relevant dimensions involved in the development of KBE by aggregating and weighting labor market, education and R&D indicators (Powell and Snellman, 2004; Wamser *et al.*, 2013). Further support for the decision to consider these pillars of development was provided by seminal contributions from the fields of sociology and economics that have analyzed this concept and emphasized the relevance of R&D and education (Bell, 1973; Drueker, 1989). The labor market dimension of the RLI is condensed into three employment rate variables: men aged 15-54, women aged 15-54 and the joint male and female 55-64 age group. In the context of a KBE, knowing implies an intrinsic relationship with doing. Hence, job training for skills advancement and learning through employment within an inclusive labor market are crucial pre-requisites for regional development. The educational dimension is approximated by three more variables: the percentage of early school leavers aged 18-24; the percentage of secondary education attainment in the 20-24 age group; and participation in life-long learning in the 25-64 age group. Finally, the R&D dimension includes R&D expenditure by businesses (BERD), and by government, higher education and non-profit organizations, in

[3]Loannou et al. (2008) develop a similar composite index framework to benchmark the LS advancements.

both cases as a percentage of GDP (GERD).

The calculation of the RLI takes into account gaps with the Lisbon targets in a readily understandable manner, by computing the relative distance from the Lisbon target instead of the absolute values of the indicators. However, the computation of the Additive Regional Lisbon Index (ARLI) developed by Dijkstra (2010) presents several shortcomings when compared to the Multiplicative Regional Lisbon Index (MRLI) version proposed here. The computation of the ARLI truncates the distribution of the scores by imputing a value of one irrespective of whether a particular region just satisfied or widely surpassed the target level. This introduces a severe bias in the distribution of relative ARLI scores. Figure (2.1) shows the distribution of the ARLI (blue-line) and MRLI (red-line) scores in the years 2000 (dashed-line) and 2010. As it can be seen in Figure (2.1) the probability mass of any region to achieve and/or overcome LS targets goes to zero when implementing the ARLI (blue line) but also creates a twin-peaks shaped relative distribution in the scores. Moreover, since the additive structure does not penalize unbalanced development patterns, a region may obtain a relatively high overall score due to marked performance improvements in only a few of the dimensions of the index.

Figure 2.1: Regional Lisbon Index 2000-2010.



The methodological proposal here is to use an alternative multiplicative index and avoid truncation in the distribution of RLI scores. Differences in the formulas used in the two approaches and the computational steps taken in each RLI version are summarized in Table (2.1). As it is shown in the second row of Table (2.1), the computation of the index does not restrict the score to a maximum of 1 if a region surpasses a given target. In the third step, each region's sub-indicator scores are aggregated using the geometric mean, which means that this new proposal, unlike the ARLI, takes into account differences in performance across the various dimensions. Poor performance in any dimension is now directly reflected in the new RLI, which captures how well a region performs across the eight dimensions under consideration. In addition, the fourth normalization/scaling step of Dijkstra (2010) was deleted given that it was producing highly counter-intuitive results. That is, even if most of indicators during the sample period where approaching to the LS targets, the overall Index was decreasing. Thus, ARLI is built here so that it maximizes comparability with the MRLI by only applying the three first steps shown in Table (2.1).

Table 2.1: Regional Lisbon Index Calculation.

Computational Step	Additive RLI	Multiplicative RLI
1. Regional Target Filter	$T_{i,t,j} = T_j - E_{i,t,j}$ $E_{i,t,j_1} = R_{i,t,j_2} - T_{j_2}$	$T_{i,t,j} = T_j - E_{i,t,j}$ $E_{i,t,j_1} = R_{i,t,j_2} - T_{j_2}$
2. Score Calculation	$S_{i,t,j} = 1 - \left(\frac{T_{i,t,j}-R_{i,t,j}}{T_{i,t,j}-R_{min,t,j}}\right)$ if $R_{i,t,j} < T_{i,t,j}$ $S_{i,t,j} = 1$ if $R_{i,t,j} \geq T_{i,t,j}$	$S_{i,t,j} = \frac{R_{i,t,j}}{T_{i,t,j}}$
3. Score Aggregation	$ARLI_{i,t} = 100\left(\frac{1}{J}\sum_{j=1}^{J}\alpha_j S_{i,t,j}\right)$	$MRLI_{i,t} = 100\left(\sqrt[N]{\prod_j^N S_{i,t,j}}\right)$
4. Normalization	$NARLI_{i,t} = \frac{ARLI_{i,t}-ARLI_{min,t}}{ARLI_{max,t}-ARLI_{min,t}}$	No Normalization

Note: In the first step E_{i,t,j_1} denotes the excess associated to the pair of overlapping indicators j_1 and j_2 at time t, $T_{i,t,j}$ is the Lisbon Target associated to indicator j of region i at time t and $R_{i,t,j}$ is the score of region i at time t for indicator j. In the third step the weights used to combine the indicators are adjusted to ensure that an increase of 1 percentage point would lead to the same increase in the Lisbon Index. The BERD target indicator is weighted by 4/3 so that $\alpha_{BERD} = 4/3$ and GERD indicator is weighted by 2/3, so that $\alpha_{GERD} = 2/3$.

Table (2.2) reports sub-indicators scores and the original targets of the LS while also allows for a global comparison of the ARLI and MRLI. As can be seen, according to the MRLI, EU regions improved their score by 9.4 points while according to the ARLI an increase of 10.1 points over the period ranging from 2000 to 2010 is observed. Final scores in 2010 were 81.5 and 80.5 respectively, which suggests there is still a large gap to be closed in order to fully achieve the LS target of 100. The similarity in the overall result is due to the fact that the global behavior in the various sub-indicators is very similar in both indexes. Nevertheless, there is a high degree of cross-region and cross-indicator variation underlying this aggregate pattern during the study period. While labor market scores improved substantially, R&D, early school leavers and life-long learning outcomes remained far away from the original targets. Thus, if policy makers aim to push European economy towards a KBE, additional efforts to develop an adequate innovative environment are needed.

Table 2.2: Regional Lisbon Indicators.

Lisbon Indicator	Target	ARLI Score 2000	ARLI Score 2010	MRLI Score 2000	MRLI Score 2010
Emp, men aged 15-54	85	0.70	0.66	0.89	0.86
Emp, women aged 15-54	64	0.86	0.98	0.92	0.99
Emp, people aged 55-64	50	0.63	0.87	0.74	0.91
Early school leavers	10	0.83	0.90	0.58	0.67
Second Educ attaintment	85	0.79	0.86	0.89	0.93
Lifelong learning	12	0.55	0.79	0.55	0.79
Private RD as % of GDP	2	0.60	0.60	0.60	0.60
Government RD as % of GDP	1	0.70	0.85	0.70	0.85
Regional Lisbon Index	100	70.4	80.5	72.1	81.5

Note: Author's own calculations based on Eurostat Database and information provided by the European Comission upon request. Results presented in this table are in all cases weighted averages.

Tables (2.3) and (2.4) show the different scores and the rankings both for regional development levels and the regional development dynamics based on the various RLI indicators and the GDP indicator. As can be observed in Table (2.3), the two RLI measures give different top and bottom rankings. However, the set of countries of the top 10 regions in both the ARLI and the MRLI are very similar given that the majority of them belong to northern European countries, suggesting some geographical clustering in development levels. This result is corroborated by simple Moran's tests measuring the degree of spatial autocorrelation for both ARLI and MRLI in levels and growth rates.[4] The MRLI gives Hovedstaden (Denmark) as the top ranking region in 2010 while according to the ARLI the regional leader was Etela-Soumi (Finland). Top positions in MRLI and ARLI indexes contrast with those given by the GDPpc indicator in terms of both, the regional ordering and the regional composition. This is because of top regions according to the GDPpc indicator are financial and political centers such as London, Luxemburg or Bruxelles. An additional feature of Table (2.3) is that regions in the bottom tend to be the same in both the MRLI and GDPpc, as they usually include regions from Eastern countries such as Bulgaria

[4]Moran's statistic for ARLI/MRLI in levels is 0.51, with p-value 0.00 and 0.47 with p-value 0.00. On the other hand, Moran's statistic for ARLI/MRLI in growth rates is 0.27 with p-value 0.00 and 0.19 with p-value 0.00.

and Romania. Thus, a differential feature of the ARLI with respect the MRLI is that the set of bottom regions is not only composed by eastern regions but also includes south-Italian regions and Malta.

Regarding the observed dynamics of the sample regions it can be seen that the fast-mover set given by the ARLI measure consists mainly of southern European regions belonging to countries such as Spain, France or Italy. According to the MRLI, the fastest mover was Lincolnshire while according to the ARLI, the region that developed the fastest during this decade was Corse. Interestingly, in the MRLI case, and contrary to the ARLI case,a more diversified set of regions appears in the top positions. This finding suggests that south-European regions may have experienced an unbalanced development, characterized by the achievement of high scores in education indicators but low scores in R&D and employment dimensions. Regarding lagging behind regions, it is observed that some UK and Netherlands regions have experienced falls in RD levels which has decreased their overall development performance. Conversely, lagging regions in GDPpc indicator are geographically located in the South of Europe while the regions experiencing the highest GDPpc growth rates are related to financial centers, abundant natural resources such as oil and gas or include the capital city.

Taken together, these results suggest that (i) RLI levels and growth rates are geographically clustered and (ii) that both, the MRLI/ARLI provide new information that cannot be gleaned from GDP data and are therefore not redundant in the formation of an economic index of development. Further information on differences in the spatial distribution of the GDP and RLI indicators can be observed in Figures (2.2) and (2.3) below.

Table 2.3: Regional Lisbon Index Ranking.

	Multiplicative RLI Ranking	2010	2000	Aditive RLI Ranking	2010	2000	GDP Per Capita Ranking	2010	2000
Top 10	Hovedstaden	1.31	1.18	Etela-Suomi	0.98	0.96	Inner London	84.24	72.17
Regions	Vstsverige	1.29	0.95	Gloucestershire	0.97	0.96	Luxemburg	58.70	50.74
	Sydsverige	1.26	1.23	Sydsverige	0.97	0.94	Rgion de Bruxelles-Capitale	51.44	49.97
	Stockholm	1.23	0.98	Lansi-Suomi	0.97	0.93	Stockholm	46.50	41,47
	stra Mellansverige	1.20	1.22	Steiermark	0.96	0.84	Hamburg	45.99	42.56
	East Anglia	1.18	1.14	Hovedstaden	0.96	0.97	Hovedstaden	43.12	40.52
	Steiermark	1.13	0.84	Vatsverige	0.96	0.98	North Eastern Scotland	40.27	38.27
	Braunschweig	1.12	1.02	Berkshire	0.96	0.83	Oberbayern	39.00	36.88
	Prov. Vlaams Brabant	1.12	0.95	Vlaams Brabant	0.96	0.88	Berkshire	38.98	38.05
	Ita-Suomi	1.12	1.03	Hampshire	0.95	0.96	Wien	38.29	36.65
Bottom 10	Yuzhen tsentralen	0.34	0.29	Severen tsentralen	0.44	0.41	Yugoiztochen	2.80	2.58
Regions	Vest	0.33	0.30	Sud-Est	0.43	0.49	Centru	2.78	2.00
	Severoiztochen	0.33	0.29	Severozapaden	0.43	0.41	Nord-Vest	2.58	1.73
	Yugoiztochen	0.32	0.28	Eszak-Magyarorszag	0.43	0.36	Severen tsentralen	2.45	1.21
	Sud - Muntenia	0.30	0.28	Campania	0.42	0.34	Yuzhen tsentralen	2.41	1.03
	Centru	0.30	0.26	Calabria	0.42	0.32	Severozapaden	2.37	2.85
	Sud-Est	0.29	0.29	Malta	0.41	0.27	Sud - Muntenia	2.32	1.44
	Sud-Vest Oltenia	0.28	0.31	Centru	0.41	0.44	Sud-Est	2.22	1.61
	Severozapaden	0.28	0.26	Puglia	0.40	0.34	Sud-Vest Oltenia	2.11	1.60
	Severen tsentralen	0.28	0.27	Sicilia	0.38	0.31	Nord-Est	1.69	1.29

Note: GDP pc data is computed in 2000 constant prices and expressed in thousands.

Table 2.4: Development Dynamics Rankings.

	Multiplicative RLI		Aditive RLI		GDP Per Capita	
Fast Moving Regions	Lincolnshire	7.36	Corse	13.57	Inner London	1.21
	Norte	6.95	Extremadura	6.30	Luxemburg	0.80
	Swietokrzyskie	5.54	Andalucia	4.37	Ovre Norrland	0.72
	Cantabria	4.97	Sardegna	4.21	Souther and Eastern	0.67
	Nyugat-Dunantul	4.75	Cantabria	4.13	Norra Mellansverige	0.62
	La Rioja	4.68	Asturias	4.09	Highlands and Islands	0.61
	Estonia	4.47	Malta	4.09	Praha	0.61
	Prov. Antwerpen	4.25	Slaskie	4.09	Groningen	0.59
	Luxemburg	4.06	La Rioja	4.06	Attiki	0.58
	Corse	3.85	Champagne-Ardenne	3.86	Aland	0.58
Lagging Behind Regions	Essex	-0.29	Centru	-0.42	Alsace	-0.15
	Friesland	-0.33	Leicester shire	-0.46	Prov Aut Bolzano-Bozen	-0.15
	Greater Manchester	-0.39	Bedfordshire	-0.48	Abruzzo	-0.16
	Dorset and Somerset	-0.47	Muntenia	-0.49	La Rioja	-0.17
	Bedfordshire	-0.47	Yorkshire	-0.59	Prov Aut Trento	-0.18
	Utrecht	-0.72	Greater Manchester	-0.59	Comunidad de Madrid	-0.19
	Ovre Norrland	-0.78	Ostra Mellansverige	-0.62	Catalunya	-0.20
	Opolskie	-1.27	Bratislavsky	-0.64	Comunidad Valenciana	-0.20
	Herefordshire	-1.59	Kent	-0.81	Canarias	-0.23
	Aland	-1.70	Sud-Est	-0.91	Baleares	-0.50

Note: GDP pc data is computed in 2000 constant prices and expressed in thousands.

Figure 2.2: GDP per capita 2000-2010.

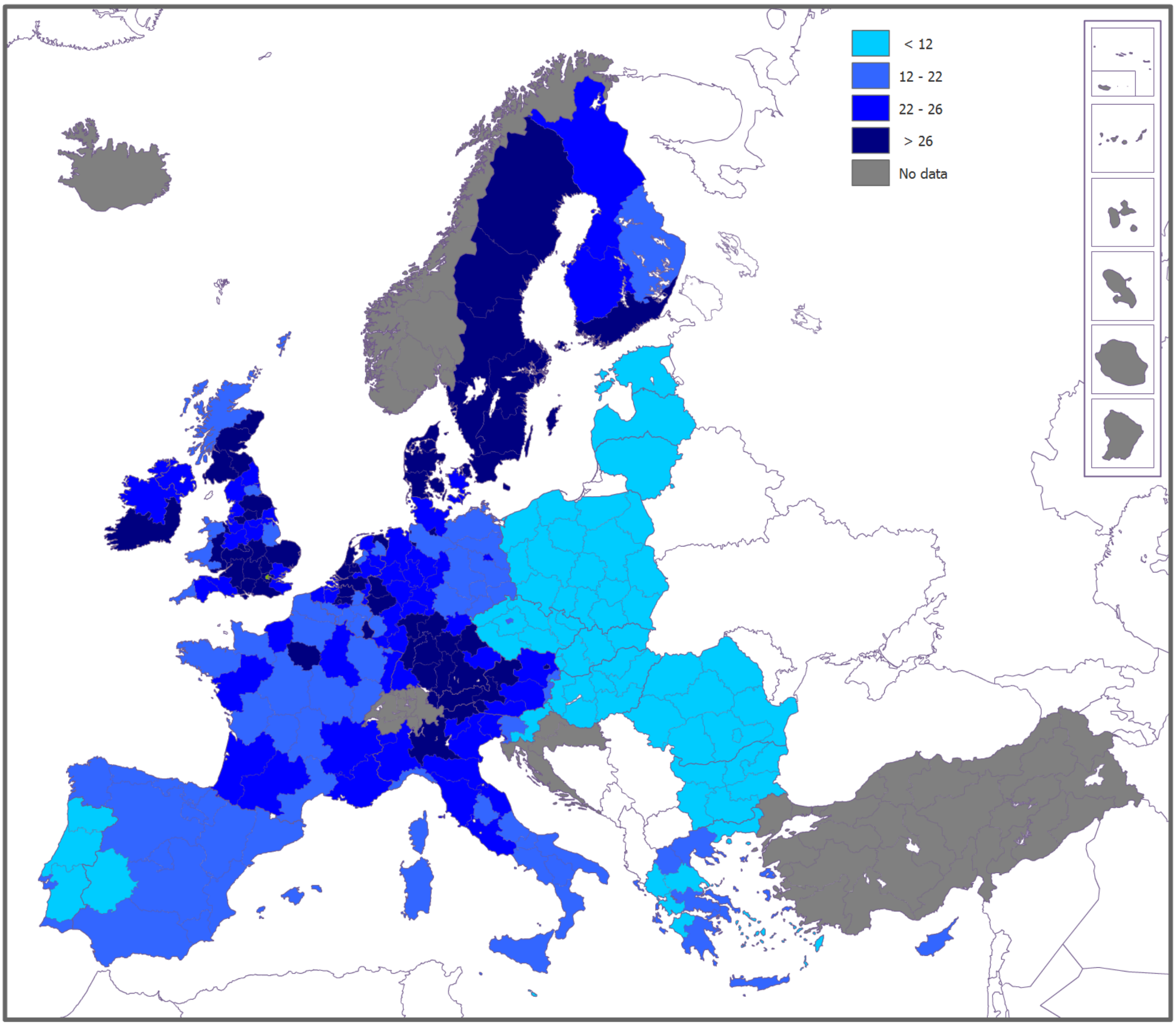
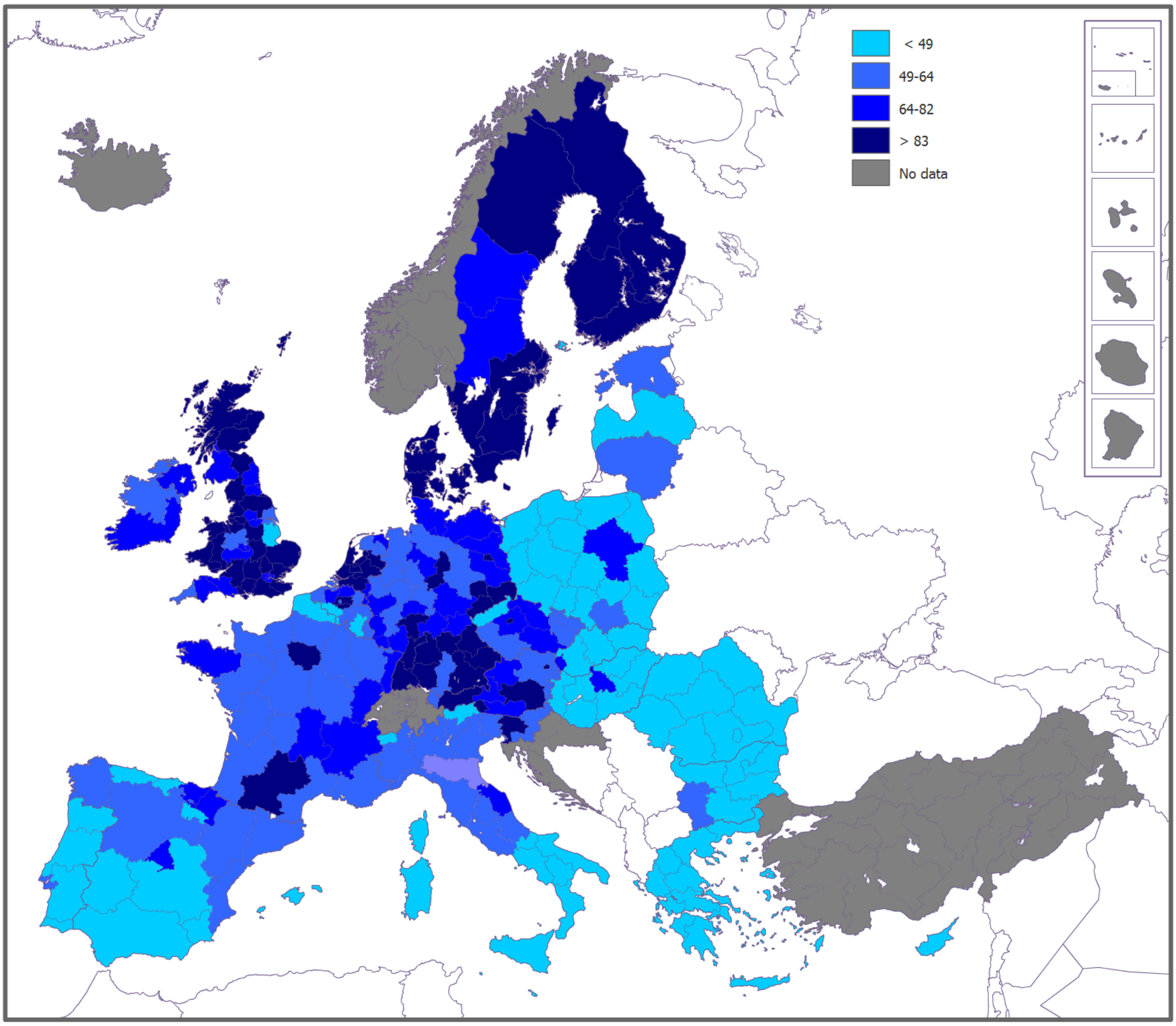


Figure 2.3: Regional Lisbon Index 2000-2010.



2.3 Data and Econometric Methodology

This section describes the data and the empirical parametric strategy that will be used to explore the role played by the various determinants of regional development rates measured by the MRLI.

2.3.1 Data and Hypothesis

The sample for the empirical exercise covers a total of 254 NUTS-2 regions for 25 EU states for a period running from 2000 to 2010, the indicated period for the achievement of the said LS objectives.[5] NUTS-2 level regions are used in the analysis instead of other possible alternatives because NUTS-2 (i) is the territorial unit most commonly employed in European regional economics literature and (ii) is particularly relevant in terms of EU regional policy, given that it is the level at which cohesion and regional policy funds are assigned. The data for this study are drawn from different data sources. Summary statistics, data sources and the precise definition are shown in Table (2.5) below.

In general terms, the development rate towards a KBE is a reduced form function of a variety of factors that can be broadly categorized as (i) the specific stage of development, (ii) regional knowledge and innovation intensity factors, (iii) regional socio-economic enabling elements that increase the probability of knowledge and innovation taking place and (iv) regional factors used to control for region economic dynamism. The control variables in the analysis have been selected on the basis of existing studies on the link between knowledge, innovation and regional development in Europe (Rodriguez-Pose and Crescenzi, 2008; Capello *et al.,* 2011; Capello and Lenzi, 2013; 2014).

A) Regional Stage of Development

Following the convention in the literature of economic development, the initial level of MRLI is used to control for convergence across regions (Barro and Sala-i-Martin, 1995). The inclusion of this variable in the analysis allows us to determine whether under-developed regions grew faster than highly-developed ones during the study period, thus providing information on the dynamics of regional disparities.

B) Regional Knowledge and Innovation intensity

The first group of variables used to explain regional development patterns in Europe are those

[5]Although the time frame is rather short for a meaningful convergence analysis there is no available data of all index components for a longer period. Moreover, data for the covariates in Malta and Lithuania were unavailable, making impossible to include these regions in the regression analysis.

capturing the intensity of invention and innovation. As shown in Capello and Lenzi (2013), knowledge and innovation do not necessarily overlap in the spatial level. Factors that enhance the creation and implementation of new knowledge can be quite different from the factors which stimulate innovation and regions may exhibit larger endowments either of the former or of the latter. Secondly, locally created knowledge does not automatically nor necessarily turn into to local innovation, or, conversely, local innovation does not inevitably come out from locally produced knowledge. Therefore, their effects are expected to be different from one another.

Formal basic knowledge/technological capital is measured by means of the number of patents per million of people. The use of technological capital is complemented with the share of population with tertiary education as a measure of human capital capabilities, provided that skilled and highly educated people increase the efficiency of the existing production and it stimulates the creation of new products and processes (Paci and Marrocu, 2013). However, patents and/or R&D expenditures are not always translated into market innovations and these controls may neglect innovative efforts than can be developed either in the form of process, organizational configuration or product. Thus, following Capello and Lenzi (2014), to approximate the degree of innovation an index measuring the share of small and medium firms introducing a new product and/or a new process in the market is employed.

C) Regional Enabling Knowledge and Innovation Factors

In many cases, the link between basic knowledge and innovation is not very manifest and several regions innovate on the basis of external knowledge, acquired through networking with leading regions, and of specific know-how in local application sectors. Moreover, as Rodriguez-Pose and Crescenzi (2008) point out, innovation is a territorially embedded process and it cannot be understood independently from the social and institutional conditions existing in a given a region. For this reason a variety of socioeconomic regional enabling factors that make the advancement towards a KBE more likely are included. A number of contributions (Tabellini, 2008; Pilececk *et al.*, 2013) highlight the role played by cooperative and trustworthy environments in promoting knowledge and innovation socialization, thus enhancing local economic development potential. For this reason, an indicator capturing social capital is included. Additionally, the stock of physical infrastructure endowments is included as a proxy for both the accessibility of the region and its connectivity with the rest of regions. However, the exact importance of infrastructure as an element in economic development is far from conclusive given that recent studies performed at the EU level find both positive (Crescenzi and Rodriguez-Pose, 2012) and negative (Capello and Lenzi, 2014) effects. To capture the functional specialization effect, the share of employed in agriculture sector is included. Knowledge and innovation are more likely to be developed through high-level than low-level functions (Duranton and Puga, 2000). Finally, it is relevant to take into account that synergies, collective learning and knowledge spillovers which are the base of regional development, are more likely to arise in highly dense regions than in isolated ones. To study the effect caused by agglomeration economies population density is included in the model.

D) Regional Dynamism

The third group of variables controls for a regions economic dynamism as in Capello and Lenzi (2013). In order to account for the dynamics of the regional labor market the aggregate employment growth rate and the long term unemployment rate are considered. Additionally, the investment to GDP ratio is included, which is also associated to a dynamic economic activity. Therefore, the expected effect of this variable is that it will affect positively the development rate as it is supposed to generate a push effect on the local economy.

2.3.2 Spatial Panel Data Models

Recent theoretical and empirical work has shown that regional development may be driven by intra-regional factors and by extra-regional factors affecting nearby regions (Ertur and Koch, 2007; Fisher, 2011, LeSage and Fisher, 2012). Thus, insofar every regional economy evolves interacting with other regions, major problems may arise if the spatial characteristics of the data and the potential role of neighboring effects in shaping regional development are ignored (Crescenzi, 2005; Fingleton and López-Bazo, 2006). Moreover, the consequences of omitting these interactions from the model specification are potentially important from an econometric perspective, and may cause estimates to become biased, inconsistent and/or inefficient (Anselin, 2010). Thus, the empirical analysis begins by considering a two-way fixed-effects *Spatial Durbin Model* (SDM), which is sufficiently general to allow for different types of spatial interactions between the sample regions. This model can be written as follows:

$$\Delta Y_t = \rho W \Delta Y_t + \beta X_t + \theta W X_t + \mu + \iota_N \alpha_t + \epsilon_t \tag{2.1}$$

where ΔY_t denotes a $N \times 1$ vector consisting of observations for the average growth rate of MRLI in region i measured over two-year periods for every region $i = 1, 2, ..N$ and X_t is an $N \times K$ matrix of exogenous aggregate socioeconomic and economic covariates with associated response parameters β contained in a $K \times 1$ vector that are assumed to influence regional development. A concern is that exogeneity of the right-hand side variables is assumed rather than tested. As a solution, lagged data values are used to minimize endogeneity. This configuration of the data implies a balanced panel data with 254 regional units and 5 time periods. Covariates in X_t, are taken at the years $t = 2000, 2002, 2004, 2006, 2008$ while ΔY_t are growth rates for the periods t =2001-02, 2003-04, 2005-06, 2007-08, 2009-2010. In turn, ρ is the spatial autoregressive coefficient which captures the spatial effects working through the dependent variable. W is a $N \times N$ matrix of known constants describing the spatial arrangement of the regions in the sample where the diagonal elements are set to zero by assumption, since no region can be viewed as its own neighbor. In addition, the model includes the spatial lag of the rest of control variables, WX_t whose impact is reflected by the $K \times 1$ vector of coefficients θ. Additionally, $\mu = (\mu_1, ..., \mu_N)'$ is a $N \times 1$ vector of region fixed effects, $\alpha_t = (\alpha_1, ..., \alpha_T)'$ denotes time specific effects and ι_N is a $N \times 1$ vector of ones. Region fixed effects control for all region-specific time invariant variables whose omission could bias the estimates while time-period fixed effects control for all time-specific, space invariant variables whose omission could bias the estimates in a typical time

Table 2.5: Data and Descriptive Statistics.

Variable	Mean	Standard Deviation	Units	Data Sources (*)
MRLI growth rate	1.69	3.86	Percentage change	Eurostat
MRLI level	65.61	22.30	Indicator in points, scale 0 to ∞	Eurostat
Innovation index$^{(a)}$	49.31	20.84	Indicator in points, scale 0 to 100	Regional Innovation Scoreboard (RIS) Innovation Comunity Survey (CIS)
Knowledge capital	21.81	8.09	Percentage (%) of population with tertiary education between 15-64 years old.	Eurostat
Technological capital	99.95	124.67	Number of patent applications to the EPO by priority year per million of inhabitans.	Eurostat
Social capital$^{(b)}$	49.81	11.07	Trust indicator in points, scale 0 to 100	Social Value Surveys
Infrastructure	229.01	262.89	Number of kilometres (Kms) of motorways network on usable land in levels	Eurostat
Functional specialization	7.73	9.13	Percentage of agriculture in total employment	Cambridge Econometrics
Aglomeration	0.36	0.92	Thousand inhabitants per squared kilometer	Cambridge Econometrics
Long term unemployment	3.56	3.01	Percentage (%)	Eurostat
Investment share	20.26	6.04	Percentage (%)	Cambridge Econometrics
Employment growth	01.01	3.92	Percentage change	Cambridge Econometrics

Notes: (*) In the cases of data gaps a variety of imputing techniques are employed. If data are missing along the cross-section of NUTS2 level regions but the aggregate for the country was available, a regionalization technique was used using country and regional level data in line with RIS methodology. In the scenario of missing data along the time-series dimension it was completed by AR(1) estimates using the h-step aheads forecasts or by backwards induction. Further details are included in the Appendix. *(a)*The innovation index is constructed as the average of country (CIS) and regional (RIS) data: $I = \frac{I_{r,t}+I_{c,t}}{2}$ where each innovation index was previously computed employing a max-min normalization. *(b)* The social capital approximated by an index of trust among citizens is computed as $Trust = 10\,(ppltrst * dw * pw)$ where $ppltrst$ where (dw) and (pw) are the design and population weights to correct for sample bias of the different waves.

series (Elhorst, 2010, 2014). Finally, $\epsilon_t = (\epsilon_{1t}, ..., \epsilon_{Nt})^{'}$ is a vector of i.i.d disturbances whose elements have zero mean and finite variance σ^2.The model is estimated following the Maximum-Likelihood Bias-Corrected procedure (ML-BC) proposed by Lee and Yu (2010) for static spatial panels.

As shown by LeSage and Pace (2009) in a SDM, a change in a particular explanatory variable in region i has a *direct effect* on that region, but also an *indirect effect* on the remaining regions. In this context, the direct effect captures the average change in the development growth rate of a particular region caused by a one unit change in that region's explanatory variable. In turn, the indirect effect can be interpreted as the aggregate impact on the growth rate of a specific region of the change in an explanatory variable in all other regions, or alternatively as the impact of changing an explanatory variable in a particular region on the growth rates of the remaining regions. Finally, the *total effect* is the sum of the direct and indirect impacts.

The above specification is particularly useful in this context, because the SDM does not impose prior restrictions on the magnitude of potential spillovers effects. Furthermore, the SDM is an attractive starting point for spatial econometric modeling because it includes as special cases two alternative specifications widely used in the literature: the *Spatial Lag Model* (SLM) and the *Spatial Error Model* (SEM). The SDM can be reduced to the SLM if $\theta = 0$ and to the SEM if -$\rho\beta = \theta$. The SLM reads as:

$$\Delta Y_t = \rho W \Delta Y_t + \beta X_t + \mu + \iota_N \alpha_t + \epsilon_t \tag{2.2}$$

while the SEM is given by:

$$\Delta Y_t = \beta X_t + \mu + \iota_N \alpha_t + \upsilon_t \tag{2.3}$$

where $\upsilon_t = \lambda W \upsilon_t + \epsilon_t$ and ϵ_t is i.i.d. Note that in this context, the SLM indicates that MRLI growth rates are partly determined by a spatial interaction substantive process while in the SEM case, deviations from the steady state in a region, may not be a function of region specific shocks but instead of a complex set of shock spillovers. An important characteristic of the spillovers produced by SLM is that they are global in nature. That is, a change in X at any location will be transmitted to all other locations following the inverse of the spatial weight matrix even if two locations are unconnected according to W. This contrasts with local spillovers which occur at other locations without involving an inverse matrix. Typically, studies on the link between development and innovation such as Paci and Marrocu (2013), Capello and Lenzi (2014) use the *Spatial Exogenous Lag* (SLX), SLM or SEM models. However, as shown by McMillen (2003,

2010) the SLM model has the problem of imposing a unique ratio between the spillover and direct effects for every explanatory variable. The disadvantage of the SEM is that it does not provide information about spillovers which is a major limitation if neighboring effects are of great interest. On the other hand, although the SLX in Equation (2.4) is a flexible model, it has the problem of not taking into consideration endogenous interactions effects. Other authors such as Gibbons and Overman (2012) also criticize the use of the SDM because of the existence of identification problems. In response to such criticisms, Vega and Elhorst (2013) and LeSage (2014a) have pointed out that traditional spatial econometric modeling strategy needs revision. They conclude that it is preferable to estimate the SDM and compare it with SLX in Equation (2.4) or *Spatial Durbin Error Model* (SDEM) in Equation (2.5) containing exogenous interaction effects rather than directly estimating SLM or SEM models.

$$\Delta Y_t = \beta X_t + \theta W X_t + \mu + \iota_N \alpha_t + \epsilon_t \tag{2.4}$$

$$\Delta Y_t = \beta X_t + \theta W X_t + \mu + \iota_N \alpha_t + \upsilon_t \tag{2.5}$$

where $\upsilon_t = \lambda W \upsilon_t + \epsilon_t$. In this paper such a renewed modeling strategy is employed in order to improve the quantitative analysis accuracy on the magnitude of the spillover and feedback effects.

2.3.3 Spatial Weights Matrix Selection

The estimation of the various spatial models described above requires to define a spatial weights matrix. At this regard, one of the most criticized aspects of spatial econometric models is that the spatial weights matrix cannot be estimated but needs to be specified in advance (Corrado and Fingleton, 2012). There have been several studies that investigated how robust results are to different specifications of W and which one is to be preferred. The most widely used criterion to select the W matrix has been the log-likelihood. However, this approach has been criticized because it only finds a local maximum among competing models (Harris *et al.*, 2011). Against this criticism Elhorst *et al.* (2013), suggest to look at the residual variance while LeSage and Pace (2009) propose the Bayesian posterior model probability as an alternative criterion to select model.

Table (2.6) reports the performance of SDM model with spatial fixed and time-period fixed effects for a broad range of alternative specifications of W and puts together the three previous selection procedures.[6] The first set of matrices consists of different versions of the inverse distance matrix with cut-offs while the second set captures gravity-type matrices whose off-diagonal elements are defined by $W_{ij} = \frac{1}{d_{i,j}^{\alpha}}$ for $\alpha = 1,,3$. The last group of spatial matrices consists on exponential-decay matrices, $W_{ij} = exp(-\theta d_{ij})$ for $\theta = 0.005,..,0.03$ respectively, which rapidly decline as distance increases (Keller and Shiue, 2007). All matrices have been row-normalized, so that the entries of each row add up to 1. In the Bayesian estimation exercise, non-informative diffuse priors for the model parameters (β, θ, σ) are used following the recommendation of LeSage (2014b). In particular, a normal-gamma conjugate prior is employed for β, θ and σ while a beta prior for ρ is employed. To that end, parameter c is set to zero and T to a very large number $(1e + 12)$ which results in a diffuse prior for β, θ. Diffuse priors for σ are obtained setting $d = 0$ and $v = 0$. Finally $a_0 = 1.01$:[7]

$$\begin{aligned} &\pi(\beta) \sim N\left(c, T\right) \\ &\pi\left(\frac{1}{\sigma^2}\right) \sim \Gamma\left(d, v\right) \\ &\pi\left(\rho\right) \sim \frac{1}{Beta\left(a_0, a_0\right)} \frac{\left(1+\rho\right)^{a_0-1}\left(1-\rho\right)^{a_0-1}}{2^{2a_0-1}} \end{aligned} \tag{2.6}$$

As it is observed the best matrix according to the different selection criteria is $W_{ij} = -exp(0.005 d_{ij})$, which imposes an speed of decay in the intensity of spatial interactions of 0.5% as distance among regional units increases. Therefore, this is the spatial weights matrix used in the rest of the paper.[8]

2.4 Results

This section reports and discusses the empirical findings. Table (2.7) reports the Maximum-Likelihood Bias Corrected (ML-BC) estimation results of the various spatial econometric models mentioned in previous section (Lee and Yu, 2010). The first column of Table (2.7) presents the

[6] Estimations with the various spatial weight matrices W have been performed in SDM models with regional and time effects. As observed, with $W_{ij} = exp(-0.05 d_{ij})$ both spatial and time-period fixed effects should be included in the model as the LR statistic on the joint significance of the spatial fixed effects is 675.19 with p-value 0.00 and that of the time-period fixed effect is 17.83 with p-value 0.00.

[7] As noted by LeSage and Pace (2009), pp. 142, the $Beta\left(a_0, a_0\right)$ prior for ρ with $a_0 = 1.01$ is highly non-informative and diffuse as it takes the form of a relatively uniform distribution centered on a mean value of zero for the parameter ρ. For a graphical illustration on how ρ values map into densities see Figure 5.3 pp. 143. Also, notice that the expression of the Inverse Gamma distribution corresponds to that of Equation 5.13 pp.142.

[8] Posterior probabilities displayed in Table (1.2) are computed by scaling log-marginal values for each group of the geographical weights matrices. This is why the overall column-sum does not add up to one. However, when integrating and scaling over all the different W matrices together, the results are even more explicit pointing with full probability to the 0.5% exponential decay matrix as the most likely spatial scheme which suggests a peak-shape posterior density distribution.

Table 2.6: Spatial Weights Matrix Selection.

Spatial Weights Matrix	Bayesian Posterior Model Probability	Log-likelihood Function Value	$\widehat{\sigma_\epsilon}^2$
Cut-off 500 km	0.94	-3012.38	8.18
Cut-off 1000 km	0.03	-3022.56	8.31
Cut-off 1500 km	0.00	-3039.06	8.53
Cut-off 2000 km	0.00	-3039.56	8.54
Cut-off 3000 km	0.03	-3031.69	8.44
$1/d^\alpha$, $\alpha = 1$	0.34	-3030.04	8.41
$1/d^\alpha$, $\alpha = 1.25$	0.52	-3024.34	8.34
$1/d^\alpha$, $\alpha = 1.5$	0.14	-3020.09	8.28
$1/d^\alpha$, $\alpha = 1.75$	0.05	-3021.46	8.30
$1/d^\alpha$, $\alpha = 2$	0.23	-3024.58	8.34
$1/d^\alpha$, $\alpha = 2.25$	0.00	-3020.24	8.29
$1/d^\alpha$, $\alpha = 2.5$	0.00	-3027.21	8.38
$1/d^\alpha$, $\alpha = 2.75$	0.00	-3029.17	8.40
$1/d^\alpha$, $\alpha = 3$	0.00	-3032.72	8.45
$exp-(\theta d)$, $\theta = 0.005$	1.00	-3008.34	8.13
$exp-(\theta d)$, $\theta = 0.01$	0.00	-3011.50	8.17
$exp-(\theta d)$, $\theta = 0.015$	0.00	-3022.04	8.31
$exp-(\theta d)$, $\theta = 0.02$	0.00	-3030.97	8.43
$exp-(\theta d)$, $\theta = 0.03$	0.00	-3042.71	8.58

Notes: Bayesian Markov Monte Carlo (MCMC) routines for spatial panels required to compute Bayesian posterior model probabilities do not exist yet. As an alternative all cross-sectional arguments of James LeSage routines were replaced by their spatial panel counterparts, for example a block-diagonal $NT \times NT$ matrix, $diag(W, ..., W)$ as argument for W. All W's are row-normalized.

results obtained with a two-way fixed-effects model estimated by OLS assuming that the disturbances are independent and identically distributed. As can be observed, the control variables included in vector X are mostly statistically significant and have the expected signs. Column 2 of Table (2.7) presents the results from the SEM, Column 3 the results of the SLM whereas the SDM, SLX and SDEM are presented respectively in columns 4, 5 and 6. Before continuing it is important to evaluate which is the best spatial specification in this context. To do so, LR-tests against the SDM are carried out to test whether this model can be restricted to simpler versions finding it should not. The results of these tests suggest that the SDM is the best fitting model.[9] This conclusion is consistent with the information provided by the various measures of goodness-of-fit included in Table (2.7).

As mentioned in the previous section, for a correct interpretation of the estimates stemming from the Spatial Durbin Model, the focus is on the direct, indirect and total effects associated with changes in the set of regressors instead of the estimated parameters. Considering the average direct impacts of Table (2.8), it is important to notice that there some differences to the SDM model coefficient estimates reported in Table (2.7). Differences between these two measures are due to feedback effects passing through the entire system and ultimately reaching the region of origin. Therefore, these effects do not refer to the traditional non-spatial impact of a change in X_{ik} in Y_i but to the effect of change in in X_{ik} on Y_i passing through all $Y_j's$ and coming back to Y_i (provided that $Y_j's$ and Y_i are spatially connected through W).

The analysis of the direct effects and feedbacks displays interesting features that are consistent with the empirical literature of development. First, a strong and negative significant impact of the initial level of development on the growth rate of subsequent periods (-0.66 percentage points) is observed. This result is robust to the spatial specification chosen, given that direct effect estimates of SLX and SDEM also account for a -0.66 percentage points impact. Second, knowledge-intensity factors behave as expected and exert a positive influence on the MRLI growth rate. Nevertheless, for this group of regressors, only the direct effects of technological capital are significant. This result is driven by feedbacks effects of the 12.39%. This result is also robust to SLX and SDEM specifications where the direct effects of technological are also positive and significant. Regarding the set of KBE enabling factors, it is observed that social capital and infrastructure have positive impacts while low-level specializations such as agriculture have a negative effect. Feedback effects in enabling factors account for a 9% and

[9] The LR statistics of the SDM vs SLX ($H_0 : \rho = 0$), SDM vs SLM ($H_0 : \theta = 0$) and SDM vs SEM ($H_0 : \theta + \rho\beta = 0$) specifications, are 76.03 with p-value of 0.00, 742.36 with p-value of 0.00 and 222.85 with p-value of 0.00 respectively.

Table 2.7: Main Results.

	OLS	SEM	SLM	SDM	SLX	SDEM
Initial MRLI	-0.619***	-0.657***	-0.571***	-0.667***	-0.667***	-0.666***
	(-26.26)	(-24.56)	(-21.48)	(-24.64)	(-26.27)	(-24.75)
Innovation	0.082***	0.036*	0.054***	0.022	0.017	0.022
	(5.08)	(1.75)	(3.72)	(1.02)	(0.85)	(1.02)
Knowledge capital	0.104	0.065	0.073	0.055***	0.058	0.054
	(1.59)	(0.90)	(2.79)	(0.76)	(0.85)	(0.75)
Technological capital	0.017***	0.009*	0.013***	0.008	0.009*	0.009*
	(3.54)	(1.78)	(2.69)	(1.59)	(1.94)	(1.74)
Social capital	0.023	0.026	0.031	0.027	0.029*	0.026
	(1.43)	(1.53)	(-0.93)	(1.57)	(1.81)	(1.54)
Infrastructure	0.009***	0.004*	0.009***	0.003	0.004*	0.004
	(4.18)	(1.68)	(3.70)	(1.33)	(1.73)	(1.42)
Agriculture	-0.168***	-0.171***	-0.115***	-0.156***	-0.155***	-0.145***
	(-3.75)	(-3.28)	(-2.84)	(-2.93)	(-3.11)	(-2.74)
Aglomeration	0.004	0.005	0.004	0.005	0.005	0.005
	(1.02)	(1.47)	(0.95)	(1.39)	(1.55)	(1.29)
Unemployment	-0.221***	-0.137*	-0.187***	-0.102	-0.072	-0.096
	(-3.33)	(-1.69)	(-2.93)	(-1.17)	(-0.88)	(-1.09)
Investment share	0.000	0.005	-0.018	-0.004	0.001	-0.002
	(0.01)	(0.12)	(0.00)	(-0.09)	(0.01)	(-0.06)
Employment growth	0.015	-0.011	-0.003	0.015	0.044*	0.030
	(0.66)	(-0.48)	(-0.13)	(0.59)	(1.89)	(1.12)
Neighbors' Initial MRLI				0.465***	0.731	0.100
				(5.76)	(1.04)	(0.84)
Neighbors' Innovation				0.013	0.117**	0.085
				(0.25)	(2.53)	(1.16)
Neighbors' Knowledge Capital				0.138	0.309	0.350
				(0.55)	(1.33)	(1.00)
Neighbors' Technological capital				0.021	0.058***	0.053*
				(1.10)	(3.35)	(1.85)
Neighbors' Social Capital				0.027	-0.017	0.080
				(0.43)	(-0.28)	(0.89)
Neighbors' Infrastructure				0.007	0.022***	0.016*
				(1.36)	(4.48)	(1.91)
Neighbors' Agriculture				0.350***	0.354***	0.234
				(2.45)	(2.64)	(1.05)
Neighbors' Aglomeration				-0.036	-0.030	-0.050
				(-1.36)	(-1.23)	(-1.43)
Neighbors' Unemployment				0.079	-0.229	0.055
				(0.39)	(-1.21)	(0.18)
Neighbors' Investment share				-0.004	-0.156	0.013
				(-0.03	) (-1.23)	(0.07)
Neighbors' Employment growth				0.422***	0.777***	0.570***
				(3.07)	(6.13)	(3.00)
Wu/WY		0.777***	0.539***	0.640***		0.654***
		(19.44)	(11.53)	(11.93)		(12.23)
Corrected R-squared	0.376	0.370	0.334	0.436	0.427	0.430
Log-Likelihood	-3106.23	-3024.34	-3066.26	-3008.87	-3046.363	-3058.82

Notes: The dependent variable is in all cases the MRLI growth rate of the various regions. t-statistics in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level. The results are obtained using the spatial weights matrix $W = exp^{-(\theta d_{ij})}$, $\theta = 0.005$

Table 2.8: SDM Effect Decomposition.

	Feedback Effect	Direct Effect	Indirect Effect	Total Effect
Initial MRLI	-0.32%	-0.665***	0.102	-0.563***
		(-24.46)	(0.55)	(-3.01)
Innovation	NR	0.023	0.076	0.100
		(1.11)	(0.62)	(0.82)
Knowledge capital	NR	0.063	0.484	0.547
		(0.86)	(0.70)	0.80)
Technological capital	12.39%	0.009*	0.072*	0.081*
		(1.81)	(1.74)	(1.75)
Social capital	10.41%	0.030*	0.123	0.152
		(1.72)	(0.69)	(0.85)
Infrastructure	9.03%	0.004*	0.027**	0.030**
		(1.75)	(1.96)	(2.07)
Agriculture share	-6.27%	-0.146***	0.731*	0.585
		(-2.62)	(1.81)	(1.42)
Aglomeration	NR	0.004	-0.092	-0.088
		(0.98)	(-1.17)	(-1.10)
Long term unemployment	NR	-0.102	0.024	-0.078
		(-1.16)	(0.05)	(-0.17)
Investment share	NR	-0.006	0.006	0.000
		(-0.14)	(0.02)	(0.00)
Employment growth	NR	0.031	1.20***	1.232***
		(1.14)	(2.80)	(2.78)

Notes: Effects are calculated using 1000 draws. t-statistics in parentheses. * Significant at 10% level, **significant at 5% level, *** significant at 1% level. NR = Not relevant. Inferences regarding the statistical significance of these effects are based on the variation of 1000 simulated parameter combinations drawn from the variance-covariance matrix implied by the BCQML estimates.

10.4% in infrastructure and social capital respectively. Regarding the effect of low functional specialization, results of Table (2.8) show that agriculture has a negative direct effect that is amplified by a 6.2% through feedback effects. Interestingly, population density does not seem to be a significant driver of MRLI changes. Additionally, the results of (2.8) indicate the direct effects of increasing infrastructures and low-level specializations are very similar among the various spatial specifications given that coefficient estimates of the SLX and SDEM in Table (2.7) match those of the SDM. Finally, it is worth mentioning any of the factors belonging to the regional dynamism group seem to have a significant direct impact on MRLI developments.

The average indirect impacts, third column of Table (2.8), represent the aggregate impact on the MRLI growth rate of a specific region of the change in an explanatory variable in all other regions. The presence or absence of these spillover effects, combined with the results for the average direct impacts allow us to better understand the spatial evolution of MRLI scores. At this point it is important to recall two aspects. First, there are discrepancies between the indirect impact and the model coefficients on the spatially lagged explanatory variables presented in Table (2.7). These discrepancies arise, as for the direct effects, from the existence of feedbacks. The spillover effects are larger than the spatial lags of the covariates from the SDM given that they capture cumulative impacts over space that would result from a change in regional development rates induced by changes in the explanatory variables. Turning to the results, it can be observed that for some covariates the local effect dominates and the spillovers may not be relevant in this context. This is the case of the initial stage of development and the social capital variables. A change in any of these variables has an effect on MRLI growth rates, but such effect is confined within regional boundaries. On the contrary, the results suggest the existence of strong and significant spillover effects in factors such as technological capital, infrastructures, agriculture and employment growth. Moreover, the estimated spillover effect for this group of covariates is robust to the spatial specification given that SLX and SDEM generate results that are similar both qualitatively and quantitatively. Remarkably, technological capital, infrastructure and agriculture present significant direct and spillover effects. This result implies that a region-specific change in any of these variables does not only affect the respective regions MRLI but also spills over into neighboring regions.

Total impact estimates are reported in the fourth column of Table (2.8). Estimates indicate that a 1 percentage point change in the initial stage of development scores registered by a specific region has a negative and statistically significant impact on its subsequent development growth rate of -0.563 percentage points, thus providing empirical evidence of decreasing inter-regional development gaps. Likewise, the estimates reveals that the evolution of the MRLI depends on the changes in the different sets of factors. Regarding the group of knowledge-intensity factors a total positive effect of technological capital in MRLI growth rates is observed. On the other hand, the results obtained here show that variables such as knowledge capital and the innovation are not statistically significant at conventional levels. It is possible to conjecture this result is due to the short time spam of the sample used in the analysis. A higher level of education or market innovations usually take time to make their effects on development to be observable. As to the set of enabling factors, the only significant control variable is the infrastructure, which exerts a positive effect as in Crescenzi and Pose (2012). Therefore, infrastructures measuring the accessibility to a given area have a positive impact in the achievement of LS goals. In addition, it is observed that the total effects of regional employment growth are a relevant driver of MRLI growth rates. That is, higher regional employment growth rates, typically associated to dynamic regions, have a positive impact of 1.2 percentage points in MRLI growth rates. The relative contribution of spillovers effects to the total effect is 88% for the technological capital, 90% for the infrastructure and 95% for employment, which highlights the relevance of interaction effects in the process of regional development. Taken together, the results obtained show that regional development in Europe depends on a multiplicity of factors which have complex patterns of spatial propagation.

2.5 Conclusions

In this chapter RLI scores are used to measure regional development in European regions. The analysis focuses its attention on the evolution of regional development towards LS goals and the emergence of regional disparities. The approach developed by Dijkstra (2010) to compute RLI is reviewed and its shortcomings are discussed. To address these problems, a new measure of progress towards a KBE based on the computation of the geometric mean of the various LS sub-indicators is proposed. The advantage of the MRLI is that it does not bias the distribution of the development scores and penalizes unbalanced patterns of development. Using this new RLI version, it is shown that during the period of study, European regions experienced a positive evolution in many dimensions, as suggested by the increase of the mean scores in most of the sub-indexes. However, private and public R&D expenditures as well as some education indicators remained far away from LS objectives limiting the overall fullfilment of the Agenda. The results show that European Union failed to reach the LS targets by a 20%, although a process of convergence among regions can be observed based on the MRLI. Results based on the ARLI, show that Southern-European regions have experienced very rapid growth, while by making use of the MRLI, a diversified set of fast movers is found. It is also important to highlight the existence of important geographical differences in the behavior of the GDP per capita and the various RLI indexes.

The econometric analysis of regional development with the SDM shows that the effects of the various factors driving regional development dynamics towards a KBE are not confined within regional boundaries and that spatial spillovers are far from negligible. Furthermore, the global spillover chain associated with technological capital and infrastructures suggests these factors are relevant drivers of development growth rates. As to the total impacts it is observed a positive effect of technological capital, infrastructures and employment growth in MRLI growth rates. A finding emerging from the modeling exercise is the statistical significance of the spatial fixed effects, which highlights the major importance of taking into account regional heterogeneity and unobservable idiosyncratic regional factors in development analysis. Additionally, in the study, different specifications of the spatial weights matrix are compared in order to investigate their performance in describing the spatial arrangement of the sample regions. The evidence points out to the employment of an exponential distance-decay matrix instead of the typical gravity type weights matrix usually employed in the literature.

The results of this study raise some policy implications. Actions aimed at fostering regional development in less-developed regions should consider the possibility of large global feedback effects of infrastructure and technological capital investments passing through neighboring regions, which could permanently alter the overall development regime. Thus, it should also be noted that coordinated R&D investment in those regions might be more successful than isolated actions, by helping to counteract the under-development trap effect due to geographical location. A third implication arising from the significance of the regional fixed effects is that of European regional policy should take into account the heterogeneity and specificities in development patterns. The new regionally-adjusted incentives in *EU 2020* policy seems to be a step in the right direction.

References Chapter 2

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Chapter 3

What Drives Unemployment Disparities in European regions? A Dynamic Spatial Panel Approach

3.1 Introduction

Over the last two decades there have been numerous studies analyzing the causes of unemployment disparities in European regions using a variety of approaches and methods (Elhorst, 2003). This rising interest has to do with the fact that the unemployment rate is a key indicator of a region's socio-economic well-being. At this regard, the rise of unemployment across Europe and the failure of labor markets to achieve full employment are considered as one of the most serious weaknesses of the European approach to economic policy (Jackman, 1998; Blanchard, 2006). In response to this problem, during the last decade, the reduction both of the aggregate level of unemployment and of regional inequality among regions have become crucial issues for policy analysis and intervention in the European Union (EU) (European Comission, 2010a). Moreover, the attainment of acceptable levels of unemployment is nowadays a top priority on the EU policy agenda (European Comission, 2010a,b).

There are important academic reasons for analyzing regional unemployment disparities in Europe. First, the detail provided by data taken at the regional scale matters in the conclusions obtained in the empirical analysis. While country aggregate data gives no information about the regional structure of unemployment it has been documented that regional clusters of unemployment do not respect national boundaries (Overman and Puga, 2002). Not only the magnitude of unemployment disparities among regions are as large as it is between countries but also regions within a country may have different sources and structures of unemployment (OECD, 2009; Zeilstra and Elhorst, 2014).[1] A second reason pointed out by Elhorst (2003) is that macroeconomic

[1] OECD (2009) reports that the differences in unemployment rates within OECD countries were almost twice

studies performed at the country level (Bean, 1994; Scarpetta, 1996), give no explanation for the existence of regional unemployment disparities. This strand of macroeconomics literature finds that labor market institutions such as wage bargaining, collective coverage and employment protection have a prominent role explaining country level differences, but in many countries, institutions do not differ to any extent between regions. The latter implies that regional level factors may be crucial to the understanding of unemployment disparities. Thirdly, according to neoclassical theory, unemployment differentials among regions reflect an inefficient regional economic system (Taylor, 1996).

Economic theory provides two different explanations as to the nature and significance of regional unemployment disparities: the equilibrium view and the disequilibrium view. According to the equilibrium view, long run differentials represent an equilibrium where factors such as favorable climate or an attractive social environment encourage people to stay in regions where the unemployment rate is high (Marston, 1985). Within this conceptual framework, each region tends toward its own equilibrium unemployment rate, which is determined by regional demand and supply factors, amenities and institutions. Therefore, a high unemployment rate in a given area needs to be compensated by some other positive factors which act as a disincentive to migration. The disequilibrium view, on the other hand, considers that all regions tend to a competitive equilibrium unemployment rate and that the unemployment rate will level off across areas (Blanchard and Katz, 1992). In the short run, regional disparities may reflect labor market rigidities that restrict mobility or slow down the adjustment to asymmetric shocks (i.e, a labor demand shortage). The adjustment process may be fast or slow. Thus, unemployment disparities across areas could persist for a long time. In the long run, however, differences are assumed to disappear through migration and factor mobility between regions.

Empirical studies are crucial in this regard, given that they provide a deeper understanding of the unemployment phenomenon by confronting the plausibility of the competing theories and the explanatory power of the variables involved in them with the data (Niehbur, 2003; Longhi *et al.*, 2005; Herwartz and Niehbur, 2011). So far, empirical observation of the economic landscape in Europe has revealed the existence of persistent disparities in unemployment rates in countries such as Spain (López-Bazo *et al.*, 2005), Italy (Cracolici *et al.*, 2007) and Germany (Patuelli *et al.*, 2012). These findings suggest that the nature of regional unemployment disparities in some European countries could be the result of a long-run equilibrium pattern rather than a short-term disequilibrium caused by temporary shocks. However, studies restricted to one country overlook

as high as those between countries in 2006.

the effect of institutional variables and cannot be generalized to the whole European setting. The omission of labor market institutional variables is of major importance in this regard, given that institutions, understood as a set of laws, rules and conventions resulting from a collective choice, provide restrictions or incentives that have an impact on the individual decisions on labor supply, demand and wages paid, which ultimately alters the level of unemployment (Boeri, 2010).

An additional feature of unemployment rates in European regions that has been overlooked by most previous studies is that they show positive spatial and positive temporal correlations. As Elhorst (2003, 2005) points out, studies explaining trends in unemployment rates without considering spatial and serial dynamic effects may have been miss-specified. The exceptions in this respect are few. Patacchini and Zenou (2007) estimated a *Time-Space Recursive Model* (TSRM) for UK regions, Basile *et al.* (2012) estimated a *Dynamic Spatial Durbin Model* (DSDM) for Italian regions and Vega and Elhorst (2014) estimated a DSDM for European NUTS2 regions. Similarly, Zeilstra and Elhorst (2014) employ a *Dynamic Spatial Error Model* (DSEM) to analyze regional unemployment differentials in Europe.

This study complements the previous studies of Vega and Elhorst (2014) and Zeilstra and Elhorst (2014) in that it integrates labor market institutions within an econometric specification that accommodates spatial and serial dynamic effects for a sample of European regions of different countries. The resemblance to the study of Vega and Elhorst (2014) lies in the estimation of a *Dynamic Spatial Durbin Model* (DSDM) employing the bias-corrected quasi maximum likelihood (BCQML) estimator developed by Yu *et al.* (2008) and Lee and Yu (2010) for dynamic spatial panels. The main similarity to Zeilstra and Elhorst (2014), meanwhile, is the consideration of regional and national factors in the model. However, there are important methodological and theoretical differences with respect to each of these studies.

First, in previous studies on regional unemployment differentials no theoretical explanations have been provided for the existence of endogenous spatial interactions between regions. As a point of fact, in Zeilstra and Elhorst (2014), interactions between regions are modeled as the result of spatially correlated shocks, which does not require any theoretical model. Against this background, this chapter presents a spatially augmented labor market model with time inertia and substantive spatial interdependence among regional economies. To this end, recent contributions regarding the spatial wage-curve and migratory processes in a spatial context are taken into account (Mitze, 2012; Fingleton and Palombi, 2013). In this framework, externalities are used to model spatio-temporal interdependence among regions, which implies that the unemployment rate of a particular region is affected not only by its own labor market characteristics but also by the labor market performance experienced of the remaining regions. Starting from the theoretical model, a DSDM specification is derived and employed in the econometric exercise using annual data for the period 2000-2011.

Secondly, the sample used in this study includes a greater number of regions than previous studies. In Vega and Elhorst (2014) the sample used in their study covers 112 NUTS-2 regions across 8 EU countries while that used in Zeilstra and Elhorst (2014) the 112 NUTS-2 regions plus the UK regions. Moreover, the time-period in Zeilstra and Elhorst (2014) goes from 1983-1997, a period of sustained unemployment growth. Vega and Elhorst (2014) employ a longer-time series but the model just includes three controls. This study, in contrast, takes into account a greater number of variables whose omission could bias the results. Specifically, the sample used in this study includes 241 NUTS2 regions from 23 European countries for the period 2000-2011, which helps to minimize the asymmetries in the response of the different regions to the phases of the cycle.

Thirdly, this study performs a variety of econometric tests regarding spatial co-integration, parameter identification and model selection which are relevant to drawing inferences in the context of dynamic spatial panels. The model selection in this context is particularly important as different models ultimately imply different spillover processes (LeSage, 2014a). Therefore, instead of assuming a specific spatial specification (the *Dynamic Spatial Error* (DSEM) in Zeilstra and Elhorst (2014) and the DSDM in Vega and Elhorst (2014)), the present study extends the methodology developed by LeSage (2014b) and implements a novel Bayesian procedure for comparing dynamic spatial panel models, which enables joint analysis of the different spatial models and the spatial interaction matrices. This procedure shows that DSDM specifications outperform alternative specifications. Importantly, with the DSDM specification in hand, it is possible to estimate short run, long-run effects and impulse-responses over time and space, thus obtaining further insight into the functioning of the European labor market.

Fourth, the study is not restricted to the computation of the effects of the various covariates. In a second phase, relative importance metrics allowing for all possible causal patterns among the regressors are computed (Groemping, 2006, 2007). These metrics perform an R^2 decomposition enabling more detailed analysis of the relative contribution of each variable to unemployment disparities than previous decompositions over regional and national level factors in Zeilstra and Elhorst (2014). Following the grouping of variables adopted by Partridge and Rickman (1997a,b) and Lopez-Bazo *et al.* (2005), the relevance of regional disequilibrium and equilibrium factors (labor market, demographic and amenities) is also calculated.

Finally, in order to deepen our understanding of the origins of regional unemployment disparities in Europe, the estimation the DSDM and the calculation of the metrics of relative importance is performed not only for the period 2000-2011 but also for the periods 2000-2008 and 2009-2011. The separate analysis of the two periods is relevant, as previous studies of regional unemployment outcomes before and after the 2008 economic crisis reveal a reversal in the dynamics in a number of labor market variables (Marelli *et al.*, 2012). Such a contrast in the behavior of the two time periods could indicate a change in both the nature and the intensity of the impact of different factors on unemployment outcomes. Thus, this analysis is intended to provide insights for policy making in the context of the sluggish recovery taking place in Europe.

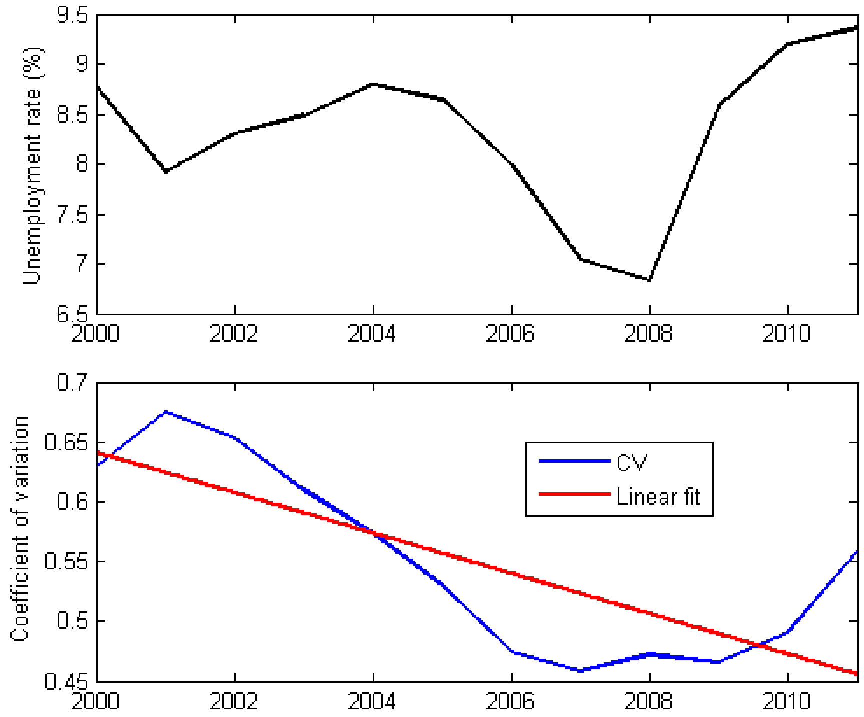
This chapter is organized as follows. Section 2, which follows this introduction, provides an exploratory analysis of unemployment rate differentials in EU. Section 3 presents a theoretical model of regional unemployment with spatial interactions. Section 4 describes the dataset used in this study and the econometric methodology used in the analysis. The empirical findings are presented in Section 5, while Section 6 concludes.

3.2 Exploratory Evidence

The sample covers a total of 241 NUTS-2 regions belonging to 23 EU countries. The analysis considers NUTS-2 level regions rather than other possible alternatives for various reasons. Firstly, the use of NUTS-2 level data allows for comparison with the previous studies of Zeilstra and Elhorst (2014) and Vega and Elhorst (2014). Secondly, NUTS-2 is the territorial unit most commonly employed in the literature on regional economic issues and it is particularly relevant in terms of EU regional policy, given that cohesion and regional policy funds are assigned at this level.

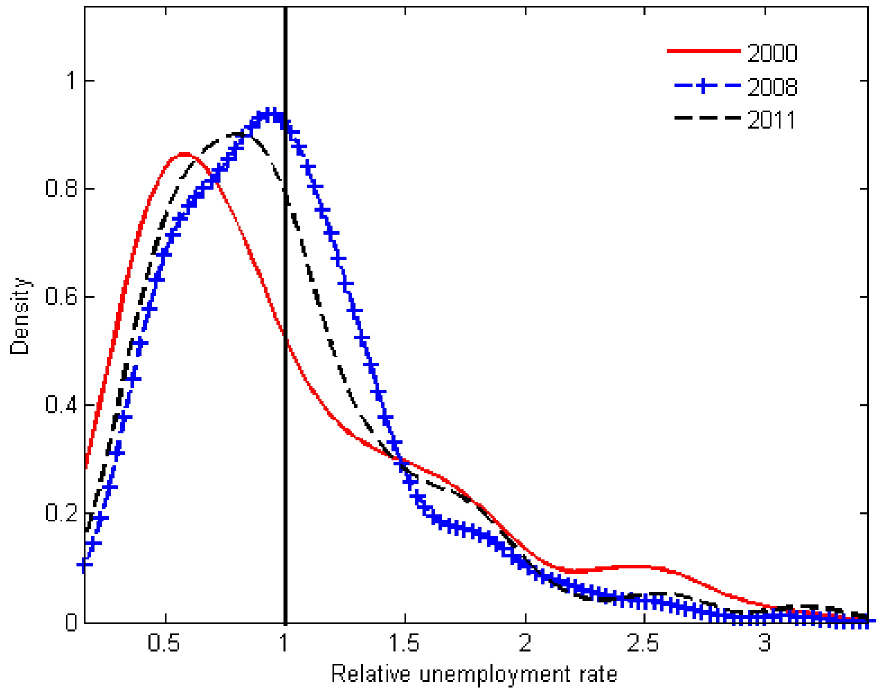
The study period goes from 2000 to 2011 and the key variable throughout the paper is the regional unemployment rate in the various regions. Changes in aggregate European unemployment rates are reported in Figure (3.1) above. As can be seen, at the beginning of the decade, the average unemployment rate was about the 9%. It remained stable around that level until 2005 and decreased to 6.76% between 2005 and 2008. Nevertheless, with the outbreak of the financial crisis and its extension to the productive economy it reached the 9.4% level in 2011. As shown in Figure (3.1), the coefficient of variation -as a first proxy of unemployment differentials in European regions- displayed a similar evolution: it decreased until 2007 and hiked from 2008 to 2011. However, the linear fit shows that the overall pattern is one of decreasing unemployment differentials between regions.

Figure 3.1: Unemployment Dynamics 2000-2011.



With the aim of providing a deeper insight into the regional pattern of unemployment disparities in Europe, the density function associated with the distribution of unemployment rates in 2000, 2008 and 2011 is estimated. Figure (3.2) plots the distribution of regional unemployment rates relative to the average of all regions, what is called the EU relative unemployment rates (i.e, $UR_{it} = \frac{U_{it}}{\bar{U}_t}$) where U_{it} is the unemployment in region i at period t and $\bar{U}_t$ is the European average unemployment rate. In this diagram, note that a value of 1 on the horizontal axes indicates the European average unemployment rate, 2 indicates twice the European average and so on. On the other hand, the height of the curve over any point gives the probability that any particular region i will have that relative rate of unemployment. As it is shown in Figure (3.2), the probability mass of any region to be allocated in the European average was higher in 2011 (80%) than in 2000 (55%). Furthermore, the probability mass in the right side of the distribution which corresponds to regions with an unemployment rate about 1.5 or 2 times above the European average has decreased. Thus, Figure (3.2) hints at a small decrease in inequality of European unemployment rates. However, the evolution of the distribution shows a different pattern between 2000-2008 and 2008-2011. Relative unemployment rates clearly converged during the period 2000-2008, while during 2008-2011 period, regional inequalities increased. This is because of the probability mass of any region to be located in the lower (0 to 0.5 times below the average) and upper extremes (above 1.5 times the average) was higher in 2011 than in 2008. Therefore, it is possible to conclude that although regional unemployment disparities decreased during 2000-2011, the sub-period ranging from 2008-2011 is characterized by an increase in disparities.[2]

Figure 3.2: Unemployment Relative Distribution.



The overall slow convergence pattern observed in Figure (3.2) is due to both: (i) the catching-up behavior of the Eastern European regional economies such as Poland, Slovenia, East-Germany or Latvia and (ii) the lagging behavior of the north of Europe that starting in most of the cases with relatively low levels of unemployment worsened their position. Nevertheless, this aggregate pattern of convergence hides a considerable degree of heterogeneity given that some regions that were initially in a bad position have worsened it even more. This is corroborated when looking at the geographical distribution of relative unemployment rates in Figures (3.3) and (3.4) where the quartiles of the relative positions in the distribution are plotted.

The first quartile of the geographical distribution covers the most successful regions in terms of relative unemployment in the years 2000 and 2011. In the year 2000, the first quartile contains

[2] The picture of the evolution of unemployment differentials provided in Figure (3.2) does not vary when using absolute deviations instead of relative deviations.

regions with unemployment rates below the 51% of the EU average, while by the year 2011 it contains those with an unemployment rate below the 61% of the European average. Examples of regions belonging to this group in the year 2000 are those of Ireland, southern UK and Sweden, northern Italy and southern Germany. On the contrary, the group of regions that belong to the fourth quartile are those displaying the relatively poorest performance, with unemployment rates above 1.3 and 1.25 times the EU average in 2000 and 2011, respectively. In the year 2000, regions with an unemployment rate above 1.3 times the EU average can be found in southern Italy, eastern Germany, southern Spain, Poland, etc. As revealed by the comparison between the two figures, an interesting case is that of regions from Poland that starting with a relative rate 1.9 times above average, converged to a level below 1.2 times the European average. A markedly good performance is also found in many regions of southern Italy and the south of France, improving by more than a 17% their relative position with respect the European average. There are also regions that starting from a relatively low level of unemployment improved their relative unemployment rate. This is the case of German Landers or regions in the east of France that improved their relative position. A divergent behavior with respect the European average is observed in northern European regions belonging to Sweden, Denmark, Ireland, United Kingdom or Hungary, whose relative position deteriorated by more than 26%. The worst results, however, are found in the periphery of Europe. Starting from relatively high unemployment levels (i.e, 1.5 times above the EU average), during the study period most of the Spanish regions have increased its distance with respect the EU average (i.e, 2.3 times above it). The Greek and Portuguese regions display a similarly bad performance.

Previous results suggest there is a geographical component behind the evolution of the distribution of unemployment rates. As a further check on the role played by spatial location of the various regions in explaining labor market outcomes the approach based on the pioneer work of Quah (1996) is used to construct a conditioned distribution, in which each region's unemployment rate is expressed relative to the average of its neighbors. Specifically, the weighted average relative unemployment rate of neighboring regions is given by WU_t where W is a $(N \times N)$ spatial weight matrix describing the spatial interdependence among the sample regions and U_t is a $N \times 1$ vector of regional unemployment rates for each period. The spatial weight matrix used in this preliminary analysis is defined as:

$$W = \begin{cases} w_{ij} = 0 \quad if \quad i = j \\ w_{ij} = \frac{1/d_{ij}^2}{\sum\limits_j 1/d_{ij}^2} \quad if \quad i \neq j \end{cases} \tag{3.1}$$

Figure 3.3: Relative Unemployment Rates 2000

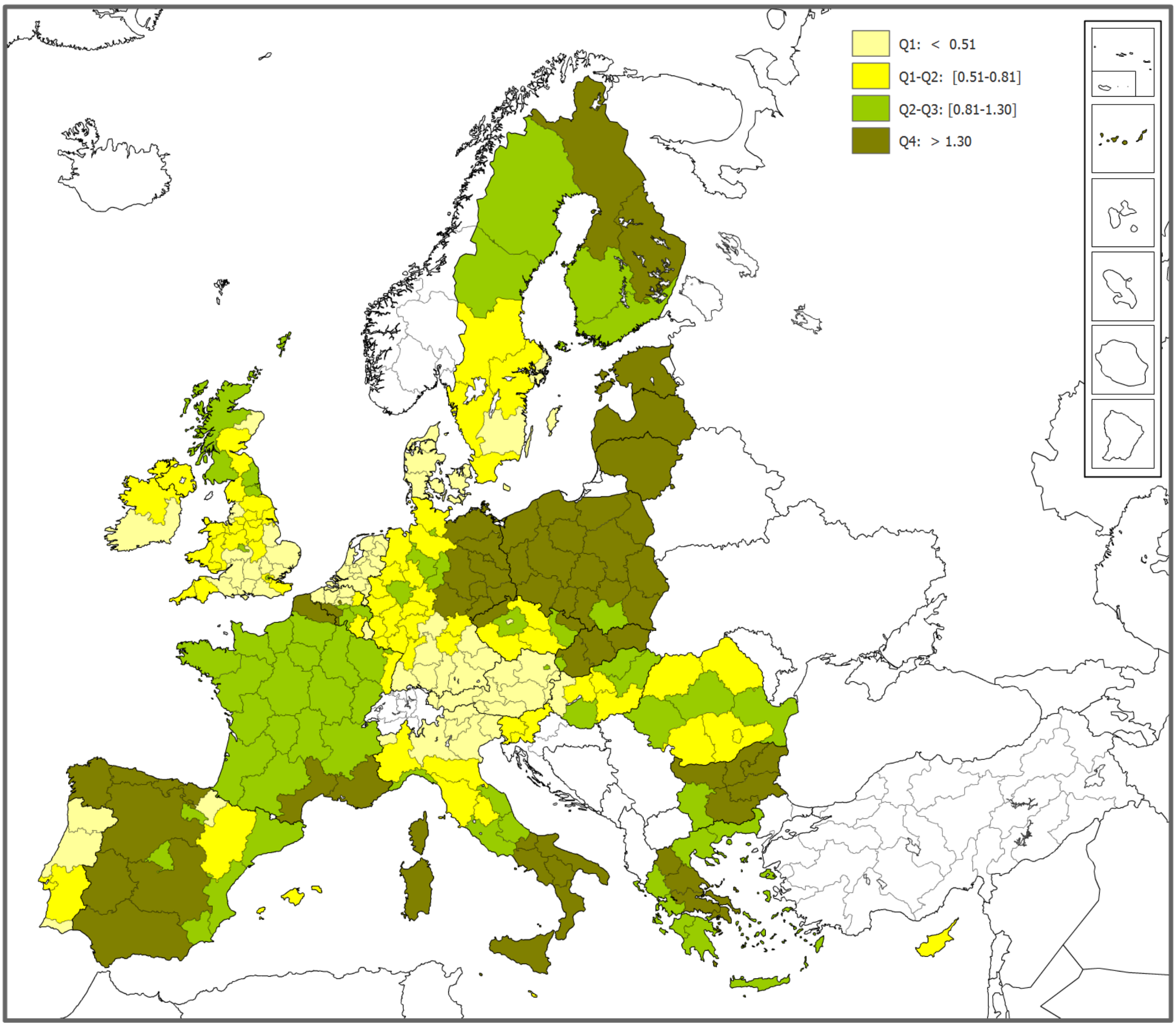
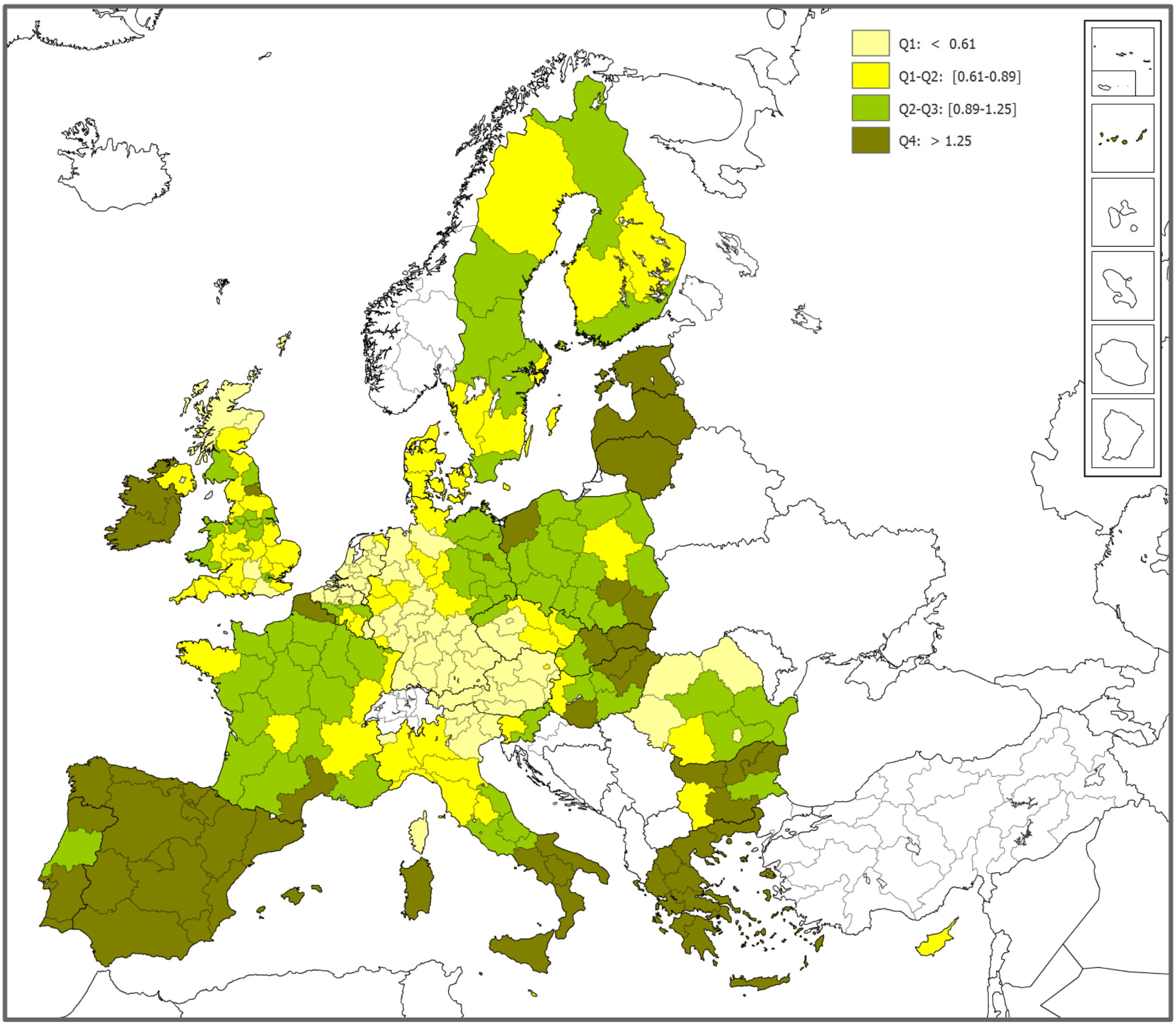
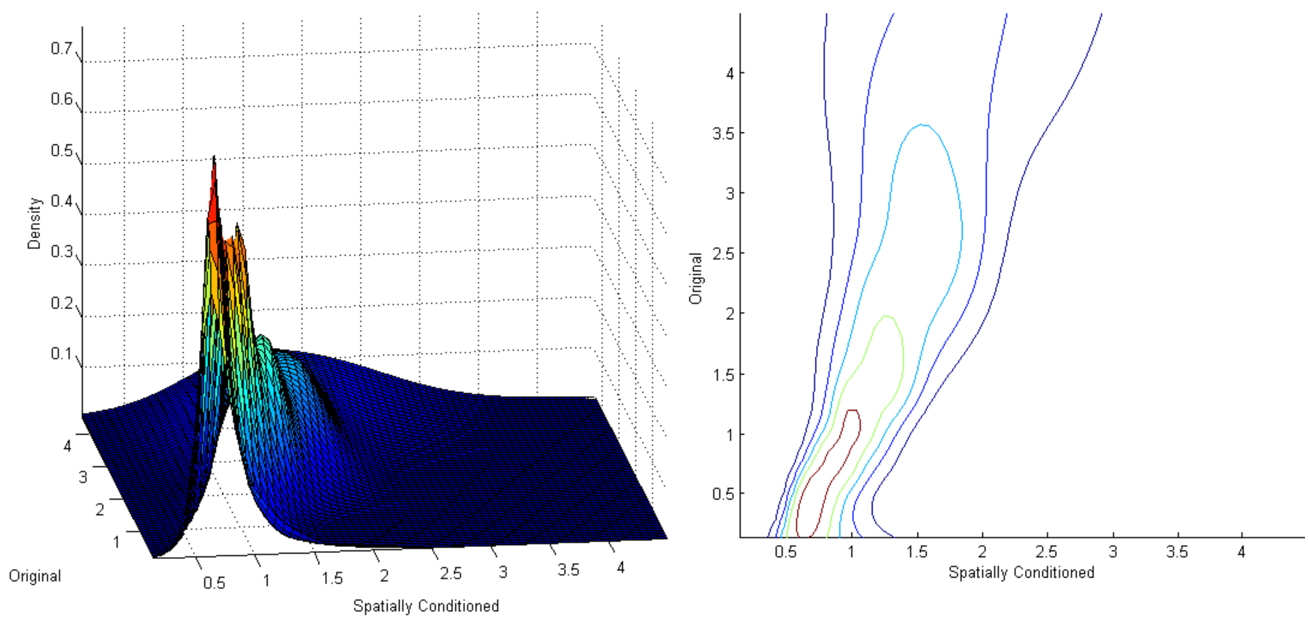


Figure 3.4: Relative Unemployment Rates 2011



where w_{ij} terms denote the spatial weights connecting i and j and d_{ij} is the great-circle distance between the centroids of regions i and j. The use the inverse of the squared distance is justified as it reflects a gravity function. Note that W is row standardized, so it is the relative, not the absolute distance that matters. Having defined this conditioning scheme, it is possible to assess the role played in this context by spatial interactions across the sample regions. In order to explore the role of spatial location a stochastic kernel following the methodology outlined by Magrini (2004, 2007) is estimated.[3] Stochastic kernel estimation allows to capture the transitions between the original distribution and the neighbor-relative unemployment distribution by employing all information available for the study period as a whole. The results are depicted in Figure (3.5).

Figure 3.5: Spatially Conditioned Stochastic Kernel.

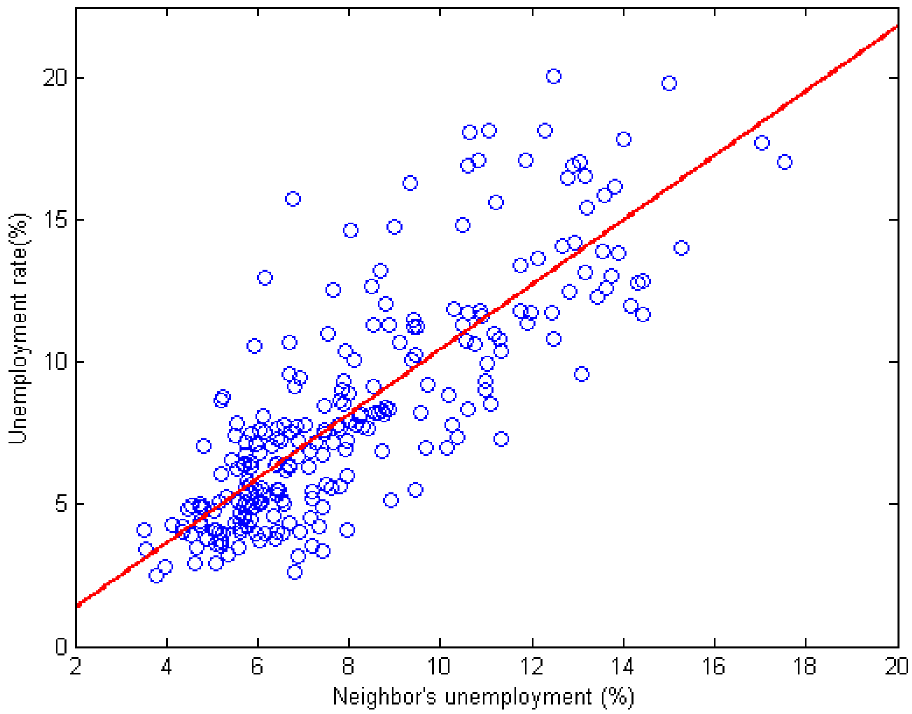


As it can be observed, neighboring effects are relevant in this context, provided that the probability mass is not centered around the main diagonal. Indeed, kernel estimates reveal that the probability mass tends to be located parallel to the axis corresponding to the original distribution and below the European average. Accordingly, spatial effects are a relevant factor explaining observed variations in unemployment rates. Further evidence on the relevance of spatial effects is provided by positive Moran's I statistic which takes a value of 0.36 (p-value=0.00) in 2000 and 0.47 (p-value=0.00) in 2011. Hence, it is possible to conclude that the regional dis-

[3]The estimation of the stochastic kernel relies in Gaussian kernel smoothing functions developed by Magrini (2007) and it is performed by employing the L-stage Direct Plug-In estimator with an adaptative bandwith that scales pilot estimates of the joint distribution by $\alpha = 0.5$, as suggested by Silverman (1986).

tribution of unemployment rates is characterized by intense positive spatial dependence. This indicates that regions with high unemployment rates are spatially close to regions with unemployment rates above the European average, while regions with unemployment rates below the average are more likely to be surrounded by other low-unemployment regions as shown in the scatter plot in Figure (3.6) below:

Figure 3.6: Unemployment Scatter Plot.



3.3 A Space-Time Regional Unemployment Model

The theoretical model used in this study to analyze the evolution of regional disparities in unemployment rates is built on previous work of Blanchard and Katz (1992) and Zeilstra and Elhorst (2014). However, in view of the empirical evidence provided in previous section, a novel feature included in this model is that regional labor market interactions are directly taken into account and regions are not considered to evolve independently. Indeed, in the context of economic integration process currently underway in Europe, the importance of inter-regional trade, capital flows, migratory movements and technology and knowledge transfer processes suggests that geographical location and spatial connectivity may play an important role in explaining regional unemployment outcomes. The model reads as:

$$\begin{aligned}
n_{it} &= -\alpha_1 \left(w_{it} - p_{it}\right) + \alpha_2 U_{it} - \beta_n X_{n,it} - \gamma_n Z_{n,it} - \varphi_n W X_{n,jt} - \pi_n W Z_{n,jt} \\
&\quad + \lambda_n M_{it} + \epsilon_{it}^d \qquad (3.2) \\
\left(w_{it} - p_{it}\right) &= \beta_w X_{w,it} + \gamma_w Z_{w,it} - \alpha_3 U_{it} - \alpha_4 \Delta U_{it} - \delta_1 W U_{jt} - \delta_2 \Delta W U_{jt} + \varphi_w W X_{w,jt} \\
&\quad + \pi_w W Z_{w,jt} + \epsilon_{it}^w \qquad (3.3) \\
l_{it} &= \alpha_5 \left(w_{it} - p_{it}\right) - \alpha_6 U_{it} + \beta_l X_{l,it} + \gamma_l Z_{l,it} + \varphi_l W X_{l,jt} + \pi_l W Z_{l,jt} + \lambda_l M_{it} \\
&\quad + \epsilon_{it}^s \qquad (3.4) \\
M_{it} &= \sum_{j \neq i}^{N} m_{ijt} = \alpha_7 \left(w_{it} - p_{it}\right) - \alpha_8 U_{it} - \delta_3 W_{ij} U_{jt} + \beta_m X_{m,it} + \gamma_m Z_{m,it} \\
&\quad + \varphi_m W X_{m,jt} + \pi_m W Z_{m,jt} + \epsilon_{it}^m \qquad (3.5) \\
U_{it} &= l_{it} - n_{it} \qquad (3.6)
\end{aligned}$$

where U_{it} is unemployment in region i at time t; n_{it} is labor demand; l_{it} is labor supply; w_{it} is the gross nominal wage, p_{it} is the price level, $w_{it} - p_{it}$ is real wage level, M_{it} is the net inward migration in region i, m_{ijt} denotes net migration flows from j to i, U_{jt} denotes unemployment in neighboring regions $j \neq i$ and $W = \sum_{j=1}^{N} w_{ij}$ is a spatial weight matrix that represent the spatial interdependence between regions i and j. As is usual in the literature, W is assumed to be non-negative, non-stochastic and finite, with $0 \leq w_{ij} \leq 1$ and $w_{ij} = 0$ if $i = j$. X_{it} and Z_{it} denote the regional-level labor market conditions and national level labor market institutional factors, respectively, while X_{jt} and Z_{jt} denote neighbor's market conditions and institutional framework. The α, λ parameters are positive, δ β, γ, φ and π are unknown and the terms, ϵ_{it}^d, ϵ_{it}^w, ϵ_{it}^s and ϵ_{it}^m denote labor demand, wage, labor supply and migration shocks respectively.

In Equation (3.2) labor demand n_{it}, is assumed to depend on real wages, unemployment rates, regional labor market factors ($X_{n,it}, X_{n,jt}$, i.e, output fluctuations, education) and institutional factors ($Z_{n,it}, Z_{n,jt}$, i.e, taxes and employment protection legislation (EPL)). Real wages have a negative effect on labor demand within a region given that a lower wage makes a region more attractive to firms ($-\alpha_1 < 0$). The effect of the unemployment rate, on the other hand, is assumed to be positive ($\alpha_2 > 0$) as a higher unemployment increases the pool of workers from which to choose and induces firm-in migration. Net migration shocks have a positive effect ($\lambda_n > 0$) on labor demand as they may increase human capital levels, foster local good consumption and rise local potential and investment (Elhorst, 2003).

Equation (3.3) is a wage setting equation where real wages depend positively on labor market factors ($X_{w,it}, X_{w,jt}$, i.e, sectoral composition) and institutional conditions ($Z_{w,it}$,$Z_{w,jt}$ i.e, coordination, union density, coverage, etc) affecting worker bargaining positions and negatively on the unemployment rate ($-\alpha_3 < 0$) and the growth rate of unemployment ($-\alpha_4 < 0$). The inclusion of the growth rate of unemployment is relevant as changes in unemployment growth rates ΔU, may have additional impacts on wages, as recent literature on the wage curve has shown (Blanchflower and Oswald, 1994; 2005). Hence, Equation (3.3) takes the form a spatial wage-curve as in recent studies of Longhi *et al.* (2006), Baltagi *et al.* (2012) and Fingleton and Palombi (2013) given that it includes the spatial lag of unemployment terms. Spatial externalities in bargaining power are given by parameters (δ_1, δ_2) and can be justified by the fact that if workers are mobile, employers in strongly interacting regions surrounded by regions with low unemployment levels cannot reduce wages without fearing a potential move of workers to adjacent areas.[4]

Equation (3.4) expresses labor supply as a function of real wages, regional labor market conditions ($X_{l,it}, X_{l,jt}$, demographic composition of the population), and institutional factors ($Z_{l,it}$,$Z_{l,jt}$ i.e, unemployment benefits) and unemployment. In Equation (3.4), higher wages will increase labor supply through more labor force participation ($\alpha_5 > 0$). Similarly, a positive change in the net-inward migration outcomes will rise the labor supply. The effect of unemployment rates on labor supply depends on whether the discouraged worker effect dominates the additional worker effect. However, given that in empirical research the discouraged worker effect appears to be specially relevant, the effect of unemployment on labor supply is assumed to be negative and given by ($-\alpha_6 < 0$) .

Finally, Equation (3.5) is a migration equation similar to that employed by Alecke *et al.* (2010), Mitze (2012) and Basile *et al.* (2012) and captures the net migration process in region i. Wages have a positive effect on migration inflows attracting the most mobile and educated workers ($\alpha_7 > 0$). A high unemployment rate in i decreases migration ($-\alpha_8 < 0$), as it indicates that the region may be coping with economic problems (i.e, fiscal crises, instability, etc) making it less attractive. Thus, if region i is under-performing, it is most likely that the higher skilled labor force can more readily migrate to another region j. Similarly, a higher unemployment rate in the region of origin j will increase population flows from j to i. As a point of fact, the effect of unemployment in region j on the migration patterns in i is modulated by the effects of distance

[4]Estimates of Longhi *et al.* (2006) show that Blanchflower and Oswald's relationship is stronger if regions are more isolated, because the mobility costs associated with a job change (commuting, migration, job search) are higher in less accessible, remote regions and thus the local labor supply is relatively inelastic.

given that higher distances imply higher costs of moving, less information, etc. Additionally, migration is affected by regional amenities and disamenities $X_{m,it}, X_{m,jt}$ (i.e, temperatures) and by institutional factors that may work as pull or push factors for regional migration $Z_{m,it}, Z_{m,jt}$ (i.e, the strictness of institutional regulations constraining the possibilities to migrate from j to i).

An innovative element of this model is the introduction of neighbor's variables in the equations of demand, supply, wages and net migration in region i, what ultimately implies that neighboring region characteristics will have an impact in the unemployment rate of region i. Moreover, it allows to explore the channels through which spatial dependence among unemployment rates in regions i and j may emerge.

The first channel of interdependence in the unemployment rates among neighboring regions operates through the spatial migration curve (Möller, 2001; Mitze, 2012). An increase in the unemployment rate of region j in Equation (3.5) could induce migration from j to i, which would have the effect of increasing the supply of labor in the receiving region i in Equation (3.4). However, migration flows effects may not be confined to changes in the labor supply and could have additional positive effects on the demand for labor in i. If the demand effect dominates the supply ($\lambda_l - \lambda_n > 0$), an increase in unemployment in j could reduce unemployment in i if $\delta_3 < 0$ creating a negative spatial dependence pattern. On the contrary, if $\delta_3 > 0$ and if the demand channel dominates the labor supply, changes in unemployment in neighboring regions will induce a positive spatial dependence pattern in regional unemployment rates.

The second channel works through the spatial wage curve. A change in unemployment rates in a neighboring region j will alter the bargaining power of workers over wages in j but also in i through Equation (3.3). If unemployment in i is high and $\delta_1, \delta_2 > 0$, an increase in unemployment in j may cause the real wages in i to fall. This is because of the bargaining power externality will favor employers in i allowing reductions in wages paid in region i. Incentives for firms originally located in j to change their location and move its production to region i to reduce their labor costs will reduce the demand for labor in j and increase it in i, in line with findings by Azariadis and Pisarides (2007) and Vallanti (2007). The negative effect on the real wages of region i will further augment this reduction by $\alpha_1 + \alpha_5$, thereby creating a negative spatial correlation dependence. On the other hand, if $\delta_1, \delta_2 < 0$, an increase in the unemployment rates of region j will drive up bargaining power and wages in i. This will reduce labor demand in i. The positive effect on unemployment rates in i will be further augmented by the direct increase in the labor supply and by migration effects. This scenario corresponds to a positive spatial dependence pattern.

Additionally, although for simplicity the interplay between the demand for goods and labor market functioning is not directly included in the model, a third channel of interaction between regions may emerge due to labor market institutional spillovers (Egger *et al.*, 2012; Felbermayr *et al.*, 2011, 2013). If as highlighted by Helpman and Itshoki (2010) in the context of trade models, institutional reforms in j affect wages, unemployment rates might become in i might become dependent of those in j. For instance, institutional reform in j decreasing taxes paid by firms will encourage businesses to locate there, thus reducing the labor demand in i. Likewise, a change in the institutional framework in j rising the bargaining power of unions and workers driving up wages will have a negative *competitiveness effect* in j. Relatively lower wage costs in i will increase i competitiveness, making harder for firms in j to sell their output which will increase unemployment in j. In addition, institutional reforms in neighboring economies may also produce *cross-income effects* between j and i. Reforms to reduce worker's wage bargaining power in j will, in the long run, reduce spending on products made by firms in i and marketed in j. This, in turn, will negatively affect labor demand in i and increase its unemployment rate. According to Mian and Sufi (2014), regions with a relatively higher share of non-tradable goods will be less vulnerable to contagions stemming from neighboring economies.

In order to solve the model for the unemployment rates the following steps are required. First, plug Equation (3.3) in Equation (3.5) to obtain the migration Equation (3.5)' as a function of wages. Then plug both, Equation (3.3) and Equation (3.5)' in Equations (3.2) and (3.4). Finally, substitute Equations (3.2)' and Equation (3.4)' in Equation (3.6) to obtain the following *Dynamic Spatial Durbin Model* specification as in Equation (3.7) below:

$$U_{it} = \tau U_{it-1} + \rho W U_{jt} + \eta W U_{jt-1} + \tilde{\beta}_1 \tilde{X}_{it} + \tilde{\beta}_2 \tilde{Z}_{it} + \tilde{\theta}_1 W \tilde{X}_{jt} + \tilde{\theta}_2 W \tilde{Z}_{jt} + \psi \tilde{\epsilon}_{it} \tag{3.7}$$

where $\tilde{X}_{it}, \tilde{Z}_{it}, \tilde{X}_{jt}, \tilde{Z}_{jt}$ and $\tilde{\epsilon}_{it}$ denote the corresponding vectors of covariates. The parameter restrictions implied by the theoretical model are shown in Table (3.1) below. Note that, in this model, starting from a steady state pattern of regional unemployment, a region-specific shock will not only affect the respective labor market, but instead spill over to neighboring regions labor market supply and demand. Given this interdependence, the induced changes of unemployment in neighboring areas may spill over again to adjacent labor markets, including the location where the shock originated.

Table 3.1: Parameter Restrictions.

Implicit Model Parameter	Theoretical Model Parameter
τ	$\frac{\alpha_4[(\alpha_1+\alpha_5)+\alpha_7(\lambda_l-\lambda_n)]}{\Phi}$
ρ	$\frac{(\delta_1+\delta_2)(\alpha_7(\lambda_n-\lambda_l)-(\alpha_1+\alpha_5))+\delta_3(\lambda_l-\lambda_n right)}{\Phi}$
η	$\frac{\delta_2(\alpha_7(\lambda_l-\lambda_n)+(\alpha_1+\alpha_5))}{\Phi}$
$\tilde{\beta}_1$	$[\beta_w^*, \beta_m^*, \beta_n^*, \beta_l^*] = \left[\frac{\beta_w(\alpha_7(\lambda_l-\lambda_n)+(\alpha_1+\alpha_5))}{\Phi}, \frac{\beta_m(\lambda_l-\lambda_n)}{\Phi}, -\frac{\beta_n}{\Phi}, \frac{\beta_l}{\Phi}\right]$
$\tilde{\theta}_1$	$[\varphi_w^*, \varphi_m^*, \varphi_n^*, \varphi_l^*] = \left[\frac{\varphi_w(\alpha_7(\lambda_l-\lambda_n)+(\alpha_1+\alpha_5))}{\Phi}, \frac{\varphi_m(\lambda_l-\lambda_n)}{\Phi}, -\frac{\varphi_n}{\Phi}, \frac{\varphi_l}{\Phi}\right]$
$\tilde{\beta}_2$	$[\gamma_w^*, \gamma_m^*, \gamma_n^*, \gamma_l^*] = \left[\frac{\gamma_w(\alpha_7(\lambda_l-\lambda_n)+(\alpha_1+\alpha_5))}{\Phi}, \frac{\gamma_m(\lambda_l-\lambda_n)}{\Phi}, -\frac{\gamma_n}{\Phi}, \frac{\gamma_l}{\Phi}\right]$
$\tilde{\theta}_2$	$[\pi_w^*, \pi_m^*, \pi_n^*, \pi_l^*] = \left[\frac{\pi_w(\alpha_7(\lambda_l-\lambda_n)+(\alpha_1+\alpha_5))}{\Phi}, \frac{\pi_m(\lambda_l-\lambda_n)}{\Phi}, -\frac{\pi_n}{\Phi}, \frac{\pi_l}{\Phi}\right]$
$\tilde{\psi}$	$\left[\psi^{w*}, \psi^{m*}, \psi^{d*}, \psi^{s*}\right] = \left[\frac{(\alpha_7(\lambda_l-\lambda_n)+(\alpha_1+\alpha_5))}{\Phi}, \frac{(\lambda_l-\lambda_n)}{\Phi}, -\frac{1}{\Phi}, \frac{1}{\Phi}\right]$

Note: $\Phi = 1 - [(\alpha_3 + \alpha_4)(\alpha_7(\lambda_n - \lambda_l) - (\alpha_1 + \alpha_5)) - (\alpha_2 + \alpha_6) + \alpha_8(\lambda_n - \lambda_l)]$

3.4 Data and Econometric Methodology

3.4.1 Data

The implicit model of unemployment obtained in Equation (3.7) above shows the unemployment rate is a reduced form function of a variety of factors affecting the labor demand, supply, migration and wages. These are referred to both, regional and national level institutional factors. To explore further the nature of unemployment differentials, the distinction between regional disequilibrium and equilibrium factors made in Partridge and Rickman (1997a,b) and López-Bazo *et al.* (2005) is also considered. The factors included in the regression analysis, the behavioral hypothesis, its computation and the data source are summarized below in Table (3.2).

A) Disequilibrium Factors.

These factors refer to unemployment differences produced by divergences in short run dynamics and asymmetric responses to shocks. The variables included are the employment growth, real wage growth and cyclical real output fluctuations. If a region creates employment at a faster rate the European average, unemployment in that region should decrease relatively (Diaz, 2011). On the other hand, a slow rate of wage adjustments explain why idiosyncratic shocks or asymmetric responses to common shocks might produce unemployment rates to differ across regions for a long time (Marston, 1985; López-Bazo *et al.*, 2005). Specifically, a positive relationship between changes in wages and unemployment rates means that the origin of most of labor market shocks arise from supply side while a negative relationship implies demand driven disequilibrium (Blanchard and Katz., 1992; Partridge and Rickman, 1997a,b). Another candi-

Table 3.2: Unemployment Drivers Summary.

Factors	Average 2000-2011	Std 2000-2011	Expected Effect	Units	Data Source[1]	Calculation
Unemployment rate	8.34	4.73		(%)	ES	No calculations are performed on the original data.
A. Disequilibrium Factors						
Employment Growth (EG_{it})	0.59	2.33	-	(%)	CE	$EG_{it} = 100\left(\frac{E_{it}-E_{it-1}}{E_{it-1}}\right)$ where E denotes total employment.
Real GDP pc Gap ($\widehat{Y}_{it}$)	-0.01	2.68	-	(%)	CE, ES	$\widehat{Y}_{it} = 100\left(\frac{\widehat{y}_{it}}{y_{it}}\right)$ where $\widehat{y}$ is the HP filtered real GDPpc and y is real GDPpc
Real Wage Growth (RWG_{it})	0.57	5.13	?	(%)	CE, ES	$RWG_{it} = 100\left(\frac{RW_{it}-RW_{it-1}}{RW_{it-1}}\right)$ where RW is the real wage level.
B. Equilibrium Factors						
B.1 Labor Market Factors						
Real Wage Level (RW_{it})	247.98	103.45	+	Index	CE, ES	$RW_{it} = \frac{W_{it}}{P_{it}}$ where W is the nominal compensation per employee and P is the HCPI.
ES Industry ($ES_{m,it}$)	17.83	6.90	?	(%)	CE	$ES_{m,it} = 100\left(\frac{E_{m,it}}{E_{it}}\right)$ where E_m is employment in manufactures
ES Non market SS ($ES_{nm,it}$)	29.88	6.31	?	(%)	CE	$ES_{nm,it} = 100\left(\frac{E_{nm,it}}{E_{it}}\right)$ where E_{nm} is employment in non-market services
Specialization (SS_{it})	23.35	2.85	?	(%)	CE	$SS_{it} = 100\left(\sum_{s=1}^{S}\frac{E_{sit}}{\sum_s E_{sit}}\right)$ where E_s is employment in sector [2]
B.2 Demographic Factors						
Population 55-64 (OS_{it})	11.48	3.33	-	(%)	ES	$OS_{it} = 100\left(\frac{OP_{it}}{n_{it}}\right)$ where OP denotes population aged 55-64 and (n) total population
Population 15-24 (YS_{it})	11.91	3.03	+	(%)	ES	$YS_{it} = 100\left(\frac{YP_{it}}{n_{it}}\right)$ where YP denotes population aged 15-24 and (n) total population
Participation Rate (L_{it})	47.34	5.44	?	(%)	ES	$PR_{it} = 100\left(\frac{AC_{it}}{n^a_{it}}\right)$ where AC is active population and n^a population aged 15-64
Education Index (ED_{it})	38.32	8.54	-	Index	ES	$ED_{it} = \frac{1}{3}(1-S_{it}) + \frac{2}{3}T_{it}$ where S and T are pop shares with lower secondary and tertiary education
Net Migration (nm_{it})	0.38	0.64	?	(%)	ES	$nm_{it} = \frac{M_{it}}{n_{it}} = \frac{(n_{it+1}-n_{it})-(b_{it}-d_{it})}{n_{it}}$ where M is net migration, b and d are total births and deaths.
B.3 Amenities						
Population Density PD_{it}	380.69	953.70	?	Pop/km^2	CE	$PD_{it} = \frac{n_{it}}{A}$ where n is population in inhabitants and A is the area in km2
Temperature T_{it}	10.51	2.45	?	Degrees	ES	$T_{it} = 18 - H_{it}/d$ where H denotes actual heating degrees days and $d = 30$ is a monthly scaling factor.
C. Labor Market Institutions						
Unemployment Benefit (UB_{it})	51.67	12.80	+	Index	OECD	$UB_{it} = UI_{it} + UA_{it}$ where UI is unemployment insurance and UA unemployment assistance).
Tax Wedge (TW_{it})	39.70	6.70	?	(%)	OECD	$TW_{it} = \frac{LT_{it}}{LC_{it}}$ where LT denotes labor taxes and LC total labor costs.
BCov & Low ccord (BCL_{it})	6.46	10.48	-	Index	ICTWSS	$BCL_{it} = UCn_{it} \mid (CCn_{it} < k1)$ where $k_1 = Q_1(CC)$ is the first quartile cut off of the distribution of CCn. $UCn = 100\left(\frac{UC_{it}-UC_{min}}{UC_{max}-UC_{min}}\right)$, $CCn = 100\left(\frac{CC_{it}-CC_{min}}{CC_{max}-CC_{min}}\right)$ with $UC_{it} = U + C$ and $CC = Ce + Co$ where U is union density, C is collective coverage and Ce and Co are the levels of centralization and coordination.
BCov & Med ccord (BCM_{it})	46.81	21.57	+	Index	ICTWSS	$BCM_{it} = UCn_{it} \mid (k_1 < CCn_{it} < k_3)$ where $k_1 = Q_1(CCn)$ and $k_3 = Q_3(CCn)$
BCov & High ccord (BCH_{it})	7.63	22.53	-	Index	ICTWSS	$BCH_{it} = UCn_{it} \mid (CCn_{it} > k_3)$ where $k_3 = Q_3(CCn)$ is the third quartile cut off of the distribution of CCn.
EPL (EPL_{it})	34.52	18.92	?	Index	OECD	$EPL_{it} = 100\left(\frac{I_{it}-I_{min}}{I_{max}-I_{min}}\right)$ where I, I_{max} and I_{min} are the original, maximum and minimum EPL scores.
Minimum Wage (MWR_{it})	29.24	23.17	+	Index	OECD, CE	$MWR_{it} = 100\left(\frac{MW_{it}}{W_{it}}\right)$ where MW is the minimum legal wage and W is the compensation per employee.
Temporary Contracts TC_{it}	38.76	17.72	+	(%)	OECD	No calculations are performed on the original data.
Migration Strictness MS_{it} [3]	8.20	1.76	?	Index	UNIIPD	$MS_{it} = \frac{1}{P}\sum_p^P S_{p,it}$ where S_p is the strictness score in the policy pillar p

Notes: (1) CE denotes the Cambridge Econometrics Database. ES denotes Eurostat, ICTWSS refers to the while UNIIPD denotes the United Nation's International Immigration Policies Database. (2) The sectors $s = 1, \ldots, S$ considered to obtain the Herfindahl Index are agriculture, manufactures, construction, distribution, non-market services and financial services. (3) The migration policy index is constructed averaging the following policy p pillars: Policy on Inmigration, Policy Integration, Policy on Settlements, Policy on Temporary Workers and Views on Inmigration.

date for explaining unemployment movements as a function of demand shocks is the deviation of GDP per capita from its full employment or long run trend level, which, according to Isserman *et al.* (1986) is the most widely used indicator of demand.

B) Equilibrium Factors

B.1) Labor Market Equilibrium Factors

Sectoral diversification in a region may affect unemployment rates (Longhi *et al.*, 2005). The more specialized a regional economy, the less it is able to adjust employment reductions in any given sector (Simon, 1988). On the other hand, firms located in more specialized regions can gain from agglomeration effects such as knowledge spillovers, and be more productive than similar firms in less specialized regions. Specialization is measured by the Herfhindal index and its expected effect uncertain. Additionally, differences in the industry mix might impact the geographical distribution of unemployment (Overman and Puga 2002, Niehbur 2003; López-Bazo *et al.*, 2005). Accordingly, the model also includes regional employment shares in manufacturing industries and non-market services. Industrial regions specializing in export-oriented manufactures may exhibit lower unemployment rates than those specializing in sheltered industries such as public services (Rodriquez-Pose and Fratesi, 2007). This might be due to the large multipliers associated to manufacture (Elhorst, 2003). However, other authors consider that a high employment share in declining industries may produce the opposite results (Diaz, 2011). Finally, a real wage level index is also included. Given that real wages are supposed to exert a negative influence on labor demand and a positive effect on labor supply, a positive relationship with unemployment is expected.

B.2) Demographic Equilibrium Factors.

The structure of the population may have important influences on labor supply and demand (Groenewold, 1997). Moreover, when the various cohorts suffer from different unemployment rates, their relative size affects the aggregate unemployment rate and labor force participation. According to previous studies older populations should display lower unemployment rates. To control for this the share of population aged between 55 and 64 years old and the share of young population aged between 15-24 years is included. Empirical studies find the participation rate, has a negative effect on unemployment outcomes (Elhorst, 2003). Nevertheless, this is at odds with the accounting identity where if the participation rate increases the number of unemployed must go up (Fleisher and Rodes, 1976). Therefore, the a priori effect of participation is uncertain. Human capital is expected to affect negatively unemployment for a considerable number of reasons such as higher demand for skills, lower probability of lay off, etc. (Nickell and Bell, 1996). Furthermore, people with higher educational attainment are likely to conduct more efficient searches and are less prone to layoffs in an economy with continued technological advancements. To proxy human capital levels in the sample regions, an index that combines the share of population with a low educational attainment and the share of population with a high educational attainment is employed (Bubbico and Dijkstra, 2011). The net migration rate is also expected to impact unemployment outcomes and relying on the neoclassical explanation it might be an important mechanism balancing regional disparities. However, as explained in theoretical model section, the expected effect of net migration is ambiguous and its determination remains as an empirical question.

B.3) Amenities.

Amenities are considered as a compensating differential for the higher probability of unemployment. Variables used to proxy for producer and consumer amenities were largely conditioned by the availability of data. Population density is included as a proxy for urbanization following López-Bazo *et al.* (2005) and Cracolici *et al.* (2007) while temperatures are introduced to proxy for climatological amenities. Regions with dense populations will provide cultural, educational and health amenities. Additionally, highly urbanized and dense areas may increase the probability of matching job seekers and firms. On the other hand, negative effects may arise if the time spent by workers to collect information about the vacancies on the job market rises. Therefore, a priori, the effect of population density is unknown. On the contrary, the effect of temperatures is not clear beforehand, as relatively higher temperatures and better climatic conditions are expected to disincentive outward-migration. Thus, the effect of this variable ultimately depends on the link between migration and unemployment.

C) Labor Market Institutions.

In order to approximate the role of labor market institutions a number of indicators are considered: an employment protection legislation index (EPL), the generosity of unemployment benefits, the tax wedge, a bargaining coverage index, a coordination index, the share of temporary contracts, an index measuring the ratio of the legal minimum wage relative to the average wage and an index measuring the strength of migration controls.

The expected effect of the EPL is ambiguous as employment protection has been designed to protect jobs and increase job stability by reducing job destruction (OECD, 2013) which may help to avoid unemployment. However, according to Boeri and Van Ours (2008) a stronger EPL reduces job creation, because employers are more reluctant to open a vacancy. Unemployment benefits also affect unemployment rates through different channels. First, they increase reservation wages of recipients, reducing their search intensity. Second, they rise the floor of wages and because of higher wages lead to lower employment, unemployment may increase. Thirdly, they increase the expected profit of participating in the labor market with respect the one associated to inactivity. Most of the literature at this respect finds a positive relationship between unemployment benefits and unemployment rates (Blanchard and Wolfers, 2000; Belot and Van Ours, 2001; 2004). Additionally, the gap between the cost of labor to the firm and the net wage of the worker, the so called tax wedge is considered. The extent to which the tax wedge affects unemployment depends on whether the taxes are passed on workers in the form of lower wages, which ultimately depends on the elasticity of labor supply and demand. As empirical studies virtually fit all possible relationships its expected effect is uncertain (Nickell, 1997; Di Tella and Macculloch, 2005; Lehman *et al.*, 2014).

The characteristics of different collective bargaining systems may affect regional unemployment rates. In centralized systems, negotiations take place at the country level between national unions and employer's associations while, in decentralized systems negotiations take place at the level of the individual enterprise. Another relevant feature of the institutional framework is the degree of coordination between the bargaining partners in order to reach consensus. However, there are only minor differences in the degrees of centralization and coordination. In view of this, these two variables are aggregated in a centralization-coordination index. Meanwhile, a bargaining coverage index is computed as the sum of the union density and the collective bargaining coverage indicators.[5] According to Calmfors and Drifill (1998) the effect of centralized and coordinated bargaining outcomes on unemployment is conditional to the bargaining coverage. These two indexes are combined into three new variables: bargaining coverage index in regions with a low, intermediate and a high coordination index. Longhi *et al.* (2005) and Zeilstra and Elhorst (2014) find evidence of a hump shaped relationship between bargaining coverage level and the level of unemployment. Hence, the relationship between bargaining coverage level and unemployment is expected to take the form of an inverted U.

The share temporary contracts is expected to increase unemployment rates as these type of contracts allow for rapid and deep employment cuts to keep productivity levels once the economy receives a negative a shock, thus raising unemployment rates (Marelli *et al.*, 2012; Gúell and Rodríguez Mora, 2014). This type of labor market institution contrasts with labor hoarding

[5]The reason for this choice is due to the relationship between union density and bargaining coverage. When the outcome of collective bargaining is extended to all workers, the incentive for workers to join unions is clearly lower than in those cases when the conditions collectively bargained are binding only for union members (Longhi *et al.*, 2005). Hence, the higher the collective bargaining coverage, the lower the union density and viceversa.

practices where adjustments against shocks is based on working hour adjustments. Similarly, minimum wage relative to average wage is expected to have a positive effect on unemployment given that it decreases the quantity of labor demanded and further increases the quantity of labor supplied (Elhorst, 2003). Empirical studies including this ratio have found a significant effect in Europe (Banerji, 2014). Finally, an index measuring the evolution of strictness in migration policy constructed with data taken from the United Nations Database is included in the econometric specification.[6] The aim of this index is to measure the overall openness to international migration.[7] An increase in the strictness will increase negative incentives to change location and reduce migration flows. While an increase in this index will tend to increase unemployment disparities by limiting the free movement of labor, the expected effect on aggregate unemployment is uncertain.

A concern is that national level institutional variables are highly correlated with some regional factors, making it impossible to disentangle between the contribution of the various factor on the unemployment rates. This does not pose problems in this context, however, given that, as can be observed in Table (3.3), correlations among the institutional labor market variables and disequilibrium factors and equilibrium factors are relatively low. Specifically, the highest correlations between institutional factors and the other variables appear in the relationships between real wages and unemployment benefits (0.52) and the bargaining coverage indicator (0.51). All the other correlations among the institutional labor market factors and regional level factors are below 0.5.

3.4.2 Econometric Approach

The empirical counterpart to the implicit model in Equation (3.7) including regional fixed and time-period fixed effects is given by:

$$U_t = \mu + \iota_N \alpha_t + \tau U_{t-1} + \rho W U_t + \eta W U_{t-1} + X_t \beta + W X \theta + \epsilon_t \tag{3.8}$$

where U_t is a $N \times 1$ vector consisting of observations for the unemployment rate measured in percentage for every region $i = 1, \ldots, N$ at a particular point in time $t = 1, \ldots, T$, X_t, is an $N \times K$ matrix of exogenous aggregate socioeconomic and economic covariates with associated

[6]This dataset is employed instead of alternative information included in the Migrant Integration Policy Index (MIPEX) of Niessen *et al.* (2007), as the later have only recently become available and the time span is rather short.

[7]However, a drawback of this index is that it does not provide information on the initial level of strictness and just informs on the evolution of migratory regulations

Table 3.3: Correlations.

	Unemployment Benefits	Tax Wedge	Bargaining Cov and Low coord	Bargaining Cov and Med coord	Bargaining Cov and High coord	EPL	Minimum Wage	Temporary Contracts	Strictness of Migration
A. Disequilibrium Factors									
Employment Growth	-0.01	-0.03	-0.04	0.04	0.06	-0.01	0.01	0.08	0.10
Real GDPpc Gap	-0.03	-0.02	-0.01	-0.01	0.01	0.01	0.02	-0.04	0.11
Real Wage Growth	-0.01	0.09	-0.10	0.05	0.01	0.21	-0.01	0.05	-0.04
B. Equilibrium Factors									
B.1 Labor Market Equilibrium Factors									
Real Wage Level	0.52	0.15	-0.35	0.51	0.20	-0.18	-0.33	0.06	-0.22
Employment Share Industry	0.00	0.30	0.08	-0.16	-0.06	0.25	-0.16	0.14	0.05
Empployment Share Non market ss	0.32	0.20	-0.20	0.37	0.05	-0.21	-0.19	0.07	-0.18
Sectoral Specialization	0.17	-0.02	0.03	0.10	-0.02	-0.20	0.03	-0.11	-0.03
B.2 Demographic Equilibrium Factors									
Population 55-64	0.19	-0.18	0.05	0.04	-0.27	-0.07	-0.15	-0.10	0.16
Population 16-25	0.43	-0.38	0.33	-0.11	-0.04	-0.38	0.10	-0.23	0.04
Participation	0.37	-0.24	0.18	-0.09	-0.04	-0.08	-0.11	-0.11	0.13
Education	0.49	0.03	0.21	-0.11	0.09	-0.39	-0.09	-0.04	0.09
Net Migration	0.05	-0.24	-0.07	0.15	0.10	-0.19	0.13	-0.04	0.00
B.3 Amenities									
Population Density	0.08	-0.03	0.16	-0.19	0.11	-0.13	-0.04	-0.08	-0.04
Climate	-0.39	-0.18	-0.20	-0.08	-0.08	0.16	0.27	0.06	-0.23
C. Labor Market Institutions									
Unemployment Benefits	1.00	0.16	-0.09	0.24	0.14	-0.05	-0.06	0.18	-0.15
Tax Wedge	0.16	1.00	-0.51	0.44	0.32	0.43	-0.52	0.39	-0.30
Bargaining cov—Low coordination	-0.09	-0.51	1.00	-0.67	-0.21	-0.60	0.42	-0.56	0.37
Bargaining cov—Med coordination	0.24	0.44	-0.67	1.00	0.43	0.26	-0.45	0.19	-0.13
Bargaining cov—High coordination	0.14	0.32	-0.21	0.43	1.00	-0.11	-0.06	-0.08	0.01
EPL	-0.05	0.43	-0.60	0.26	-0.11	1.00	-0.35	0.51	-0.19
Minimum Wage	-0.06	-0.52	0.42	-0.45	-0.06	-0.35	1.00	-0.34	-0.01
Temporary Contracts	0.18	0.39	-0.56	0.19	-0.08	0.51	-0.34	1.00	-0.14
Migration Strictness	-0.15	-0.30	0.37	-0.13	0.01	-0.19	0.00	-0.14	1.00

response parameters β contained in a $K \times 1$ vector that are assumed to influence unemployment. τ, the response parameter of the lagged dependent variable U_{t-1} is assumed to be restricted to the interval $(-1, 1)$ and $\epsilon_t = (\epsilon_{1t}, \ldots, \epsilon_{Nt})^{'}$ is a $N \times 1$ vector that represents the corresponding disturbance term which is assumed to be i.i.d with zero mean and finite variance σ^2. The variables WU_t and WU_{t-1} denote contemporaneous and lagged endogenous interaction effects among the dependent variable. In turn, ρ is called the spatial auto-regressive coefficient. W is a $N \times N$ matrix of known constants describing the spatial arrangement of the regions in the sample. $\mu = (\mu_1, \ldots, \mu_N)^{'}$ is a vector of region fixed effects, $\alpha_t = (\alpha_1, ..., \alpha_T)^{'}$ denote time specific effects and ι_N is a $N \times 1$ vector of ones. Region fixed effects control for all region-specific time invariant variables whose omission could bias the estimates, while time-period fixed effects control for all time-specific, space invariant variables whose omission could bias the estimates in a typical time series (Baltagi, 2001; Elhorst, 2010).

The estimator employed in this research to explore the relationship between the set of variables and unemployment is the bias-corrected quasi maximum likelihood BCQML developed by Lee and Yu (2010). The QML estimator is biased when both the number of spatial units and the points in time in the sample go to infinity. However, by providing an asymptotic theory on the distribution of this estimator they show how to introduce a bias correction procedure that will yield consistent parameter estimates provided that the model is stable. If $\tau + \rho + \eta$ turns out to be significantly smaller than one the model is stable. On the contrary, if $\tau + \rho + \eta > 1$ the model is explosive and if the hypothesis $\tau + \rho + \eta = 1$ cannot be statistically rejected, the model is said to be spatially co-integrated (Yu *et al.*, 2012). A concern is that the BCQML corrects for the endogeneity of the space-time lags but not for the possible endogeneity of the right-hand side variables. Therefore, the results should be taken with caution.

To carry out inference about short run dynamics with the DSDM of Equation (3.8), the matrix of partial derivatives of U_t with respect the *k-th* explanatory variable of X_t in region 1 up to region N at a particular point in time t is given by:

$$\frac{\partial U_t}{\partial X_t^k} = (I - \rho W)^{-1} \left[\mu + \iota_N \alpha_t + \beta^{(k)} + \theta^{(k)} W \right] \tag{3.9}$$

Direct effects (diagonal terms in Equations (3.9) and (3.13) capture the effect on unemployment in i caused by a one unit change in an exogenous variable X_k in i. In turn, the *indirect effect* (off-diagonal terms) can be interpreted as the effect of a change in X_k in all other regions $j \neq i$ on the unemployment rate in i. The dynamic space-time model above enables the computation of own $\frac{\partial U_{it+T}}{\partial X_{it}^{k}}$ and cross-partial derivatives $\frac{\partial U_{it+T}}{\partial X_{jt}^{k}}$ that trace the effects through time and space. Specifically, the cross-partial derivatives involving different time periods are referred as diffusion effects, since diffusion takes time. Conditioning on the initial period observation and assuming this period is only subject to spatial dependence (Debarsy *et al.*, 2012) the data generating process can be expressed as:

$$U_t = \sum_{k=1}^{K} Q^{-1}\left(\beta^{(k)} + \theta^{(k)} W\right) X_t^{(k)} + Q^{-1}\left(\mu + \iota_N \alpha_t + \epsilon_t\right) \tag{3.10}$$

where Q is a lower-triangular block matrix containing blocks with $N \times N$ matrixes of the form:

$$Q = \begin{bmatrix} B & 0 & \dots & & 0 \\ C & B & & & 0 \\ 0 & C & \ddots & & \vdots \\ \vdots & & \ddots & & \\ 0 & \dots & & C & B \end{bmatrix} \tag{3.11}$$

with $C = -(\tau + \eta W)$ and $B = (I_N - \rho W)$. One implication of this, is that by computing C and B^{-1} it is possible to analyze the -own and cross-partial derivative impacts for any time horizon T. Generally, the T-period ahead (cumulative) impact on unemployment from a permanent change at time t in k-th variable is given by:

$$\frac{\partial U_{t+T}}{\partial X_t^k} = \sum_{s=1}^{T}\left[(-1)^s \left(B^{-1}C\right)^s B^{-1}\right]\left[\mu + \iota_N \alpha_t + \beta^{(k)} + \theta^{(k)} W\right] \tag{3.12}$$

When T goes to infinity, the previous expression collapses to the long run effect, which is given by:

$$\frac{\partial U_t}{\partial X_t^k} = \left[(1-\tau) I - (\rho + \eta) W\right]^{-1}\left[\mu + \iota_N \alpha_t + \beta^{(k)} + \theta^{(k)} W\right] \tag{3.13}$$

The model in Equation (3.8) can be contrasted against alternative dynamic spatial panel data model specifications such as the *Dynamic Spatial Lag Model* (DSLM), the *Dynamic Spatial Error Model* (DSEM) and the *Dynamic Spatial Durbin Error Model* (DSDEM). As can be checked, the DSDM can be simplified to the DSLM by shutting down exogenous interactions $\theta = 0$:

$$U_t = \mu + \alpha_t + \tau U_{t-1} + \rho W U_t + \eta W U_{t-1} + X_t \beta + \epsilon_t \tag{3.14}$$

to the DSDEM if $\eta = \rho\beta = 0$

$$\begin{aligned} U_t &= \mu + \iota_N \alpha_t + \tau U_{t-1} + X_t \beta + \theta + \upsilon_t \\ \upsilon_t &= \lambda W \upsilon_t + \epsilon_t \end{aligned} \tag{3.15}$$

where $\epsilon_t \sim i.i.d.$, and to the DSEM if $\eta = \theta + \rho\beta = 0$

$$\begin{aligned} U_t &= \mu + \iota_N \alpha_t + X_t \beta + W X_t \theta + \upsilon_t \\ \upsilon_t &= \lambda W \upsilon_t + \epsilon_t \end{aligned} \tag{3.16}$$

In any case, the estimation of the above equations involves defining a spatial weights matrix. Given that this is a critical issue in spatial econometric modeling (Corrado and Fingleton, 2012) a variety of row-standarized W geographical distance based matrices between the sample regions are considered. The use of geographical distance matrices ensures the exogeneity of the W, as recommended by Anselin and Bera (1998) and avoids the identification problems raised by Manski (1993). Several matrices based on the k-nearest neighbours ($k = 5, 10, 15, 20, 25, 30$) computed from the great circle distance between the centroids of the various regions are considered. Additionally, various inverse distance matrices with different cut-off values above which spatial interactions are assumed negligible are employed. As an alternative to these specifications, a set of inverse power distance and exponential distance decay matrices whose off-diagonal elements are defined by $w_{ij} = \frac{1}{d_{ij}^{\alpha}}$ for $\alpha = 1, \ldots, 3$ and $w_{ij} = exp(-\theta d_{ij})$ for $\theta = 0.005, \ldots, 0.03$ (Keller and Shiue, 2007; Elhorst *et al.*, 2013) is taken under consideration. The latter matrices, although assume spatial interactions are continuous are characterized by faster decays.

In order to choose between DSDM, DSAR, DSDEM and DSEM specifications of the unemployment rate, and thus between a global-local, global, local or zero spillovers specifications as well as to choose between different potential specifications of the spatial weight matrix W, a Bayesian comparison approach is applied. Note that this exercise is relevant as it helps to validate whether or not the spillovers and the nature of interactions in the theoretical model are supported by the data. This approach determines the Bayesian posterior inclusion probabilities (PIP) of the alternative specifications given a particular spatial weight matrix, as well as the PIP of different spatial weight matrices given a particular model specification. These probabilities are based on the log marginal likelihood of a model obtained by integrating out all parameters of the model over the entire parameter space on which they are defined. If the log marginal likelihood value of one model or of one W is higher than that of another model or another W, the PIP is also higher. One advantage of Bayesian methods over Wald and/or Lagrange multiplier statistics is that instead of comparing the performance of one model against another model based on specific parameter estimates, the Bayesian approach compares the performance of one model against another model (in this case DSDM against DSDEM, DSLM and DSEM), on their entire parameter space. Moreover, inferences drawn on the log marginal likelihood function values for the models under consideration are further justified because they have the same set of explanatory variables, X and WX, and are based on the same uniform prior for ρ and λ. In this exercise, non-informative diffuse priors for the model parameters $(\tau, \eta, \beta, \theta, \sigma)$ are used following the recommendation of LeSage (2014). In particular, the normal-gamma conjugate prior for $\beta, \theta, \tau, \eta$ and σ and a beta prior for ρ:[8]

$$\begin{aligned} &\pi(\beta) \sim N(c, T) \\ &\pi\left(\frac{1}{\sigma^2}\right) \sim \Gamma(d, v) \\ &\pi(\rho) \sim \frac{1}{Beta(a_0, a_0)} \frac{(1+\rho)^{a_0-1}(1-\rho)^{a_0-1}}{2^{2a_0-1}} \end{aligned} \tag{3.17}$$

Columns 1 to 4, in Table (3.4) report the PIP for the different spatial specifications including spatial fixed and time-period fixed effects given alternative specifications of W which allows the comparison of the different models for each W. In columns 5 to 8 for a given spatial specification, PIP across spatial weight matrices are reported. As shown in Table (3.4), for all the spatial processes considered exponential decay matrices with a 2% decay as distance increases are preferred to the rest. For this W, the DSDM specification is the one that displays a higher PIP. This finding supports the DSDM specification derived from the theoretical model including endogenous and exogenous interaction. The model comparison also reveals that the DSEM process is never the best candidate to describe unemployment rate outcomes. Importantly, this result suggests that the spatial specification employed by Zeilstra and Elhorst (2014) may not be the most adequate for modeling the evolution of unemployment rates in European regions.

As regards the inclusion of time period fixed effects F-tests are used to check whether time effects parameters could be restricted. The corresponding F-tests on the inclusion of time-period fixed effects when using $W_{ij} = exp - (0.02d_{ij})$ display an F-test statistic of 2.42 with

[8] Parameter c are set to zero and T to a very large number $(1e + 12)$ which results in a diffuse prior for β, θ, τ, η while diffuse priors for σ are obtained by setting $d = 0$ and $v = 0$. Finally $a_0 = 1.01$. As noted by LeSage and Pace (2009), pp. 142, the $Beta(a_0, a_0)$ prior for ρ with $a_0 = 1.01$ is highly non-informative and diffuse as it takes the form of a relatively uniform distribution centered on a mean value of zero for the parameter ρ. For a graphical illustration on how ρ values map into densities see Figure 5.3 pp. 143. Also, notice that the expression of the Inverse Gamma distribution corresponds to that of Equation 5.13 pp.142.

Table 3.4: Model Selection.

	Posterior Probabilities Across Spatial Models				Posterior Probabilities Across Spatial Weight Matrices			
Spatial Weight Matrix	DSDM	DSLM	DSEM	DSDEM	DSDM	DSLM	DSEM	DSDEM
Cut-off 500 km	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Cut-off 1000 km	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
Cut-off 1500 km	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
Cut-off 2000 km	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
Cut-off 2500 km	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
Cut-off 3000 km	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
$exp-(\theta d)$, $\theta = 0.01$	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$exp-(\theta d)$, $\theta = 0.02$	1.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00
$exp-(\theta d)$, $\theta = 0.03$	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$exp-(\theta d)$, $\theta = 0.04$	0.98	0.02	0.00	0.00	0.00	0.00	0.00	0.00
$exp-(\theta d)$, $\theta = 0.05$	0.91	0.09	0.00	0.00	0.00	0.00	0.00	0.00
$1/d^{\alpha}$, $\alpha = 1$	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
$1/d^{\alpha}$, $\alpha = 1.25$	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
$1/d^{\alpha}$, $\alpha = 1.5$	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
$1/d^{\alpha}$, $\alpha = 1.75$	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00
$1/d^{\alpha}$, $\alpha = 2$	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$1/d^{\alpha}$, $\alpha = 2.25$	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$1/d^{\alpha}$, $\alpha = 2.5$	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$1/d^{\alpha}$, $\alpha = 2.75$	0.98	0.02	0.00	0.00	0.00	0.00	0.00	0.00
$1/d^{\alpha}$, $\alpha = 3$	0.80	0.20	0.00	0.00	0.00	0.00	0.00	0.00
K-nearest neighbors ($K = 1$)	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 2$)	0.98	0.02	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 3$)	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 4$)	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 5$)	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 6$)	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 7$)	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 8$)	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 9$)	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 10$)	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 15$)	0.70	0.30	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 20$)	0.93	0.07	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 25$)	0.26	0.74	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 30$)	0.05	0.95	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 35$)	0.09	0.91	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 40$)	0.08	0.92	0.00	0.00	0.00	0.00	0.00	0.00
K-Nearest neighbors ($K = 50$)	0.08	0.92	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Bayesian Markov Monte Carlo (MCMC) routines for spatial panels required to compute Bayesian posterior model probabilities do not exist yet. As an alternative all cross-sectional arguments of James LeSage routines are replaced by their spatial panel counterparts, for example a block-diagonal $NT \times NT$ matrix, $diag(W, ..., W)$ as argument for W. All W's are row-normalized.

p-value 0.003. Thus, the null hypothesis that the model with both spatial fixed and time-period fixed effects does not provide a significantly better fit than the one-way fixed effects model is rejected. Finally, to find out whether the two-way effects models are stable the value of $\tau+\rho+\eta$ is calculated and a two-sided Wald-test is carried out to investigate the null hypothesis $\tau+\rho+\eta = 1$. Importantly, when using $W_{ij} = exp(-0.02d_{ij})$ the model is stable and does not suffer from spatial co-integration (i.e, $\tau + \rho + \eta = 0.89$, F=34.14 with p-value 0.00). An additional issue in the estimation of Equation (3.8) is the identification of the DSDM parameters. Elhorst (2012b) recommends imposing zero restrictions on the model parameters to avoid the identification problems and provides an overview of the main restrictions that have been considered in the literature to get rid of this identification problem. However, in a recent study, Lee and Yu (2015) using Monte Carlo experiments show that the omission of relevant Durbin terms can significantly bias regression estimates, while the inclusion of an irrelevant Durbin term causes no obvious loss of efficiency. Moreover, they provide sufficient rank conditions under which the parameters of the DSDM of equation (3.8) can be identified when estimating the model by QML. These conditions are checked before estimations. In this specific case, the rank conditions to the transformed data are both satisfied.

3.5 Results

3.5.1 Dynamic Spatial Durbin Model Results

Table (3.5) shows the results of the estimation of the DSDM employing the optimal spatial weight matrix $W_{ij} = exp(-0.02d_{ij})$. Column 1 reports the own-region coefficient estimates, while Column 2 shows the estimated parameters for the effect of changes in the regressors of neighboring regions. However, before continuing, it is important to evaluate some features of the model estimation. First, as can be observed in Column 1, the coefficients estimates of the dependent variable lagged in time U_{t-1} and in space WU_t are both positive and significant, while the coefficient of the dependent variable lagged in space and time WU_{t-1} is negative and significant. This result confirms that the dynamic spatial panel data modeling framework used in this analysis is suitable for studying the evolution of unemployment rates and that unemployment problems tend to be transmitted from one region to another.

The results obtained here for the parameter values of the spatial lag, time lag and space-time lag terms are consistent with a number of combinations in the theoretical model. Given that positive spatial dependence is predominant in spatial analysis (Kao and Bera, 2013), it may be interesting to analyze the theoretical foundation of a negative space-time diffusion term in unemployment rates. Let us assume a combination of parameters such that: (i) $\delta_1, \delta_2, \delta_3 < 0$ (ii) $\lambda_l - \lambda_n > 0$ or $\lambda_n - \lambda_l < 0$ and (iii) $\Phi > 0$. Under this parameterization, the value of τ will be positive $\tau > 0$ given that $\lambda_l - \lambda_n > 0$ and all $\alpha > 0$. Similarly, the value of ρ will be positive as $\delta_1(\lambda_n - \lambda_l) > 0$, $\delta_2(\lambda_n - \lambda_l) > 0$ and $\delta_3\,(\lambda_l - \lambda_n) > 0$. Additionally, η will be negative as: $\delta_2 < 0$ and $(\alpha_7\,(\lambda_l - \lambda_n)) > 0$. Hence, a possible interpretation for the negative space-time diffusion will be the following. In the spatial wage curve, an increase in neighboring unemployment rates in $t-1$, would produce a bargaining power externality reducing the capability of workers in i lowering their wages. This is because of $\partial(w_{it} - p_{it})/\partial U_{jt-1} = \delta_2 < 0$. This lower wage in i will produce two effects. The direct effect on labor demand and supply will tend to reduce unemployment in i by $A = \delta_2(\alpha_1 + \alpha_5) < 0$. As the attractiveness of region i for inmigrants will be reduced, this will produce a contraction in both labor supply and labor demand in region i. If, as assumed, the labor supply channel is stronger than that of the labor demand, the contraction in migration will produce an additional effect on unemployment rate in i of $B = \delta_2\alpha_7(\lambda_l - \lambda_n) < 0$ given that $\delta_2 < 0$ and $(\lambda_l - \lambda_n) > 0$. Thus, as $A + B < 0$, an increase in WU_{jt-1} may end up decreasing U_{it}. Note, however, that there are other possible parameter combinations compatible with the empirical findings.

Table 3.5: Dynamic Spatial Durbin Results

			Short Run				Long Run			
Factors	Coefficient	Neighbor	Direct Effect	Feedback Effect (%)	Indirect Effect	Total Effect	Direct Effect	Indirect Effect	Total Effect	Expected Effect
A. Disequilibrium Factors										
Employment Growth	-0.104***	-0.148***	-0.126***	20.17	-0.316***	-0.441***	-0.387***	-2.272***	-2.660***	-
Real GDPpc Gap	-0.044***	0.023	-0.043***	2.44	0.007	-0.036*	-0.097***	-0.109	-0.207*	-
Real Wage Growth	0.004	-0.009	0.003	NS	-0.012	-0.009	0.003	-0.059	-0.056	?
B. Equilibrium Factors										
B.1 Labor Market Factors										
Real Wage	0.006**	-0.001	0.006***	1.98	0.002	0.008**	0.014***	0.035	0.049**	+
Emp. Share Manufactures	-0.104***	-0.147***	-0.126***	20.32	-0.314***	-0.439***	-0.385***	-2.235***	-2.620***	?
Emp. Share Non Market SS	0.103***	-0.092*	0.097	3.91	-0.077	0.02*	0.196***	-0.12	0.076	?
Specialization	0.036***	-0.042	0.033**	7.52	-0.046	-0.013	0.061	-0.141	-0.079	?
B.2 Demographic Factors										
Population 55-64	-0.102***	-0.087**	-0.116***	12.22	-0.213***	-0.329***	-0.331***	-1.632***	-1.963***	-
Population 16-25	0.095***	-0.084**	0.09***	4.26	-0.072	0.018	0.185***	-0.084	0.101	+
Participation	0.09***	0.061**	0.101***	11.62	0.163***	0.264***	0.282***	1.302***	1.584***	?
Education	-0.078***	-0.006	-0.082***	5.22	-0.063*	-0.144***	-0.207***	-0.655**	-0.862**	-
Net Migration	-0.161**	0.204*	-0.145*	6.72	0.227	0.082	-0.263	0.783	0.52	?
B.3 Amenities										
Population Density	0.001	0.005***	0.002	NS	0.010***	0.012***	0.008**	0.064***	0.072***	?
Temperatures	-0.356***	0.352*	-0.32**	5.09	0.311	-0.008	-0.643**	0.584	-0.059	?
C. Institutional Factors										
Unemployment Benefits	0.081***	-0.099***	0.073***	9.76	-0.103***	-0.030	0.137***	-0.319**	-0.182	+
Tax Wedge	-0.078***	0.057***	-0.077	3.46	0.040	-0.037	-0.166***	-0.053	-0.218	?
Bargaining cov & Low coord	-0.017*	-0.004	-0.018*	5.09	-0.019	-0.037*	-0.048*	-0.179	-0.227*	-
Bargaining cov & Med coord	-0.004	0.045	0.000	NS	0.070	0.070	0.023	0.408*	0.431*	+
Bargaining cov & High coord	-0.026***	0.018*	-0.025***	2.75	0.012	-0.013*	-0.054***	-0.025	-0.079*	-
EPL	-0.014*	-0.045***	-0.019*	42.84	-0.083***	-0.102***	-0.068**	-0.538***	-0.606***	-
Minimum Wage	-0.009	0.037***	-0.005	NS	0.053***	0.048**	0.005	0.289**	0.294**	+
Temporary Contracts	-0.034***	0.028**	-0.032***	3.33	0.023	-0.009	-0.067***	0.009	-0.058	+
Migration Strictness	0.004	-0.001	0.004*	NS	0.001	0.005	0.010*	0.019	0.029	?
Spatial Lag	0.426***									?
Time Lag	0.504***									?
Space-Time Lag	-0.029*									?
R^2	0.951									
$Corr(\hat{U}, U)$	0.775									

The dependent variable is in all cases the unemployment rate of the various regions., NS denotes not significant, * Significant at 10% level, ** significant at 5% level, *** significant at 1% level. The results are obtained using the spatial weights matrix $W = exp^{(-\theta d_{ij})}$, $\theta = 0.02$. Inferences regarding the statistical significance of these effects are based on the variation of 1000 simulated parameter combinations drawn from the variance-covariance matrix implied by the BCQML estimates.

A distinctive feature of the framework adopted here with respect that of Zeilstra and Elhorst (2014) is the possibility of assessing the relevance of direct and indirect effects. Direct, indirect and total short run effects are reported in columns 3, 5 and 6 respectively. Direct effect estimates reported in column 3 include feedback effects that arise as a result of impacts passing through neighboring regions and back to the region where the change was originated (from i to j to k and back to i). The absolute size in percentage points of these feedback effects for each variable is reported in column 4. On average, feedback effects increase by 9.3% the coefficient estimate. However, there is variability among them and some variables generate larger feedback effects on unemployment than others. In particular, the strongest feedback effects are observed in the employment protection legislation (42.84%), the share of employment in manufactures (20.38%), employment growth rates (20.32%) and the share of population with age between 55-64 years old (12.22%). On the other hand, there are variables, such as the case of the level of real wages (1.98%) or the output fluctuations (2.44%), for which the feedbacks effects are small.

The direct impact estimates displayed in Table (3.5) show some interesting features that are consistent with the empirical literature analyzing unemployment rates in European regions. First, as regards regional disequilibrium factors, there is evidence that an increase in the employment growth rates and positive aggregate demand fluctuations in region i reduce unemployment rates in i. Second, with respect to labor market equilibrium variables it is observed that higher real wages and sectoral specialization are positively related to the unemployment rate while the share of employment in manufactures has a negative effect. Demographic factors display the expected effects. An increase in the share of older population, education and net migration decreases unemployment while an increase in the participation rate and in the share of young population increases it. As to the role played by the amenities it is observed that the direct effect population density is not significant while that of temperatures is negatively related to unemployment rates. On the other hand, institutional factors such as unemployment benefits and the strictness of in-migration policy have a positive effect on unemployment rates while the tax-wedge, the EPL indicator, the share of temporary contracts and a high bargaining coverage conditional to a high level of centralization and coordination have a negative effect on unemployment rates. The effects of minimum wages and bargaining coverage conditional to medium levels of coordination and centralization are not statistically significant.

Short run indirect effects are significant at the 5% level for eight variables while three variables appear to be significant at the 10% level. Indirect effects significantly amplify direct effects in most cases. The results show that the amplification phenomenon is particularly pronounced, accounting in several cases for more than a half the total effect. The interpretation of this result is that if all regions $j = 1, \ldots, N$ other than i experience a change in X^k, this will have a stronger effect in i that if only i experiments a change in X^k even if i generate spillover effects that go back to i. This is due to the fact that the DSDM contains a global spillover multiplier. As can be observed, the sign of the indirect effects goes in line with that of the direct effects in employment growth, output fluctuations, the share of employment in manufacture, the share of old population, education, participation, population density, the minimum to average wage ratio and in the EPL. On the contrary, for some other variables such as the employment share in non-market services, sectoral specialization, migration, temperatures, unemployment benefits and the share of temporary contracts the indirect effects have the opposite sign than that observed in the direct effects.

As shown in Table (3.5) the simultaneous total effect of a unit increase in the growth rate of employment exerts a negative impact on the unemployment rate of about -0.44 percentage points. This result goes in line with that obtained in Zeilstra and Elhorst (2014) or Vega and Elhorst (2014) who find a total negative effect. Additionally, a one percentage point aggregate demand fluctuation has a negative effect of -0.036 percentage points. As regards regional labor market equilibrium factors, marginal effects of real wages are 0.008 percentage points, what supports the findings of Partridge and Rickman (1997a,b). The total effects associated to changes in the productive structure show that regions with a high share of employment in industry tend to have lower levels of unemployment. On the other hand, regions with a high share of employment in the non-market services sector have higher unemployment rates. Specifically, Table (3.5) shows that the simultaneous effect of a unit increase in the share of industry reduces unemployment rates by -0.43 percentage points whereas the effect of an increase in the share of employment in non-market services increases the unemployment rate in 0.02 percentage points. This result can be explained by the large multipliers associated to the manufacturing sector and supports the findings of Overman and Puga (2002), where the industry mix had a relevant effect in the distribution of unemployment. Specialization does not exert a significant effect in the reduction of unemployment. However, this result masks the fact that the direct effect a change in specialization exerts a positive effect on unemployment, as suggested by Simon (1988).

As regards the effect of demographic equilibrium factors it is observed that an increase in the share of population between 55-64 years old has a negative effect on unemployment rates of -0.33 percentage points while the total effect of an increase in the share of population between 16-25 years old is not significant. Nevertheless, the direct of the latter is positive which, overall, supports previous findings of authors such as Molho (1995a,b). Thus, younger populations tend to suffer more unemployment problems that beset those with a proportion of older people. Likewise, the direct effect of increasing migration rates is negative but total effects do not appear to be significant due to the strong dispersion in the indirect effects. As expected, increasing education attainment reduces unemployment which can be explained by the higher demand for skills, lower probability of lay off, etc (Nickell and Bell, 1996). Finally, the link between participation rates and unemployment is positive, which goes in line with the accounting identity. Specifically, increasing participation rates have a positive effect on the evolution of unemployment, with a simultaneous impact of 0.26 percentage points. On the other hand, population density is found to be positively related to regional unemployment while temperatures do seem to exert any statistically significant effect.[9]

Concerning national institutional variables, the results obtained in the 2000-2011 period show that the generosity of unemployment benefits, the share of temporary contracts the tax wedge or the migration strictness indicator are not significant while increasing minimum wages relative to average wages has an upward significant effect on unemployment rates. On the contrary, the total effect of an increase in the EPL index reduces unemployment. This finding contradicts previous insights reported by Boeri and Van Ours (2008), who argue that a higher EPL may reduce job creation as employers become reluctant to open vacancies. However, the result can be explained by the fact that the higher the EPL the higher the job stability and the stronger the reduction of job destruction. Finally, the results regarding the effect of the bargaining coverage conditional to centralized and coordinated environments provide evidence in favor of the inverted U shape hypothesis of Longhi *et al.* (2005) and Zeilstra and Elhorst (2014). Thus, higher levels of bargaining coverage conditional to decentralized or highly centralized systems outperform medium centralized systems. However, these results should be qualified, given that the total effects are only weakly significant.

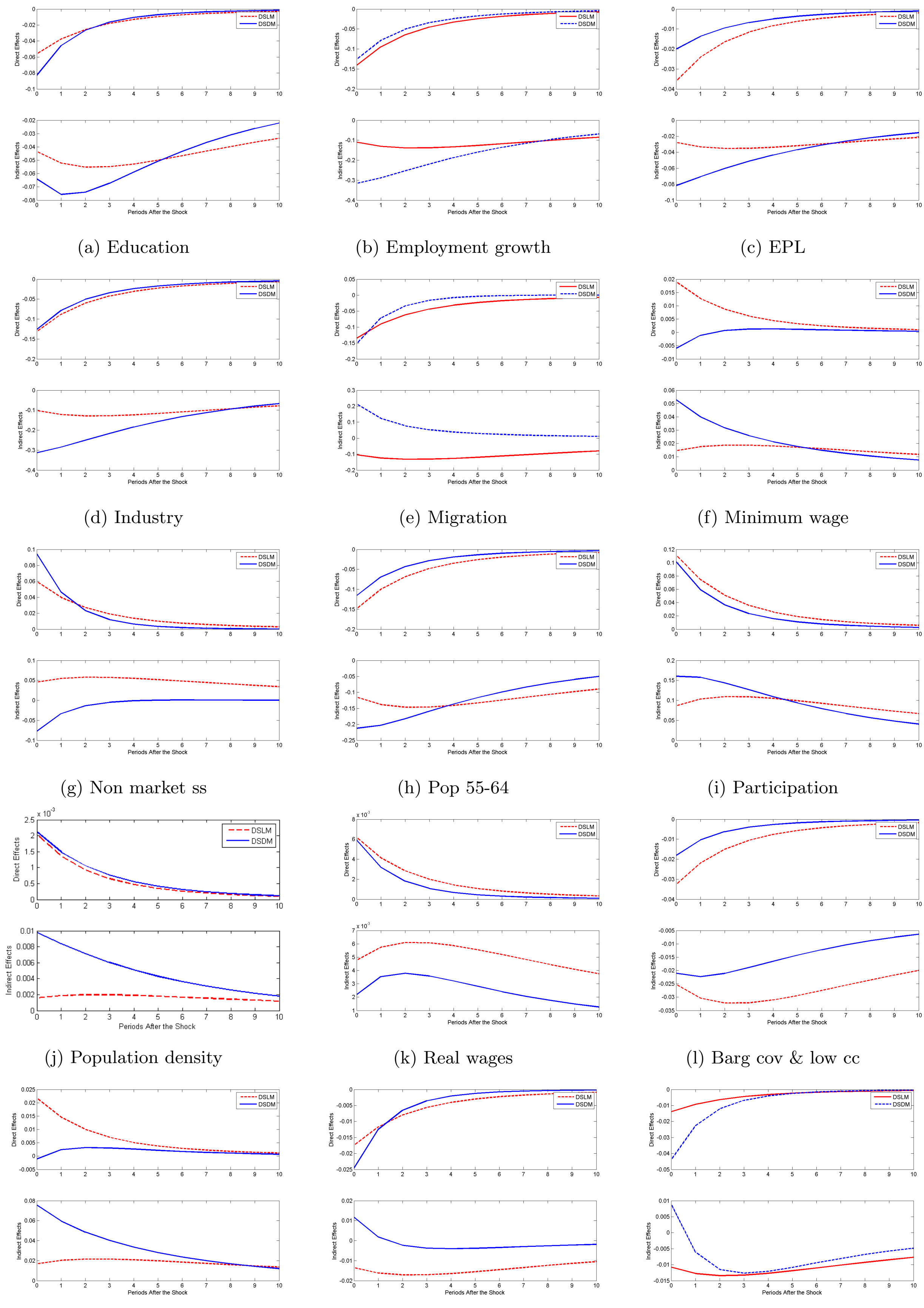
Columns, 6 to 9, display long run effects, while column 10 displays the expected effects. As shown, most of the variables in the analysis generate expected results and display qualitatively similar effects in both, the short term and in the long term. Moreover, the positive differences between the long run and the short run effects are consistent with macroeconomic theory and imply that, apart from the first period where interaction effects are mainly pure spatial feedback effects, space-time feedbacks passing from one region to another seem to be relevant in order

[9]This could be explained by the fact that the econometric specification already includes spatial fixed effects and the average temperature of a region does not change significantly over such a short period of time.

to explain unemployment rate movements. Furthremore, the fact that simultaneous effects only account for a 16.3% of the total long run effect suggests that the diffusion of shocks takes time.

To study the dynamic responses of unemployment rates to changes in the different regressors, the model is used to perform impulse-response analysis using Equation (3.12). Impulse-response functions in a dynamic spatial panel context contain both, temporal dynamic effects and spatial diffusion effects which correspond to exogenous changes that propagate across space. Figure (3.7) decomposes the dynamic trajectory of unemployment after a transitory change in a regressor into direct and indirect responses while Figure (3.8) displays the total effect when using the results obtained with the DSDM and the DSLM. The impulse-response analysis shows that both DSDM (continuous lines) and DSLM (dashed lines) tend to produce qualitatively and quantitatively similar direct effects results for most of the variables. However, there are sizeable differences in the estimated magnitudes of the indirect effects, which is due to the fact that the DSLM omits the local spillover multiplier matrix. The greater discrepancies are observed in the effect of non-market services, net migration, the share of old population and the participation rate. Further comparison between the DSDM the and DSLM total effects reveals that the main discrepancies are obtained in the window that ranges between the period of impact and the next five time periods. Additionally, the observed decay pattern in the DSDM is faster than the one predicted by the DSLM. As shown in Figure (3.10), three periods after the shock, the cumulative effect accounted for 50.2% of total long-term effect. After five periods, the cumulative effect accounted for 64.3% of the long-term effect while after ten periods the cumulative effect was about the 83.4% the long-run effect. These results suggest that the full effect on unemployment rates resulting from changes in the model regressors takes time to materialize and that the short run analysis may considerably under-estimate the final effects.

Figure 3.7: Unemployment Dynamic Diffusion Effects: Transitory Shocks.



(a) Education (b) Employment growth (c) EPL

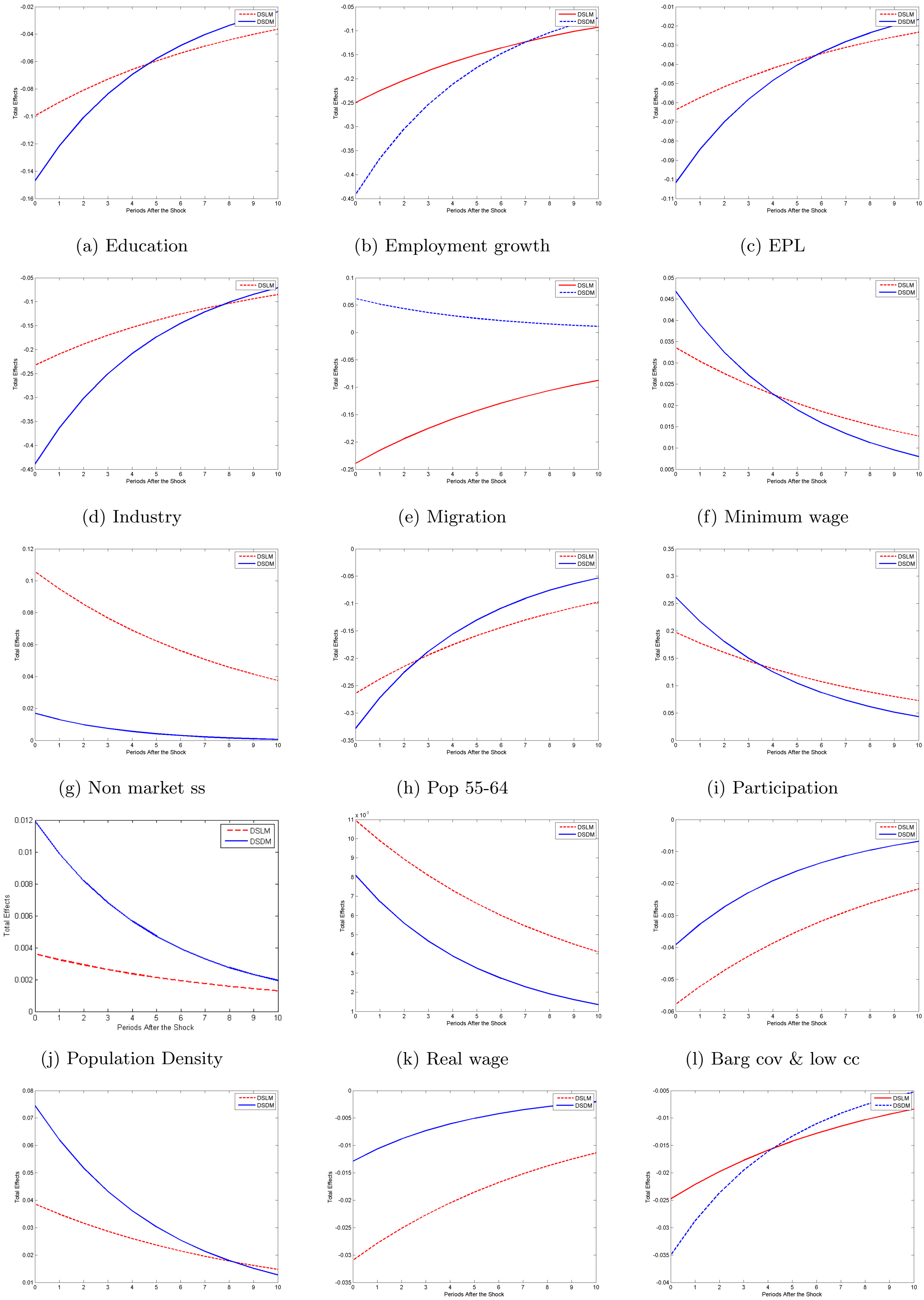
(d) Industry (e) Migration (f) Minimum wage

(g) Non market ss (h) Pop 55-64 (i) Participation

(j) Population density (k) Real wages (l) Barg cov & low cc

(m) Barg cov & med cc (n) Barg cov & high cc (o) Output gap

Figure 3.8: Unemployment Dynamic Total Effects: Transitory Shocks.



(a) Education (b) Employment growth (c) EPL

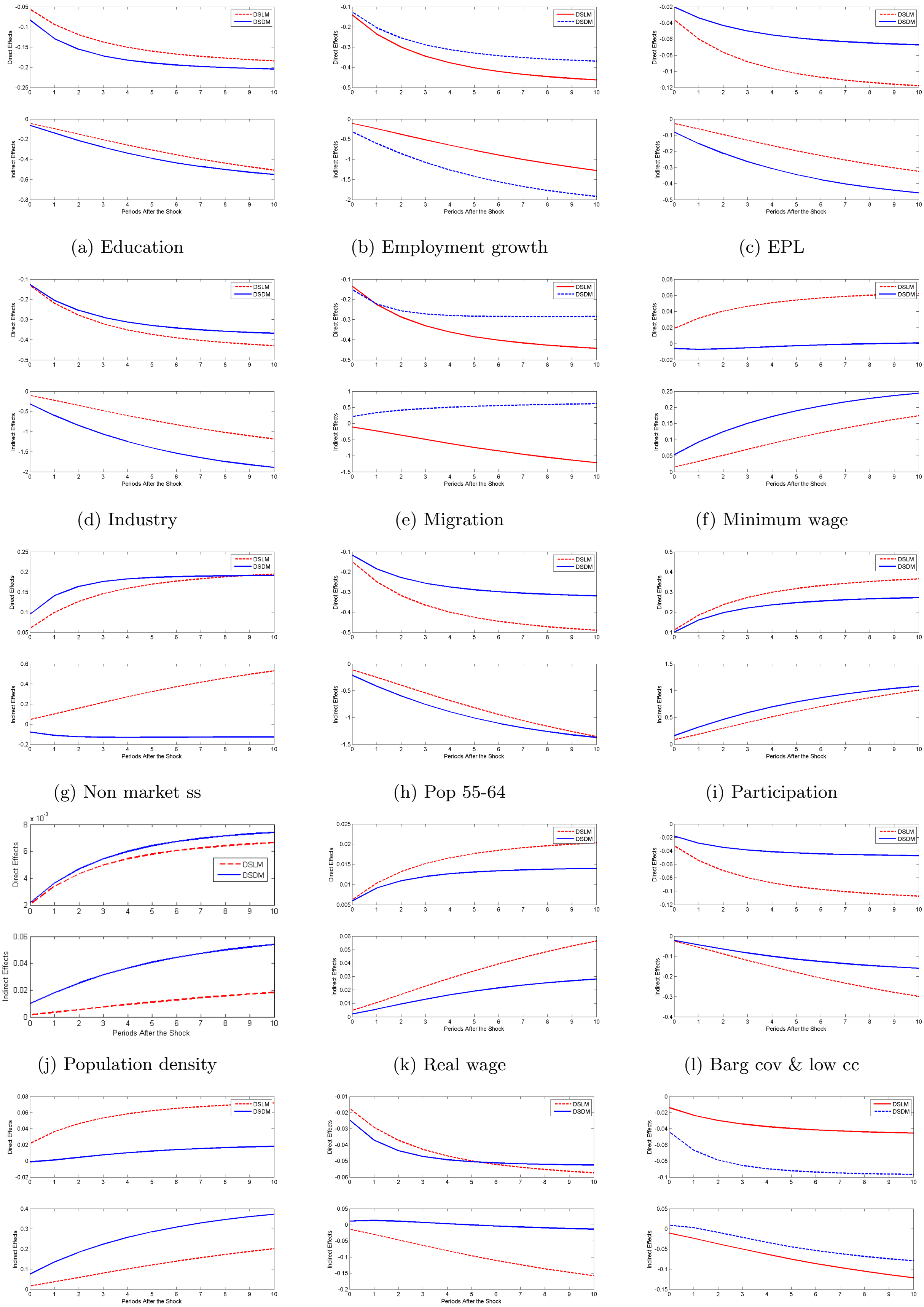
(d) Industry (e) Migration (f) Minimum wage

(g) Non market ss (h) Pop 55-64 (i) Participation

(j) Population Density (k) Real wage (l) Barg cov & low cc

(m) Barg cov & med cc (n) Barg cov & high cc (o) Output gap

Figure 3.9: Unemployment Dynamic Diffusion Effects: Permanent Shocks.



(a) Education (b) Employment growth (c) EPL

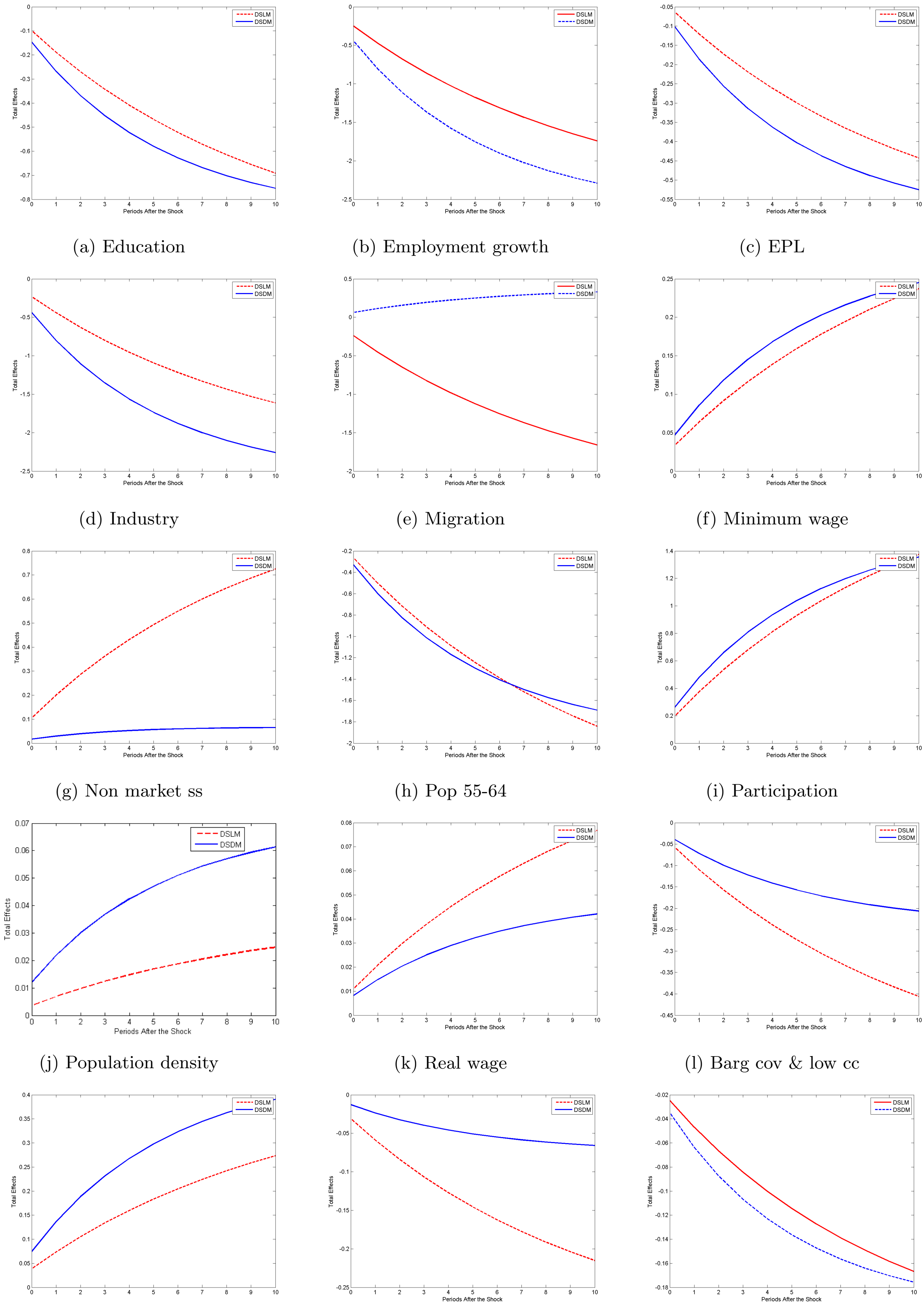
(d) Industry (e) Migration (f) Minimum wage

(g) Non market ss (h) Pop 55-64 (i) Participation

(j) Population density (k) Real wage (l) Barg cov & low cc

(m) Barg cov & med cc (n) Barg cov & high cc (o) Output gap

Figure 3.10: Unemployment Dynamic Total Effects: Permanent shocks.



(a) Education (b) Employment growth (c) EPL

(d) Industry (e) Migration (f) Minimum wage

(g) Non market ss (h) Pop 55-64 (i) Participation

(j) Population density (k) Real wage (l) Barg cov & low cc

(m) Barg cov & med cc (n) Barg cov & high cc (o) Output gap

3.5.2 Unemployment Disparities Before and After the Crisis

Previous results indicate the sign and the strength of the link between the various regressors and unemployment in the period 2000-2011, but are silent on the relative explanatory power of each of the variables driving unemployment disparities. The investigation of the drivers of disparities is relevant from a policy-making perspective given that if unemployment disparities are of equilibrium nature, policies may not be able to reduce unemployment permanently (Marston, 1985). To explore this issue, a variety of relative importance metrics that decompose the R^2 of the model are calculated. [10] For the correect interpretation of the R^2 decomposition, recall that in the context of a spatial panel data, with $n = 1, \dots, N$ and $t = 1, \dots, T$, the R^2 informs on the model's explained variability across spatial units and time. Thus, decompositions on the relative importance of a factor X^k tell us the percentage of explained disparities across spatial units and across time-periods by k. In particular, the LMG metric is computed following Groemping (2007) while GENIZI and CAR scores are computed following Zubber and Strimmer (2011). Given that results produced by them were similar, only the average of the three for is reported in Table (3.6).

Moreover, with the aim of analyzing the relevance of the various the drivers of regional unemployment in Europe, the DSDM is re-estimated for the periods 2000-2008 and 2009-2011 and R^2 decompositions are carried out. This extended analysis is justified given that Chow-tests for the existence of structural breaks for the year 2008 are significant (F=114.27, p-value 0.00). Additionally, a test on the significance of the differences regarding the relative contribution of each factor is computed. Overall, the results shown in Table (3.6) suggest that not only the link between some regressors and unemployment is phase-dependent but also its relative importance.

For the period 2000-2011, the variability in the spatial lag of neighboring regions explains a 21.97% of disparities, while the space-time lag explains 9.04%. The strong importance of neighboring effects in this study supports previous findings of Overman and Puga (2002). In addition, differences in the time lag explain a 28.89% while the set of regressors explain the 38.45% of the variability. 52.47% of disparities stems from differences in own regional factors, while 47.53% of disparities are due to differences in neighbors' exogenous characteristics. Among the set of

[10]Note that the computation of a goodness-of-fit measure in many spatial panel data modeling contexts is problematic since there is no precise counterpart to the R^2 of an OLS regression with disturbance covariance $\sigma^2 I_n$. Indeed, an objection of is that there is no assurance that adding or eliminating a variable to (from) the model will result in an increase (decrease) of the R^2. This issue affects fixed effects SEMs/SDEMs and random effects models of all types. However, as pointed out by Elhorst (2014) this is not an issue in the context of fixed effects DSDM employed in this study. Moreover, given that the relative importance analysis is concerned about the share of variability in the dependent variable explained by the spatial lag, the R^2 is employed to explain disparities.

Table 3.6: Unemployment Disparities Before and After the Crisis

	Relative Importance Decomposition (%)				Total Short Run Effects	
Factors	Sample 2000-2011	Sample 2000-2008	Sample 2009-2011	Sub-Sample Difference	Sample 2000-2008	Sample 2009-2011
Unexplained	4.90	7.06	1.43			
Explained	95.10	92.94	98.57			
Spatial Lag	21.98	25.39	14.44	- 10.99***		
Time Lag	28.90	26.88	2.68	-24.25***		
Space-Time Lag	9.04	8.58	3.99	-4.63*		
Regressors	38.45	36.83	78.86	39.88***		
Regional Fixed Effects	1.63	2.32	2.93			
A.) Disequilibrium Factors	22.33	18.22	25.73	7.51***		
Employment Growth	15.65	13.19	1.71	-11.48***	-0.325***	-0.230**
RGDP pc Gap	6.59	4.61	19.36	14.75**	-0.030	-0.189***
Real Wage Growth	0.09	0.42	4.65	4.24***	-0.016	0.113***
B.) Equilibrium Factors	54.90	63.69	35.41	-28.27***		
B.1) Labor Market	22.68	22.04	11.62	-10.42***		
Real Wage	0.98	1.42	1.43	0.01	0.011*	0.043***
Emp. Share Manufactures	8.67	9.26	0.72	-8.53***	-0.486***	-0.318
Emp. Share Non Market Services	11.22	6.40	2.23	-4.17***	0.104*	0.491*
Specialization	1.81	4.97	7.24	2.27*	0.130*	0.362*
B.2) Demographic Factors	18.69	27.00	15.88	-11.12**		
Population 55-64	8.54	3.99	3.69	-0.29	-0.272**	-0.426**
Population 16-25	1.05	10.72	1.75	-8.96***	0.193***	0.585***
Participation	2.01	4.95	3.06	-1.89	0.267**	0.696*
Education	1.13	5.05	3.05	-2.00	-0.185***	0.019
Net Migration	5.95	2.31	4.33	2.02***	0.599***	-0.164*
B.3) *Amenities*	9.29	8.34	2.79	-5.56***		
Population Density	8.93	4.16	1.92	-2.24**	0.011**	0.25
Temperatures	0.37	4.19	0.86	-3.32***	-0.506***	0.165
B.4) Regional Fixed Effects	4.24	6.30	5.13	-1.17		
C.) Labor Market Institutions	22.77	18.10	38.86	20.76***		
Unemployment Benefits	4.49	5.63	2.12	-3.51*	0.053*	-0.143***
Tax Wedge	1.15	1.52	5.51	4.00***	0.024**	0.222*
Bargaining cov & Low coord	1.78	2.72	0.42	-2.30**	-0.014	0.029
Bargaining cov & Med coord	1.66	1.40	1.28	-0.11	0.005	0.153***
Bargaining cov & High coord	3.18	0.38	4.37	3.99***	-0.003	-0.037***
EPL	2.50	1.08	18.25	17.17***	-0.003	-0.162***
Minimum Wage	3.74	1.16	0.57	-0.59	-0.130***	-0.048
Temporary Contracts	3.01	2.94	3.79	0.85	-0.022*	0.134**
Migration Strictness	1.26	1.28	2.54	1.26***	0.118**	-0.195

Note: The dependent variable is in all cases the unemployment rate of the various regions. * Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Relative importance values are obtained by averaging the results obtain with the LMG metric and with CAR and GENIZI scores. The t-test on the statistical significance of disparities in the two sub-samples, s_1 and s_2 for each factor k is computed as $t_k = \frac{D_k}{\sqrt{\Sigma_k}} = \frac{R_{k(s1)}R_{k(s2)}}{\sigma^2_{k(s1)}+\sigma^2_{k(s2)}-2Cov_{k(s1),k(s2)}}$ where $R_{k(s)}$ is the average across metrics in the sub-sample s and $\sigma^2_{k(s)}$ and $Cov_{k(s1),k(s2)}$ denote the variances and covariance of the relative importance metrics estimates for factor k.

regional level factors, disequilibrium factors explain a 22.32% while the equilibrium component explains a 54.90%. Within this group, regional labor market factors explain 22.68% of disparities, demographic factors explain 18.68% and amenities a 9.29%. National level institutions, also play a relevant explaining a 22.77% of disparities. Thus, estimates for the period 2000-2011 suggest that unemployment disparities mainly reflect a spatial equilibrium where differences in the productive structure (19.89%), age composition (9.59%) and population density (8.92%) are responsible of unemployment disparity across regions and time.

In general, the results for the period 2000-2008 are very similar to those obtained for the period 2000-2011. However, with the outbreak of the financial crisis in 2008, and its extension to the labor markets in 2009, unemployment rates correlations across time and space decreased considerably, which explains the fall in relative importance of the spatial and serial dynamic effects and the increase in the explanatory relevance of regressors in the period 2009-2011. After the crisis, although equilibrium factors explain a higher share of disparities than disequilibrium ones (35.41% vs 25.72%), the gap between these two sets of factors decreased markedly. During 2009-2011 disequilibrium factors increased their importance from 18.21 to 25.72%. This increase is mainly produced by the increasing importance of real output per capita fluctuations and real wage growth rates. Moreover, in the second sub-sample, real wage growth appears to be positively linked to unemployment rates. Taken together, these results suggest that the temporary disequilibrium component of unemployment disparities in the post-crisis period increased its relevance due to a combination of asymmetric negative labor demand and wage shocks.

Equilibrium factors, on the other hand, decreased in importance from 61.68% to 35.41% as explained in the drop in the three categories. With respect to regional labor market factors, there are two relevant differences. Firstly, as refers to the employment share in manufactures, the variable became insignificant and reduced its importance from 9.25 to a 0.72%. Secondly, sectoral specialization became significant after the crisis and increased its relative importance from 4.96 to 7.24%. Given that the effect of sectoral specialization in 2009-2011 was positive, it is possible to conclude that diversified regional economies performed better because of the possibility to re-allocate jobs from one sector to another. Demographic factors also decreased in importance from 27% to 15.88%, mainly because of the decreasing importance of disparities in the share of young population. The latter could be related to an age composition effect (different cohorts have different age specific unemployment rates) or a cohort size effect (cohort size affects the age-specific unemployment rates). In addition, amenities decreased in relevance and lost their significance as explanatory factors of unemployment outcomes while the share of regional fixed effects remained relatively constant.

On the contrary, the most relevant finding arising from this exercise is the sharp increase in the relative importance of national level labor market institution after the crisis, from a 18.10% level to a 38.86%. The most pronounced change is observed in the EPL indicator as it displays an increase from 1.08 to 18.25%. This finding suggests that differences in the protection of workers are crucial to explain the emergence of divergences of unemployment rates after the crisis. Second, the relative importance of the tax wedge increased to a 5.81% level and its effect became positive and significant. This result suggests disparities on taxes became a relevant driver of unemployment outcomes after the crisis and that regions with high tax wedges discouraged job creation and reduced labor demand. Additionally, it is observed that the set of indicators related to the bargaining coverage framework increased their explanatory power.

Finally, the changing role in some institutional level factors is worth mentioning. While the generosity of unemployment benefits had a positive effect increasing unemployment rates before the crisis as usual in the literature (Belot and Van Ours, 2001), its effect became negative after it. This finding suggests that the positive link between the generosity of benefits and unemployment may operate with more strength in booming phases by reducing search intensity and increasing reservation wages. On the contrary, after the crisis, the negative link could be explained by the fact that unemployment benefits act as a buffer helping to keep consumption levels and firms' activity over a threshold. A changing role is also observed in the link between temporary contracts and unemployment. While flexibility may have contributed to job creation in the booming phase, after the 2008 recession, regions with an excess of temporary contracts performed worse than those with other contractual forms (i.e, labor hoarding practices where adjustments against shocks were based on working hour adjustments). This is because of temporary contracts allow for rapid and deep employment cuts to keep productivity levels once the economy receives a negative a shock, thus raising unemployment rates (Marelli *et al.*, 2012). At this regard, this supports previous analysis of Bentolila and Saint-Paul (1992) and Boeri and Garibaldi (2007), who argue that two-tier labor market reforms have a transitional honeymoon, job-creating effect which typically precedes reductions in employment as a result of temporary workers lower labor productivity. To conclude, it can observed that minimum wages and migration strictness became insignificant after the crisis and that they do not help to explain differences in unemployment rates.

3.6 Conclusions

This chapter explores changes over time in the distribution of European unemployment rates and the role played by different factors shaping the evolution of regional disparities. The analysis of the distribution of unemployment rates during the period 2000-2011 reveals that overall, regional disparities have decreased because of the catch-up process experienced by eastern European regions with relatively high unemployment rates in the year 2000. Nevertheless, regional unemployment gaps seem to be highly persistent as indicated by the distribution dynamics analysis. The exploratory analysis also reveals a distinct behavior before and after the economic crisis: while convergence took place during 2000-2008, after the crisis, European regions experienced an important process of divergence characterized by the fact that economies of the periphery of Europe worsened their relative position.

As shown in the exploratory analysis, the unemployment rate in a region is affected by labor market outcomes in neighboring regions. Taking this into account, a theoretical model to explain regional unemployment rates with spatial interactions among regions is developed. This theoretical model helps in understanding the channels through which spatial dependence in unemployment rates emerges in European regions. The solution of the theoretical model implies a DSDM empirical specification containing endogenous and exogenous interactions among spatial units. In order to analyze the relationship between explanatory variables and unemployment, as well as the dynamic responses of unemployment to changes in the various groups of factors, an impulse response analysis is carried out and used a variety of R^2 decomposition methods. R^2 decomposition metrics for the period 2000-2011 suggest that the regional equilibrium component may be the most relevant driver of regional unemployment disparities and that regional disparities may reflect a spatial equilibrium in which regional equilibrium factors play a major role.

However, this aggregate analysis does not seem to be completely satisfactory for the understanding on the nature of unemployment disparities, given that Chow tests suggest that there are structural differences in the way the various factors under consideration are related to regional unemployment rates before and after the economic crisis. Additionally, a t-test statistic on the relative importance differences in the two subsamples reveals that the different factors have a time-dependent relevance. The separate analysis of the contributions of explanatory variables in the different sub-samples and the evolution of the various regressors shows that the convergence process experienced from 2000-2008, was mainly due to a combination of positive temporary labor demand shocks and demographic outcomes. On the contrary, the emergence of disparities during 2009-2011 are mainly explained by regional disequilibrium and national level institutional factors. Although the results should be taken with caution, two key findings emerge of this analysis. The first is that asymmetric demand fluctuations account for a considerable share of unemployment disparities. This finding suggests that some of the divergence process characterizing the period 2009-2011 could be reversed once the shocks are fully absorbed. Additionally, it is shown that national-level institutional variables before the crisis were not so relevant, in the aftermath of the crisis, they account for almost the 40% of them. Within this group of factors, employment protection legislation, the tax wedge and the collective bargaining setting are the most important ones.

Therefore, the results of this study pose some interesting policy implications. First, given that the nature of unemployment disparities reflects a mix between regional disequilibrium and equilibrium factors, together with country level institutional characteristics, there seems to be some role for national and regional economic policies to mitigate the increase of unemployment differentials observed in 2009-2011. Second, the articulation of stimulus policies to boost real GDP per capita and labor demand in regions affected by high unemployment rates may generate beneficial effects. However, in view of the fiscal restrictions affecting many European regions after the 2008 crisis, the scope of this option may be limited. As an alternative, regional authorities could act on equilibrium factors. At this level of intervention, policy options aiming at the reduction of unemployment rates may focus on the diversification of the productive structure as this may help to buffer recessive shocks and increase regional adaptability to future crisis. Third, given that national level labor market factors seem to be the key driver of unemployment disparities after the crisis, legislative reforms affecting the institutional framework may have important effects. The findings of this study suggest that policies aimed at protecting jobs and reducing tax burdens may help to improve the functioning of regional labor markets. In this sense, future research could take into account interactions among institutional characteristics in order to gain knowledge on what labor market reforms should be implemented. An interesting issue that could be further explored in the future is the interplay between the components of the EPL and other institutional factors. For instance, the increase in job destruction induced by temporary jobs may have a stronger effect on unemployment if the gap in firing costs in favor of permanent contracts is high, given that this will lower the the proportion of temporary jobs transformed into permanent jobs.

Finally, the implementation of labor market policies should be coordinated and take into account the existence of strong spillover effects, as one of the key findings of this study is that space-time interactions among regions are a key element shaping the evolution of unemployment rates.

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Chapter 4

Dynamic Local Government Spending Interactions among Spanish Municipalities

4.1 Introduction

How relevant are space-time interactions when modeling government spending? What are the effects of the various economic, demographic and political factors on local government spending? Does the intensity of spatial spillovers processes vary across different functional spending categories? These questions are of key importance both to our understanding of local public finance and for local fiscal policy alike. This chapter analyzes the evolution of local government spending in a sample of 1,230 Spanish municipalities, over the period 2000 to 2012 with population size above 5,000 inhabitants. A novel feature of the analysis carried out is that it takes into account the existence of temporal and spatial interactions among neighboring municipalities by employing dynamic spatial panel modeling techniques and relative importance metrics.

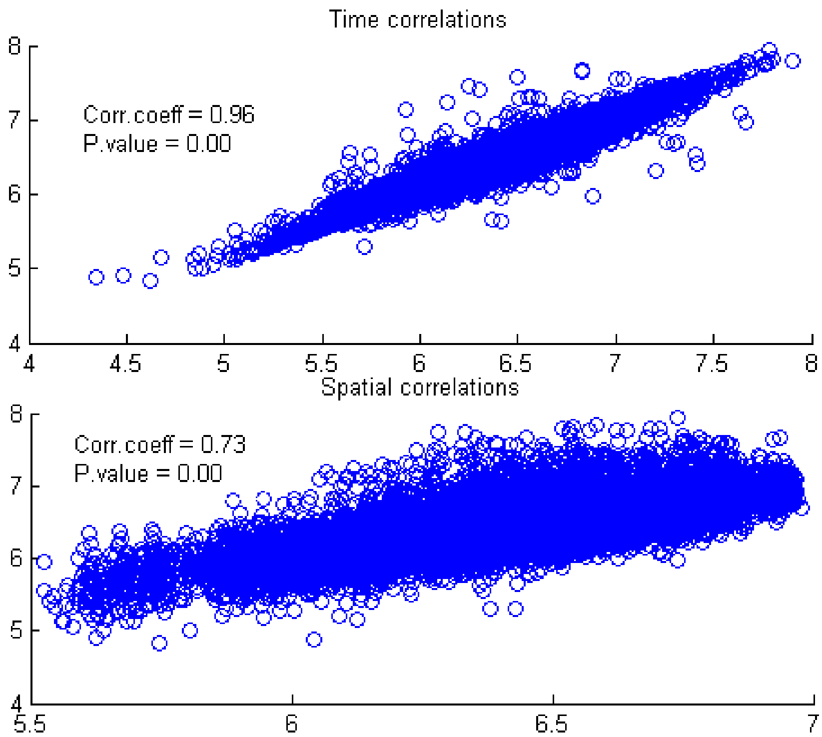
The study of local government spatial interactions has attracted a significant amount of research in the fields of public finance and regional science. Frequently, empirical studies have found that municipalities consider both the tax rate and the government expenditure of their neighbor's when making their own fiscal policy decisions. In this regard, the economic literature has proposed various theories to explain the existence of spatial interactions between municipalities. The strand of literature on tax welfare and competition models, which analyzes interactions in taxation policies, suggests that spatial interactions may emerge because of taxes are chosen strategically as reactions to neighboring fiscal policies (Brueckner, 2003; Devereux *et al.*, 2008). In a similar vein, the literature of benefit spillovers investigates if public government spending of a juridisdiction generates beneficial or negative effects that spread across boundaries, affecting the welfare of residents in neighboring jurisdictions (Kelejian and Robinson, 1992; Case *et al.*, 1993; Revelli, 2002; 2006). The main focus of this line of research has been to analyze whether the spending decisions of a local government depend on policies chosen elsewhere.

Other explanations such as the political yardstick competition hypothesis (Salmon, 1987; Besley and Case, 1995; Bordignon *et al.*, 2003; Santolini and Bartolini, 2012) emphasize the relevance of political factors as the sources of spatial interdependence. According to the yardstick competition hypothesis spatial interactions may arise from the existence of an informational spillover from the fiscal policies enacted in the neighboring regions. This information spillover will affect the beliefs of the electorate in a local jurisdiction and the local incumbent's behavior (Elhorst and Freret, 2009). The key prediction emerging from this strand of literature is that weak local governments will tend to mimic with more intensity the behavior of neighbor's. To explain tax mimcking, Santolini (2008, 2009) has introduced the idea of social partisan trend hypothesis, which proposes that fiscal policy interactions at the municipal level may be driven by ideological similarities between the governing parties involved.

The set of previous theoretical approaches to explain the existence of spatial correlations in the levels of public spending has been accompanied by the development of a variety of spatial econometric methods (LeSage and Pace, 2009; Anselin, 2010; Elhorst, 2010; Elhorst 2014; Lee and Yu, 2010a). Nevertheless, most studies on fiscal interactions at local level ignored one of the key political science contributions to the research on budgetary processes: the fact that budgets are highly correlated over time and that they follow an incremental pattern (Lindblom, 1959; Wildavsky, 1964; Davis *et al.*, 1966; Dezhbakhsh *et al.*, 2003). Early contributions from Dempster and Wildavsky (1979) or Berry (1990), identify incrementalism with regular annual change in a budget category and close adherence to previous existing levels. This means that expenditure in a given year t depends to some extent on that in year $t-1$. Political scientists have argued that incrementalism in budgetary processes may emerge due to the existence of (i) information costs, (ii) political constraints in complex and uncertain environments, (iii) the need to maintain political conflict and citizen demands under tolerable limits and (iv) the institutionalized bureaucracy of the budgetary process (Robinson, 2003; 2006). Under such scenarios, decision makers cannot proceed deliberately and comprehensively when deciding how much to spend, but must proceed through small, incremental changes.

As regards the case of Spain, there are few studies analyzing time-series behavior of budgetary processes. However these find that incrementalism is of particular importance (Dorta *et al.*, 2010; Camaño and Lago-Peñas, 2011). Similarly, Solé-Ollé (2006) and Bastida *et al.* (2013) analyze the existence of spatial interactions for various government expenditures categories in Spain while Lopéz-Hernadéz *et al.* (2015) analyze interactions for counties. However, none of the previous analysis integrate both spatial and temporal dynamics within a unified modeling framework. The lack of econometric analysis integrating both types of effects is especially remarkable in view of the abundant statistical and theoretical arguments supporting the existence of a link, not only between own and neighboring levels of expenditures but also between past and future expenditures along time. As suggested by the strong spatial and temporal correlations reported in Figure (4.1) below, studies that have analyzed the drivers of local government spending taking into account spatial lags but omitting time dynamics may have been miss-specified and could suffer from the omitted-variable bias which would ultimately lead to biased and inconsistent estimates of the model parameters.[1]

Figure 4.1: Space-Time Government Spending Correlations.



Importantly, the existence of positive or negative spatial spillovers poses potentially important implications for policy design given that the presence of positive spillovers as found in Bastida *et al.* (2013), may suggest that local spending behaves as a complementary public good. Nevertheless, in the presence of spatial interdependence and spatial externalities, if a local entity spends heavily in a particular expenditure category, neighboring local bodies might reduce their

[1]The only exception including space-time endogenous interactions to describe the government expenditure process in a spatial panel setting is that of Costa *et al.* (2013), who estimate a *Dynamic Spatial Lag* (DSLM) specification for Portuguese municipalities using the system GMM estimator.

spending in that category because of their citizens could benefit from the services provisioned by the first (i.e, free-ride). Therefore, if locally provided public goods behave as substitutes, the reaction to changes in public expenditures in neighboring municipalities should be negative, as empirically observed by Solé-Ollé (2003).

In order to complete the results obtained so far in the existing literature, this paper aims to examine further the process of local government spending in Spanish municipalities. To that end, a *Dynamic Spatial Durbin Model* (DSDM) is estimated employing the bias-corrected quasi-maximum likelihood (BCQML) estimator for dynamic spatial panels developed by Lee and Yu (2010b). The contributions of this extended model are: (i) the unrealistic assumption of government budgets to be independent over space and time has no longer to be made, (ii) enables the investigation of the magnitude and significance of spillovers in a variety of spending categories and (iii) facilitates assessment of the relative importance of spatial spillover theory and the incrementalist theory of budgeting for explaining public spending patterns. Relevant methodological issues for dynamic spatial panel modeling such as the inclusion of fixed-spatial and time-period fixed effects, the estimation method, spatial co-integration, parameter identification and the selection of the spatial matrix will be addressed.

The chapter is organized as follows. After this introduction, Section 2 briefly reviews the literature on fiscal policy interactions at the local level in Spain and the basic institutional structure of local administration in Spain. Section 3 presents the model used to analyze local government spending interactions. Section 4 examines the data set and the behavioral hypothesis related to the various covariates. Section 5 discusses the econometric methodology used in this analysis while the main empirical findings of the paper are documented in Section 6. Finally, Section 7 offers the main conclusions from this work.

4.2 Literature Review and Institutional Setting

Spain has five vertical layers of government: central, regional, provincial, county and municipal ones. There are seventeen regional governments, the so-called Autonomous Communities (AC), which have fairly wide-ranging spending responsibilities including, for example, the provision of healthcare, education and welfare. Across most of the country, the 51 provincial councils and 324 counties have no real say in government spending decisions as their basic function is to assist in the management of municipal activity. Moreover, county councils in most AC's have no specifically designated task.[2] The local layer of Spanish government, on the other hand, consists of more than eight thousand municipalities. 88.6% of them are very small, have fewer than five thousand inhabitants and account for no more than a 25% of the population. However, municipalities with more than 5,000 inhabitants account for 75.2% of the population and have several economic tasks, with major expenditure categories corresponding to the traditional responsibilities assigned to the local public sector (environmental services, urban planning, public transport, water supply, culture, welfare, etc). As explained in García-Sanchéz *et al.* (2012) Spanish municipalities provide specific services as population size increases. Table (4.1) below summarizes local government's service provision related to different population sizes.

Table 4.1: Local Government Services in Spain.

Essential Services	Compulsory services		
All Municipalities	Municipalities > 5000 inhabitants	Municipalities > 20000 inhabitants	Municipalities > 50000 inhabitants
Street lighting	Public parks	Civil defense	Public transport
Cementeries	Public libraries	Social Services	Environmental Protection
Waste collection	Market	Fire prevention	
Street cleaning	Waste treatment	Public sports facilities	
Domestic supply of drinking water			
Sewer system and drains			
Road access			
Paving of public roads			
Food and drink control			

Source: García-Sanchéz *et al.* (2012)

As Delgado *et al.* (2014) point out, Spain is probably one of the most suitable cases in which to study the issue of interactions in government spending at the municipal level, given that the Spanish regional government is highly decentralized. As shown in Table (4.2) below, Solé-Ollé (2006) and Bastida *et al.* (2013) study municipal government expenditure interactions. In his seminal paper, Solé-Ollé (2006) presents a framework to measure benefit spillovers emerging from the provision of local public goods and crowding spillovers, arising from the crowding of facilities by residents in neighboring municipalities. Using a sample of 2,610 municipalities for the year 1999 he estimates a *Static Spatial Durbin Model* (SSDM) by means of an instrumental variable (IV) estimator and finds a negative spatial interaction between neighbor's government level of spending and the existence of relevant crowding spillovers. Bastida *et al.* (2013) using 2005 data for 3,204 municipalities, estimate *Static Spatial Lag Model* (SSLM) and a *Static Spatial Error Model* (SSEM) specifications by means of an IV estimator. They distinguish between a

[2]Spain's counties are territorial divisions defined by physical and geographic boundaries and the affinity of their inhabitants. They are known in Spanish as "comarcas"

variety of functional spending categories finding that there are positive spatial spillovers among all expenditure categories. Finally, in a recent study, Lopéz-Hernadéz *et al.* (2015) explore the existence of spatial spillovers in government spending in a sample of 313 counties for the period 2010-2012 finding positive spatial interactions in cultural, sport and environmental expenditures.

Table 4.2: Empirical Studies on Government Spending Interactions in Spain.

Authors (year)	Sample and Period	Spending Variable	Estimation Method	Spatial Specification	Spillover Results
Solé-Ollé (2006)	N =2610 T=1999	Total per capita	2SLS-IV	SDM	-
Bastida *et al.* (2013)	N = 3204 T=2005	Total	2SLS-IV	SLM, SEM	+
		Security		SLM, SEM	+
		Education		SLM, SEM	+
		Waste		SLM, SEM	+
		Culture		SLM, SEM	+
		Housing		SLM, SEM	+
		Water		SLM, SEM	+
Lopéz-Hernadéz *et al.* (2015)	N= 313	Cultural	NS	SARAR/SLM	+
	T= 2010-2012	Sport	NS	SARAR/SLM	+
		Environmental	NS	SARAR/SLM	+

Notes: SDM denotes *Spatial Durbin Model*, SARAR denotes *Mixed Regressive Spatial Autoregressive Model with a Spatial Autoregressive Disturbance*, SLM denotes *Spatial Lag Model*, SLX denotes the exogenous spatial lag and SEM denotes spatial error model. NS means that it is not specified in the corresponding study.

Apart from the spatial analysis of Lopéz-Hernadéz *et al.* (2015), where the unit of study is the county, as can be observed in Table (4.2), the available empirical evidence at the municipal level is contradictory with regard to the nature of spatial interaction in spending levels between neighboring municipalities. The reasons for these controversial results may have to do with the fact that these contributions differ considerably in terms of sample composition, time-period and spatial specification. As a consequence, the question of whether a change in government spending in a given municipality has a positive or negative impact on neighboring municipalities is far from settled and further empirical research is required. This paper distinguishes itself from earlier studies by Solé-Ollé (2006), Bastida *et al.* (2013) and Lopéz-Hernadéz *et al.* (2015) in four major methodological aspects:

First, the three aforementioned studies use cross-sectional data frameworks to investigate the existence of spatial spillovers whereas this analysis is based on panel data. The problem of cross-sectional studies is that, by construction, they omit time-period fixed effects which may induce an upward bias of the estimated coefficients of the spatial lags (Lee and Yu, 2010c). This problem could be solved by introducing time-period fixed effects in a panel data setting.

Moreover, the inclusion of time-period effects in the context of local government is highly relevant given that public expenditures are likely to exhibit a common municipal temporal behavior as the opportunistic cycles literature has shown (Shi and Svensson 2006; Fiva and Natvik, 2013; Forte-Deltell *et al.*, 2013; Guillamón *et al.*, 2013). Furthermore, given the strong cross-sectional variability of Spanish municipal attributes argues for the inclusion of spatial fixed effects in order to capture unobserved heterogeneity specific to the municipality. Additionally, the employment of panel data usually results in a greater availability of degrees of freedom, thus reducing the collinearity among explanatory variables and improving the efficiency of the estimates (Baltagi, 2001; Hsiao, 2003).

The second and most relevant difference with respect to previous studies is that the above-cited authors omit time-lag government spending dynamic effects while this study takes into account both spatial and temporal correlations in spending. As explained above, the omission of these terms implies that previous studies may have ruled out an important explanation developed in the field of political science and they may suffer from a serious miss-specification bias. Moreover, the DSDM containing endogenous and exogenous interactions contrasts favorably with static and more restrictive SLM spatial specifications adopted by Bastida *et al.* (2013) and Lopéz-Hernadéz *et al.* (2015) given that the spillovers produced by the SLM are global in nature and impose a unique ratio between the spillover effect and direct effects for every explanatory variable which is not realistic (Mc Millen, 2003; 2010; Vega and Elhorst, 2013). Similarly, the adoption of a dynamic spatial panel allows for a time-varying ratio between the direct and the spillover effect instead of a fixed ratio across time as in Solé-Ollé (2006).

Third, unlike the present study, which bases the estimation is based on the BCQML estimator for dynamic spatial panels of Lee and Yu (2010b), both Solé-Ollé (2006) and Bastida *et al.* (2013) estimate their respective SDM and SLM models employing 2SLS-IV estimators whose main drawback is that the coefficient estimate of the spatial autoregressive term may fall outside its parameter space (Elhorst and Freret, 2009).

Fourth, Solé-Ollé (2006) and Bastida *et al.* (2013) present point estimates to analyze the effect of the different regressors. However, as pointed by LeSage and Pace (2009) and Elhorst (2010), inferences based solely in the estimation of the model may lead to erroneous conclusions. Partial derivative interpretation of the impact from changes to the variables of the model are the current state of the art in the spatial econometrics literature and provide a more valid basis for testing for the existence of spatial spillovers.

4.3 The Model

4.3.1 Theoretical Framework

This section develops a simple model of fiscal policy interdependence for Spanish municipalities. The model draws on previous contributions from the literature on government spillover models (Case *et al.*, 1993; Brueckner, 2003; Revelli, 2005). In each municipality $i = 1, 2, \ldots, N$, there is a representative consumer who derives utility from the consumption of a private good (C) and a public good (G). Following the convention in expenditure spillover models, it is assumed that the welfare of the representative consumer depends, apart from residents' private consumption and a vector of own characteristics X_{it}, on own local public services and on own G_{it} and neighbor's public spending $\tilde{G}_{jt}$. Thus, the inclusion of X_{it} reflects the assumption of welfare in municipality i is related to the amenities or disamenities in the own local economy.

The main differences with respect to previous theoretical models of spillovers is that the present framework further assumes that the representative's consumer utility function of municipality i may also be affected by own G_{it-1} and past neighbor's $\tilde{G}_{jt-1}$ expenditures as well as by neighbor's characteristics $\tilde{X}_{jt}$. The first two terms reflect the existence of public good provision habits in the policy-maker and help to capture incremental budget behavior stemming from complex bureocratic and political processes. On the other hand, exogenous characteristics extend the idea of welfare interdependence among agents for some exogenous variables. As explained by Brueckner (2003), people might use facilities in other localities and population dynamics or labor market outcomes can generate feelings of insecurity in adjacent neighborhoods. Thus, the characteristics of neighboring municipalities, such as population size, its composition and growth rate, may generate important disamenities (crime, pollution, noise, difficult commutes, crowds, a reduced sense of com- munity, and a greater transience of social relationships). For instance, an increase in neighboring municipalities migration will rise the costs of migration, and if the population size increases rapidly, expansions in public goods, infrastructure, and housing might not be able to keep pace, thus reducing welfare of municipality i.

Therefore, the utility function of the representative agent of municipality i at time t is given by:

$$V_{it} = v\left(C_{it}, G_{it}, G_{it-1}, \tilde{G}_{jt}, \tilde{G}_{jt-1}, X_{it}, \tilde{X}_{jt}\right) \tag{4.1}$$

where the function $v\,(.)$ satisfies the conditions of monotonicity and concavity for C_{it} and G_{it}. In this setting, private consumption C_{it} depends via the budget constraint on the level of the public good provision G_{it}, income net of taxes Y_{it}^d and transfers I_{it} such that $C_{it} = c\left(Y_{it}^d, G_{it}, I_{it}\right)$. The budget constraint reads as:

$$p_{it}G_{it} + C_{it} = I_{it} + Y_{it}^d \tag{4.2}$$

where p_{it} is the price of public goods G_{it} and the price of the private good has been normalized to 1. In this setting, any jurisdiction will typically interact with a potentially large number of other jurisdictions with decreasing intensity as distance between jurisdiction increases. Therefore, neighbors' expenditure is taken to be a weighted average of the expenditures of other jurisdictions:

$$\tilde{G}_{jt} = \frac{1}{N}\sum_{j=1}^{N} w_{ij}G_{jt} \tag{4.3}$$

where the weights w_{ij} are a negative unknown function of geographical distance between i and j. The maximum utility level derived from G_{it} is given by the equalization of the marginal rate of substitution between C_{it} and G_{it}. As shown by Akai and Suhara (2013), the first-order condition of this type of problem reads as:

$$R^i\left(Y_{it}^d + I_{it} - p_{it}G_{it}, G_{it}, \tilde{G}_{jt}; G_{it-1}, \tilde{G}_{jt-1}, X_{it}, \tilde{X}_{jt}\right) = p_{it} = \frac{V_{G_{it}}}{V_{C_{it}}} \tag{4.4}$$

By differentiating Equation (4.4) with respect to G_{it} and $\tilde{G}_{jt}$ we get:

$$\left(R_{G_{it}}^i - p_{it}R_{C_{it}}^i\right)dG_{it} + \left(R_{\tilde{G}_{jt}}^i\right)d\tilde{G}_{jt} = 0 \tag{4.5}$$

Therefore the simultaneous effect of municipality i when other municipalities $j \neq i$ increase their supply of the public good is:

$$\frac{dG_{it}}{d\tilde{G}_{jt}} = -\frac{1}{R_{G_{it}}^i - p_{it}R_{C_{it}}^i}R_{\tilde{G}_{jt}}^i \tag{4.6}$$

From $R_{G_{it}}^i < 0$ and $R_{C_{it}}^i > 0$, the expression $-\frac{1}{R_{G_{it}}^i - p_{it}R_{C_{it}}^i}R_{\tilde{G}_{jt}}^i$ in Equation (4.6) is positive. This implies that the direction of i's response depends on the sign of i's marginal rate of substitution $\left(R_{\tilde{G}_{jt}}^i\right)$. Thus, it is possible to describe the behavior of public spending in municipality i as follows:

(a) When $R_{\tilde{G}_{jt}}^i < 0$, $\frac{dG_{it}}{d\tilde{G}_{jt}} < 0$. The behavior of the public good provided by municipality i is a strategic substitute.

(b) When $R^i_{\tilde{G}_{jt}} = 0$, then $\frac{dG_{it}}{d\tilde{G}_{jt}} = 0$. The behavior of the public good provided by municipality i is independent.

(c) When $R^i_{\tilde{G}_{jt}} > 0$, then $\frac{dG_{it}}{d\tilde{G}_{jt}} > 0$. The behavior of the public good provided by municipality i is a strategic complement.[3]

Notice, however, that the inclusion of own municipal and exogenous lagged endogenous interactions into the utility function implies that there is also an optimal best-response of G_{it} with respect changes in $\tilde{G}_{jt-1}$ which reflects diffusion effects over space and time of government policy. These diffusion effects may operate through two different channels. First, a change in $\tilde{G}_{jt-1}$ could affect the response of government spending in municipality i in G_{it-1}, and as far as G_{it-1} and G_{it} are correlated because of the incremental budgetary process and the time inertia implied by bureaucratic processes, such a change could produce and impact in governments spending at time t. The second channel of diffusion follows the same reasoning and consists on the following sequence. A change in $\tilde{G}_{jt-1}$ could have an impact in $\tilde{G}_{jt}$ and insofar as there are any beneficial spillovers arising from j to i, $\tilde{G}_{jt}$ may affect G_{it}. Therefore, the effect of a change in $\tilde{G}_{jt-1}$ on G_{it} is given by the following set of cross-reaction functions:

$$\frac{dG_{it}}{d\tilde{G}_{jt-1}} = \frac{R^i_{G_{it-1}} R^i_{\tilde{G}_{jt-1}}}{\left(R^i_{G_{it}} - p_{it} R^i_{C_{it}}\right)\left(R^i_{G_{it-1}} - p_{it-1} R^i_{C_{it-1}}\right)} + \frac{R^i_{\tilde{G}_{jt}} R^j_{\tilde{G}_{jt-1}}}{\left(R^i_{G_{it}} - p_{it} R^i_{C_{it}}\right)\left(R^j_{\tilde{G}_{jt}} - p_{jt} R^j_{\tilde{C}_{jt}}\right)} \tag{4.7}$$

Additionally, given that preferences are interdependent with neighbor characteristics, the response of G_{it} to changes in exogenous characteristics of neighboring municipalities X_{jt} is given by:

$$\frac{dG_{it}}{d\tilde{X}_{jt}} = \frac{R^i_{\tilde{G}_{jt}} R^j_{\tilde{X}_{jt}}}{\left(R^i_{G_{it}} - p_{it} R^i_{C_{it}}\right)\left(R^j_{\tilde{G}_{jt}} - p_{jt} R^j_{\tilde{C}_{jt}}\right)} - \frac{R^i_{\tilde{X}_{jt}}}{\left(R^i_{G_{it}} - p_{it} R^i_{C_{it}}\right)} \tag{4.8}$$

Equation (4.8) states that the spending decision of a particular municipality to behave in some way depends on explanatory variables of other units through a direct $\left(R^i_{\tilde{X}_{jt}}\right)$ and indirect channel $\left(R^i_{\tilde{G}_{jt}} R^j_{\tilde{X}_{jt}}\right)$. According to the terminology developed by Elhorst (2014) and LeSage (2014a), the direct channel in this setting reflects a local spatial spillover as it does not require endogenous feedback effects passing through optimal reactions in j while the indirect channel

[3] Note that G_{it} and G_{jt} are not regarded as homogeneous within municipality i. This would have implied a utility function $V_{it} = v\left(C_{it}, G_{it}, G_{it-1}, +\tilde{G}_{jt}, +\tilde{G}_{jt-1}, X_{it}, \tilde{X}_{jt}\right)$ inducing the fact that $R^i_{G_{it}}$ and $R^i_{G_{jt}}$ have the same sign < 0. Also note that weakly separable utility functions may have implied that $V_{it} = v\left(c\left(C_{it}, G_{it}\right), G_{it-1}, \tilde{G}_{jt}, \tilde{G}_{jt-1}, X_{it}, \tilde{X}_{jt}\right)$ which in turn may produce that $dG_{it}/dG_{jt} = 0$ as in case (b).

reflects a global spillover process where optimal reactions in $\tilde{G}_j$ due to a change in the $\tilde{X}_j$ characteristic, set in motion a sequence of adjustments in potentially all municipalities in the sample such that a new long-run steady state equilibrium of government spending in municipality i arises.

To investigate endogenous and exogenous fiscal policy interactions of local government spending such as those predicted by the model Equations (4.6), (4.7), (4.8) among Spanish municipalities, the following DSDM with both spatial fixed and time-period fixed effects is estimated:

$$Y_t = \mu + \iota_N \alpha_t + \tau Y_{t-1} + \rho W Y_t + \eta W Y_{t-1} + X_t \beta + W X_t \theta + \epsilon_t \tag{4.9}$$

where Y_t denotes a $N \times 1$ vector consisting of observations for the government expenditure per capita for every municipality $i = 1, \ldots, N$ at a particular point in time $t = 1, \ldots, T$, X_t and WX_t are $N \times K$ matrices of exogenous aggregate socioeconomic and economic covariates with associated own β and neighbor's θ response parameters contained in $K \times 1$ vectors that are assumed to influence government expenditure. τ, the response parameter of the lagged dependent variable Y_{t-1} and $\epsilon_t = (\epsilon_{1t}, ..., \epsilon_{Nt})'$ is a vector of i.i.d disturbances whose elements have zero mean and finite variance σ^2. The variables WY_t and WY_{t-1} denote contemporaneous and lagged endogenous interaction effects among the dependent variable. ρ is called the spatial autoregressive coefficient. W is a $N \times N$ matrix of known constants describing the spatial arrangement of the municipalities in the sample. $\mu = (\mu_1, ..., \mu_N)'$ is a vector with region fixed effects, $\alpha_t = (\alpha_1, ..., \alpha_T)'$ denotes time specific effects and ι_N is a $N \times 1$ vector of ones. Region fixed effects control for all region-specific time invariant variables whose omission could bias the estimates, while time-period fixed effects control for all time-specific, space invariant variables whose omission could bias the estimates in a typical time series (Baltagi, 2001; Elhorst, 2010).

The DSDM in Equation (4.9) is an attractive starting point for spatial econometric modelling because, as special cases, it nests alternative specifications which are widely used in the literature: the *Dynamic Spatial Lag Model* (DSLM) and the Dynamic Non-Spatial Model (DLM). As can be checked, the DSDM can be simplified to the DSLM by shutting down exogenous interactions $\theta = 0$:

$$Y_t = \mu + \iota_N \alpha_t + \tau Y_{t-1} + \rho W Y_t + \eta W Y_{t-1} + X_t \beta + \epsilon_t \tag{4.10}$$

and to the DLM by shutting down both, exogenous and endogenous interactions such that $\theta = \rho = \eta = 0$:

$$Y_t = \mu + \iota_N \alpha_t + \tau Y_{t-1} + X_t \beta + \epsilon_t \tag{4.11}$$

where $\epsilon_t \sim i.i.d.$

4.4 Data and Hypothesis

The sample used to investigate government space-time dynamics covers a total of $1,230$ municipalities above $5,000$ inhabitants and accounting for 75% of the Spanish population and the study period runs from 2000 to 2012. The data for this study are drawn from different data sources. Table (4.3) below summarizes the set of political, economic and demographic factors used in the study, its mean, standard deviation and the data source. Column 4 of Table (4.3) shows the expected effect of a wide range of controls and spending drivers based on a review of international and Spanish local government finance studies.

Table 4.3: Descriptive Statistics.

Variable	Mean	Standard deviation	Expected Effect	Source
Outcome Variable				
log Government expenditure pc	6.43	0.35		MPF
log Education expenditure pc	1.85	2.08		MPF
log Housing expenditure pc	3.78	1.399		MPF
log Waste expenditure pc	3.42	1.42		MPF
log Water expenditure pc	2.07	1.98		MPF
log Security expenditure pc	3.51	1.33		MPF
log Culture expenditure pc	2.79	1.86		MPF
Explanatory Factors				
A. Political Factors				
Political Power	55.06	0.13	?	MI
Ideology	5.59	1.95	-	Deusto Polls
Regional Alignment	0.31	0.46	?	MI
National Alignment	0.44	0.50	?	MI
B. Economic Factors				
log Tax pc	4.96	1.66	+	MPF
log Transfers pc	5.81	0.66	+	MPF
Unemployment Rate (%)	7.42	4.41	?	AE La Caixa
log GDP pc	9.70	0.43	+	Klein Institute
C. Demographic Factors				
log Population Density	4.49	1.55	-	INE
Net Migration (%)	1.80	2.92	?	INE
People % above 65y	19.73	7.16	?	INE

Notes: MPF denotes the Ministry of Public Finance, MI the Interior Ministry and INE the National Statistics Institute. The data used to define the municipal public spending have been obtained from the consolidated budgets of settlements of Local Bodies, published by the Ministry of Finance. Total expenditure corresponds to Operating Expenses, as defined by Chapters 1 (Personal), 2 (Purchase of current goods and services) and 4 (Current transfers) of the economic classification of expenditure. Education expenditures, includes the operating expenditure policy 32, Housing includes the operating expenditure expenditure policy 15, Waste includes the operating expenditure program group 162, Water includes expenditure operating the program group 161, Security includes operating expenses policy of spending 13, and finally Culture includes expenditure operational expenditure policy 33. Order EHA/3565/2008. MHAP (BOE, 297/10-12)

Outcome Variables: Government Expenditure (per capita). In the baseline analysis, the dependent variable is the logarithm of current government expenditure per capita. Additionally, the sign and strength of spatial spillovers for a variety of government spending categories is analyzed. The concrete expenditure functionalities are the expenditures in (i) education, (ii) housing, (iii) waste and collection of residuals, (iv) water supply, (v) citizen security and (vi) cultural and recreational services.

Covariates: The municipal government expenditure is modeled as a reduced form function of a variety of factors that can be broadly categorized as (i) political factors, (ii) economic factors and (iii) demographic factors.

A) Political Factors.

The management of local public administration is the result of a combination of political factors (Borge, 1995; Volkerink and de Haan, 2001; Astworth and Mesquita, 2006). There are two approaches in the theoretical debate over the influence of government strength on the fiscal situation of public authorities. Roubini and Sachs (1989a,b) suggest that weak governments can impose notable costs and show that government weakness in OECD countries increases government spending, deficit and debt. This hypothesis is known in the literature as the *weak government hypothesis.* At the local level, studies of Ashworth et al. (2005) and Borge (2005) find that strong local governments spend less. Nevertheless, other authors employing theoretical models show that divided governments may have a moderating influence on fiscal policy (Alesina and Rosenthal, 1994). In the case of Spain the evidence is contradictory. Bastida *et al.* (2013) employing a Herfhindal Index conclude that greater political concentration increases government spending. However, the sign is not robust to the specific functional spending category considered. Meanwhile, García-Sánchez *et al.* (2012) using a variety of budgetary solvency indicators find that political strength is positively related to budgetary solvency. In a similar vein, Solé-Ollé (2003) finds that higher electoral margins allow local politicians to implement higher taxes, which may help to balance the budget for a given level of expenditure. In order to proxy political power concentration, the share of seats (%) in the local council is computed by applying the electoral *D'hondt rule* operating in Spain to the votes obtained by the different parties and taking into account the distinct minimum requirements to obtain representation. In view of the discrepancies among previous studies, there is no a priori expectation regarding the effect of political strength on per capita government expenditures.

Partisan ideology measures the impact of ideological differences on fiscal policy outputs. Traditionally, Spain has had two main national left-wing parties: PSOE (socialists) and IU (communists), one national right-wind party (PP) and a national center party (UPyD). However, there are many parties regional parties, some to the left and some to right of the political spectrum, as well as candidates who run as independents, mostly in small municipalities. The ideology variable is computed for a great number of parties with an index ranging from 0 (left) to 10 (right) taken from Deusto polls Database and from a review of political party manifestos. Whenever information on independents was unavailable, a value of 5 was assigned to the party. Various authors have argued that the alternation in power between the different political parties could induce significant changes in the size of public budgets given that left and right wing parties differ with respect to their handling of government resources (Imbeau *et al.*, 2001; Santolini, 2008). It is commonly argued that left-wing parties favor income redistribution and an active role of the state which in turn may increase public spending while right-wind parties aim at budget reductions (Tellier, 2006). Bastida *et al.* (2013) find that the effect of ideology on aggregate municipal spending varies depending on the concrete spending functionality while García-Sánchez *et al.* (2012) find evidence supporting the view that leftist parties spend more. Given the definition of the ideological variable, a negative effect is expected.

Regarding the alignment effect, it has been argued that municipalities aligned with upper-tier grantor governments (controlled by the same party) will receive more grants than those that are unaligned, and consequently will spend more (Grossman, 1994). Solé-Ollé and Sorribas-Navarro (2008) suggest that partisan alignment has a positive effect on the amount of grants received by Spanish municipalities whereas Bastida *et al.* (2013) do not find a significant effect of grants on government spending. In order to test the hypothesis that regional and national alignment has a positive impact on municipal expenditure dummy variables for regional and national alignment are employed. These dummies take value of 1 if the municipal and higher-level government party are of the same party and 0 otherwise.

B) Economic Factors.

According to the traditional theory on sub-national government spending, the economic variables believed to influence local expenditures are real per capita personal income, per capita real intergovernmental revenue and per capita real unemployment compensation. Although the set of economic controls included in the model is theoretically well grounded (see, Bails and Tieslau 2000) it ultimately depends on data availability. The economic factors included are the log per capita transfers, log per capita tax revenue, log GDP per capita and the unemployment rate in the municipality. From a theoretical point of view, GDP per capita is expected to have a positive impact on per capita government spending as in Solé-Ollé (2006). Nonetheless, Bastida *et al.* (2013) find a non-significant effect of GDP per capita on expenditure. Regarding the effect of transfers, the empirical literature finds the effect of grants on government spending to be positive (Hines and Richard, 1995). Indeed, many studies show that spending is stimulated by much more than theory predicts. This has been labeled as the *flypaper-effect* since the money the government sends out *'sticks where it hits'*. Another relevant control is the per capita level of tax revenues since a reduction in taxes generally leads to a reduction in government spending (Gabe and Bell, 2004). In this regard, Bastida *et al.* (2013) find a weakly significant effect of taxes and transfers. Finally, according to Carruthers and Ulfarsson (2008), unemployment may reflect weak municipal labor markets, which are expected to influence spending negatively. On the other hand, Bails and Tieslau (2000) find that the higher the level of unemployment, the higher the level of local spending. For the Spanish case, Bastida *et al.* (2013) find a negative effect of unemployment on government expenditure. Thus, a positive effect of GDP, transfers and taxes is expected, but not a priori expectations are placed on the effect of unemployment.

C) Demographic Factors.

Population density is likely to affect government spending through economies of scale. At this regard Bastida *et al.* (2013) find a negative effect. This result goes in line with Solé-Ollé (2006) and Hortas-Rico and Salinas (2014) who, using a variety of measures, found that there is a negative relationship between population density and government expenditure per capita. Therefore, a negative effect of population density is expected. Additionally, several authors have observed that the age composition of the population is one of the main factors explaining varying demand across authorities and changing demand over time (Poterba, 1994;. 1997). The demographic features have to do with the interest groups problem given that different groups of population will pressure politicians to meet their needs. The literature has used many demographic variables to account for these interest groups: the rate of young, the rate of old population and the rate of immigrants. A positive net migration rate means that there are more people entering the municipality than leaving it, while a negative value means more people leaving than entering it. In order to control for such characteristics the share of population above 65 years and the net migration rate are introduced in the empirical specification. Solé-Ollé (2006) finds an insignificant effect of the share of young and a negative and significant effect of the share of old population. On the other hand, Bastida *et al.* (2013) include the share of young finding an insignificant effect. Thus, it is unclear how these variables may infuence government per capita spending.

4.5 Econometric Methodology

The set of econometric issues to perform inference in this context are (i) the spatial weight matrix selection and effect specification (ii) the identification of the parameters and (iii) the model estimation and interpretation.

4.5.1 Model Selection

An important issue in spatial econometrics and model selection is that of the selection of the spatial connectivity matrix W to be used by the researcher. There are several studies investigating the robustness of results to different specifications of W and which one is to be preferred. The most widely used criterion to select the W matrix has been the log-likelihood. Nevertheless, this approach has been criticized because it only finds a local maximum among competing models (Harris *et al.*, 2011). In relation to this criticism LeSage and Pace (2009) propose the Bayesian posterior model probability as an alternative model selection criterion. In a recent study, Herrera *et al.* (2014) show that the Bayesian criteria outperforms J-tests and entropy measures in small samples. The underlying idea of Bayesian W selection is to consider a finite set of alternative models $M = M_1, M_2, .., M_N$ based on different spatial weight matrices, while holding the other model aspects constant (i.e, the explanatory variables). Denote by Θ the vector of parameters $3 + 2 * K$ parameters of the DSDM where K is the number of regressors. Then, the joint probability of the set of N models, parameters and observations correspond to:

$$p\left(M, \Theta, y\right) = \pi\left(M\right) \pi\left(\Theta|M\right) L\left(y|\Theta, M\right) \tag{4.12}$$

where $\pi\left(M\right)$ is the prior probability assigned to the model[4], $\pi\left(\Theta|M\right)$ reflects the priors of the vector of conditional parameters to the model and $L\left(y|\Theta, M\right)$ is the likelihood of the data conditioned on the parameters and models. As shown in Equation (4.13) below we use the Bayes rule to derive the posterior probability of model i:

$$p\left(M^i, \Theta^i|y\right) = \frac{p\left(M^i, \Theta^i, y\right)}{p\left(y\right)} = \frac{\pi\left(M^i\right) \pi\left(\Theta^i|M^i\right) L\left(y|\Theta^i, M^i\right)}{p\left(y\right)} \tag{4.13}$$

[4]In order to make each model equally likely a priori, the same prior probability $1/N$ is assigned to each model M_i under consideration.

Integrating with respect Θ^i one can obtain the marginal likelihood, the key metric used to compare the various models based on different spatial weight matrices.

$$p\left(y|M_i\right) = \int p\left(y|\Theta^i, M_i\right) p\left(\Theta^i|M_i\right) d\Theta^i \tag{4.14}$$

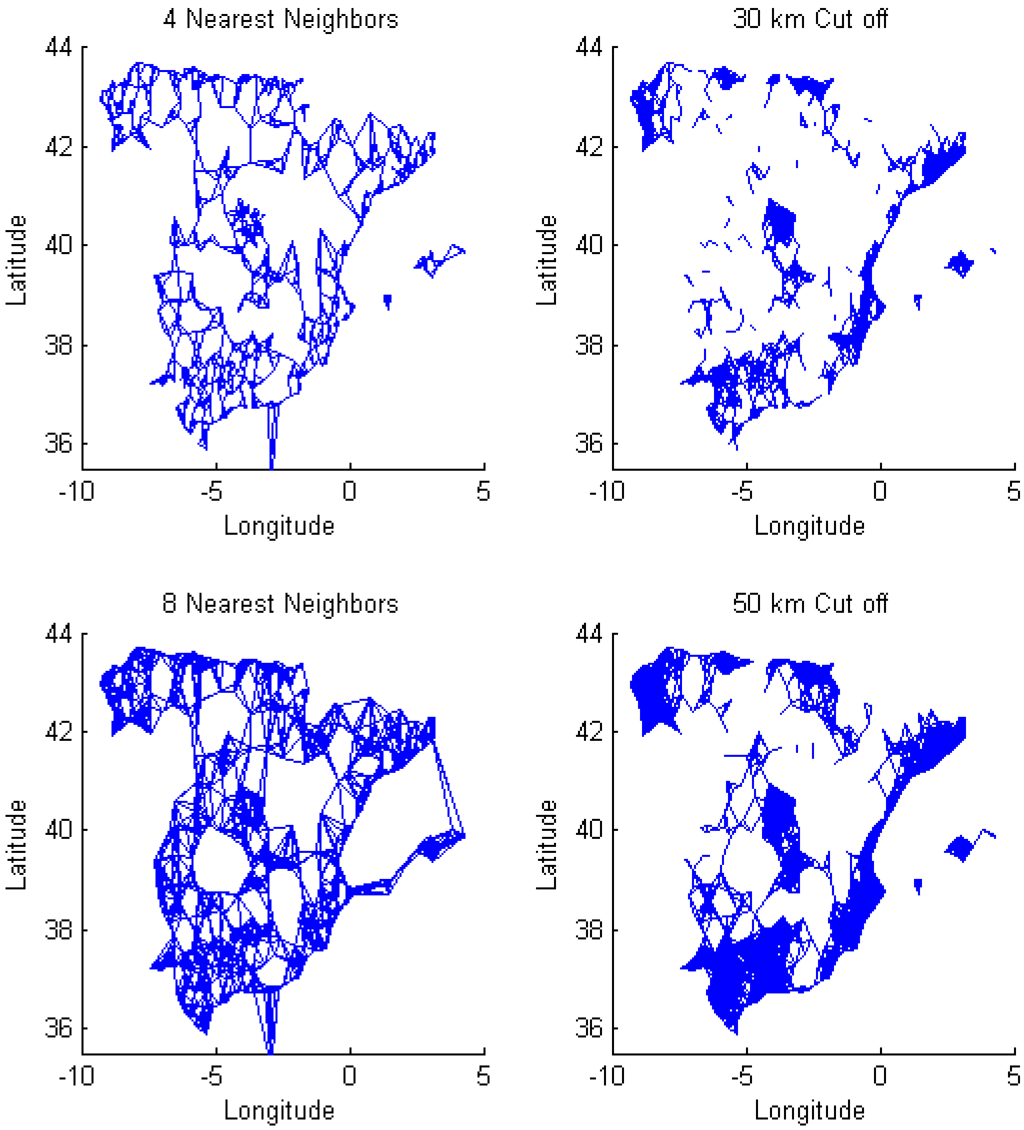
In this exercise, non-informative diffuse priors for the model parameters $(\tau, \eta, \beta, \theta, \sigma)$ are used. In particular, the normal-gamma conjugate prior is used for the parameters $\beta, \theta, \tau, \eta$ and σ while a uniform proper prior ranging between 0 and 1 is employed for ρ such that:[5]

$$\begin{aligned}
&\pi(\beta) \sim N\left(c, T\right) \\
&\pi\left(\frac{1}{\sigma^2}\right) \sim \Gamma\left(d, v\right) \\
&\pi\left(\rho\right) \sim U\left[0, 1\right]
\end{aligned} \tag{4.15}$$

Prior hyper-parameters c and T are set to zero and to a very large number $(1e+12)$ respectively, which results in a diffuse prior for β, θ, τ, η. To impose diffuse priors for σ hyper-parameter d and v are set to zero. These priors are implemented following LeSage (2014b) recommendations, as they do not require subjective information on the part of the practitioner. To carry out W selection several matrices based on the k-nearest neighbors ($k = 1, 2, .., 25$) computed from the great circle distance between the centroids of the various regions are considered. Additionally, inverse distance matrices with different cut-off values above which spatial interactions are assumed negligible are designed. As an alternative, inverse power distance and exponential distance decay matrices whose off-diagonal elements are defined by $w_{ij} = \frac{1}{d_{ij}^{\alpha}}$ for $\alpha = 1, \ldots, 3$ and $w_{ij} = exp(-\theta d_{ij})$ for $\theta = 0.005, \ldots, 0.03$ are considered. As can be observed, the different matrices described above are based in all cases on the geographical distance between the sample regions, which in itself is strictly exogenous. This is consistent with the recommendation of Anselin and Bera (1998) and allows us to avoid the identification problems raised by Manski (1993). All the spatial weight matrices employed in this analysis are row-normalized. An example of the differences involved by the use of different spatial weight matrices in the context of interactions between municipalities can be seen in Figure (4.2) below. As can be observed, the network of interactions becomes denser when increasing the number of neighbors or the distance over which interactions are set to zero. Table (4.4) shows that, depending on the concrete effect specification there are different optimal spatial weight matrices. For the specification with only

[5]Note that the use of beta priors or uniform priors taking into account the possibility of negative spatial auto-correlation values $U \sim [-1, 1]$ did not alter the results of the spatial weight matrix selection.

Figure 4.2: Spatial Weight Matrices.



municipal fixed effects, the highest probability model is $W_{ij} = exp(-0.01d_{ij})$ with $p = 57\%$. In the model with municipal and time-period effects the Bayesian Posterior suggests to use the 4-nearest neighbors with $p = 99\%$. In order to discriminate between these alternative spatial interaction matrices likelihood ratio tests is applied to check what specification of the effects is to be preferred. The results of LR-tests in both cases favor the inclusion of time-period fixed effects, which ultimately suggests the employment of a 4 nearest-neighbor's spatial connectivity matrix. LR test statistic for the 4-nearest neighbors W specification is 150.99, p-value = 0.00, while for $W = exp\,(-0.01d_{ij})$ the LR-statistic is 33.3, p-value=0.00.

Table 4.4: Bayesian Posterior Model Probabilities.

Spatial Matrix Definition	Spatial Fixed and Time Effects Model	Spatial Fixed Effects Model
Cut-off 15 km	0.00	0.00
Cut-off 30 km	0.00	0.00
Cut-off 50 km	0.00	0.00
Cut-off 75 km	0.00	0.00
Cut-off 100 km	0.00	0.00
Cut-off 150 km	0.00	0.00
Cut-off 250 km	0.00	0.00
Cut-off 350 km	0.00	0.00
$1/d^{\alpha}$, $\alpha = 1$	0.00	0.00
$1/d^{\alpha}$, $\alpha = 1.25$	0.00	0.00
$1/d^{\alpha}$, $\alpha = 1.5$	0.00	0.00
$1/d^{\alpha}$, $\alpha = 1.75$	0.00	0.00
$1/d^{\alpha}$, $\alpha = 2$	0.00	0.00
$1/d^{\alpha}$, $\alpha = 2.25$	0.00	0.00
$1/d^{\alpha}$, $\alpha = 2.5$	0.00	0.00
$1/d^{\alpha}$, $\alpha = 2.75$	0.00	0.00
$1/d^{\alpha}$, $\alpha = 3$	0.00	0.00
$exp - (\theta d)$ $\theta = 0.005$	0.00	0.00
$exp - (\theta d)$ $\theta = 0.01$	0.00	0.57
$exp - (\theta d)$ $\theta = 0.015$	0.00	0.43
$exp - (\theta d)$ $\theta = 0.02$	0.00	0.00
$exp - (\theta d)$ $\theta = 0.03$	0.00	0.00
K-nearest neighbors $(K = 1)$	0.00	0.00
K-nearest neighbors $(K = 2)$	0.00	0.00
K-nearest neighbors $(K = 3)$	0.00	0.00
K-nearest neighbors $(K = 4)$	1.00	0.00
K-nearest neighbors $(K = 5)$	0.00	0.00
K-nearest neighbors $(K = 6)$	0.00	0.00
K-nearest neighbors $(K = 7)$	0.00	0.00
K-nearest neighbors $(K = 8)$	0.00	0.00
K-nearest neighbors $(K = 9)$	0.00	0.00
K-nearest neighbors $(K = 10)$	0.00	0.00
K-nearest neighbors $(K = 15)$	0.00	0.00
K-nearest neighbors $(K = 20)$	0.00	0.00
K-nearest neighbors $(K = 25)$	0.00	0.00

Notes: Bayesian Markov Monte Carlo (MCMC) routines for spatial panels required to compute Bayesian posterior model probabilities do not exist yet. Thus, all cross-sectional arguments of James LeSage routines are replacced by their spatial panel counterparts, for example a block-diagonal $NT \times NT$ matrix, $diag(W, ..., W)$ as argument for W.

4.5.2 Parameter Identification

Identification of the DSDM is a great concern in the spatial econometrics literature. Anselin (2010) and Elhorst (2012) recommend imposing zero restrictions on the model parameters to avoid the identification problems. Elhorst (2012) gives an overview of the main restrictions that have been considered in the literature to get rid of this identification problem. The restrictions considered by Elhorst (2012) consist in imposing (i) $\theta = 0$ to exclude exogenous interaction effects (WX_t), (ii) $\rho = 0$ to exclude contemporaneous endogenous interaction effects (WY_t); (iii) $\eta = 0$ to exclude lagged endogenous interaction effects (WY_{t-1}), and (iv) $\eta = -\tau\rho$. The disadvantage of imposing the restriction $\theta = 0$ is that the ratio between the indirect effect and the direct effect becomes the same for very explanatory variables. The disadvantage of imposing the restriction $\rho = 0$ is that the short-term indirect effects depend on θ only. This loss of flexibility makes the model less suitable for empirical research focusing on short-term effects. By contrast, if the restriction $\eta = 0$ is imposed, no prior restrictions are imposed on the effects estimates, even though still some flexibility of the model gets lost. Finally, the disadvantage of imposing the restriction is $\eta = -\tau\rho$ is that the ratio between the indirect effect and the direct effect of a particular explanatory variable remains constant over time.

Importantly, in a recent study, Lee and Yu (2015) provide sufficient rank conditions under which the parameters of the DSDM of Equation (4.9) can be identified when estimating the model by QML. For a DSDM with fixed municipal and time-period effects these conditions are summarized below. Given $(\eta + \rho\tau, \beta + \rho\theta) \neq 0$, ρ is identified if the columns of M_1 are linearly independent:

$$M_1 = (I_T \otimes J_n)\left[Y^*_{T-1}, WY^*_{T-1}, W^2Y^*_{T-1}, X^*_T, WX^*_T, W^2X^*_T\right] \tag{4.16}$$

Given ρ, the rest of parameters are identified if M_2 has full column rank where:

$$M_2 = (I_T \otimes J_n)\left[Y^*_{T-1}, WY^*_{T-1}, X^*_T, WX^*_T\right] \tag{4.17}$$

where $Y^*_{T-1} = Y_{T-1} - \left(\frac{1}{T}\iota_T\iota_T' \otimes I_N\right) E\left[Y_{T-1}\right]$, $X^*_T = (I_T \otimes J_n)\left[X_T, X_{T-1}\right]$, $J_n = I_n - \frac{1}{n}\iota_T\iota_T'$. These parameter identification conditions imply that M_1 should have a column rank of $3*K+3$ and M_2 of $2*K+2$. This condition is checked before estimations. In this specific case, the rank conditions required that $rank\,(M_1) = 36$ and $rank\,(M_2) = 24$ which is fortunately satisfied in this analysis.

4.5.3 Model Estimation and Interpretation.

The estimator employed in this research to explore the relationship between the set of variables and municipal spending is the BCQML for dynamic spatial panels developed by Lee and Yu (2010b,c). As shown in Yu *et al.* (2008) and Lee and Yu (2010b,c) the estimation of Equation (4.9) including both time effects and individual effects will yield a bias of the order $O\left(max\left(n^{-1}, T^{-1}\right)\right)$ for the common parameters. By providing an asymptotic theory on the distribution of this estimator, they show how to introduce a bias correction procedure that will yield consistent parameter estimates provided that the model is stable, (i.e, $\tau + \rho + \eta < 1$). As Elhorst *et al.* (2013) explain, the estimation of a dynamic spatial panel becomes more complex in the case the condition $\tau + \rho + \eta < 1$ is not satisfied. If $\tau + \rho + \eta$ turns out to be significantly smaller than one the model is stable. On the contrary, if its greater than one, the model is explosive and if the hypothesis $\tau + \rho + \eta = 1$ cannot be statistically rejected, the model is said to be spatially co-integrated. Under explosive or spatially co-integration model scenarios, Yu *et al.* (2012), propose to transform the model in spatial first differences to get rid of possible unstable components in Y_t. This important condition is verified when the estimations are carried out.

Many empirical studies use point estimates of one or more spatial regression models to test the hypothesis as to whether or not spatial spillover effects exist. However, LeSage and Pace (2009) have recently pointed out that this may lead to erroneous conclusions and that a partial derivative interpretation of the impact from changes to the variables of different model specifications provides a more valid basis for testing this hypothesis. Within the context of the DSDM of equation (4.9), the matrix of partial derivatives of Y_t with respect the *k-th* explanatory variable of X_t in municipality 1 up to municipality N at a particular point in time t is:

$$\frac{\partial Y_t}{\partial X_t^k} = \left[(I - \rho W)^{-1}\right]\left[\mu + \iota_N \alpha_t + \beta^{(k)} + \theta^{(k)} W\right] \tag{4.18}$$

Interestingly, in the previous model it is possible to compute own $\partial Y_{it+T}/\partial X_{it}^k$ and cross-partial derivatives $\partial Y_{it+T}/\partial X_{jt}^k$ that trace the effects through time and space. Specifically, the cross-partial derivatives involving different time periods are referred as diffusion effects, since diffusion takes time. Conditioning on the initial period observation and assuming this period is only subject to spatial dependence (Debarsy *et al.*, 2012) the data generating process can be expressed as:

$$Y_t = \sum_{k=1}^{K} Q^{-1}\left(\beta^{(k)} + \theta^{(k)} W\right) X_t^{(k)} + Q^{-1}\left(\mu + \iota_N \alpha_t + \epsilon_t\right) \tag{4.19}$$

where Q is a lower-triangular block matrix containing blocks with N matrixes of the form:

$$Q = \begin{bmatrix} B & 0 & \dots & & 0 \\ C & B & & & 0 \\ 0 & C & \ddots & & \vdots \\ \vdots & & \ddots & & \\ 0 & \dots & & C & B \end{bmatrix} \tag{4.20}$$

with $C = -(\tau + \eta W)$ and $B = (I_N - \rho W)$. One implication of this, is that by computing C and B^{-1} it is possible to analyze the -own and cross-partial derivative impacts for any time horizon T. Generally, the T-period ahead (cumulative) impact on government spending from a permanent change at time t in k-th variable is given by:

$$\frac{\partial Y_{t+T}}{\partial X_t^k} = \sum_{s=1}^{T} \left[(-1)^s \left(B^{-1}C\right)^s B^{-1}\right] \left[\mu + \iota_N \alpha_t + \beta^{(k)} + \theta^{(k)} W\right] \tag{4.21}$$

When T goes to infinity, the previous expression collapses to the long run effect, which is given by:

$$\frac{\partial Y_t}{\partial X_t^k} = \left[(1-\tau) I - (\rho + \eta) W\right]^{-1} \left[\mu + \iota_N \alpha_t + +\beta^{(k)} + \theta^{(k)} W\right] \tag{4.22}$$

According to Elhorst (2014), the properties of this partial derivatives are as follows. First, if a particular explanatory variable in a particular region changes, per capita government expenditure will change not only that municipality but also in other municipalities. Hence, a change in a particular explanatory variable in municipality i has a *direct* effect on that municipality, but also an *indirect* effect on the remaining municipalities. Finally, the *total* effect, which is object of main interest, is the sum of the direct and indirect impacts. Following LeSage and Pace (2009) the direct effect are measured by the average of the diagonal entries whereas the indirect effect is measured by the average of non-diagonal elements.

4.6 Results

4.6.1 Baseline Results

Table (4.5) shows the results of the estimation of the DSDM using the 4-nearest neighbors W matrix. Column 1 reports the own-municipality coefficient estimates while column 2 shows the estimated parameters related to the effect of changes in the regressors of neighboring municipalities. Before continuing, it is important to evaluate some features of the model estimation. First, as can be observed in Column 1, the coefficients estimates of the dependent variable lagged in time Y_{t-1} and in space WY_t are both positive and significant, while the coefficient of the dependent variable lagged in space and time WY_{t-1} is negative and significant. This result confirms that the dynamic spatial panel data modeling framework used in this analysis is suitable for studying the evolution of municipal government spending per capita. Importantly, these results suggest the existence of simultaneous positive benefit spillovers and complementarity in local public goods provision. However, the fact that WY_{t-1} is negative and significant indicates a negative diffusion spillover effect which suggests that once municipality i the provision at time $t-1$ the optimal reaction of local government would be to free-ride on neighboring regions and thereby reduce own expenditure.

These results are consistent with two alternative scenarios in Equation (4.7). First, note that simultaneous complementarity requires $R^i_{\tilde{G}_{jt}} > 0$ and that monotonicity and concavity conditions for C and G in t and $t-1$ imply that the multiplication of the terms in the denominator $R^i_{G_{it}} - p_{it}R^i_{C_{it}}$ and $R^i_{G_{it-1}} - p_{it-1}R^i_{C_{it-1}}$ yield a positive value. Hence, the empirical results are supported by the theoretical model whenever conditions (i) If $R^i_{\tilde{G}_{jt-1}} < 0$ then $R^j_{\tilde{G}_{jt-1}} < 0$ and $|A| < |B|$ or (ii) If $R^i_{\tilde{G}_{jt-1}} > 0$ then $R^j_{\tilde{G}_{jt-1}} > 0$ and $|A| > |B|$ hold, with $A = \frac{R^i_{G_{it-1}} R^i_{\tilde{G}_{jt-1}}}{\left(R^i_{G_{it}} - p_{it}R^i_{C_{it}}\right)\left(R^i_{G_{it-1}} - p_{it-1}R^i_{C_{it-1}}\right)}$ and $B = \frac{R^i_{\tilde{G}_{jt}} R^j_{\tilde{G}_{jt-1}}}{\left(R^i_{G_{it}} - p_{it}R^i_{C_{it}}\right)\left(R^j_{\tilde{G}_{jt}} - p_{jt}R^j_{\tilde{C}_{jt}}\right)}$.

To find out whether the model under consideration is stable, the sum of the parameters $\tau + \rho + \eta$ is calculated and a two-sided Wald-test is carried out to investigate the null hypothesis of $\tau + \rho + \eta = 1$. The last rows of the Table (4.5) report the parameter sum and the corresponding p-values of the F-test. Importantly, the model is stable and does not suffer from spatial co-integration (i.e, $\tau + \rho + \eta = 0.72$ with p-value 0.00). Columns 3, 4 and 5 of Table (4.5) report the simulated effects. As observed, simultaneous direct effects shown in column (3) are slightly different from the estimates of the response parameters shown in column (1) of Table (4.5). This discrepancy is caused by the feedback effects that arise as a result of impacts passing through to other municipalities and back to the municipality itself. As regards the indirect (spillover) effects of the controls considered, only taxes and regional alignment display a weakly significant effect.

Table 4.5: Estimation Results and Short Run Effects.

	Coefficient Estimate	Neighbor's Estimate	Direct Effect	Indirect Effect	Total Effect
A. Political Factors					
Political Power	0.015*	-0.023	0.005	-0.016	-0.011
Ideology	0.000	0.002	0.000	-0.001	-0.001
Nat Align	-0.003*	0.003	-0.002***	0.001	-0.001
Reg Align	0.001	0.004	0.001	0.005*	0.006*
B. Economic Factors					
log GDP pc	0.050	-0.013	0.010***	-0.002	0.008*
Unemployment	-0.003	0.000	-0.003	0.000	-0.003
log Tax pc	0.004	0.014**	0.005***	0.010*	0.015**
log Transfers pc	0.024***	-0.007**	0.021***	-0.003	0.018***
C. Demographic Factors					
log Pop density	-0.134***	0.037	-0.130***	0.021	-0.109**
Migration	-0.070***	0.015***	-0.074***	0.010	-0.063***
Population > 65	-0.001	0.001	0.001	0.001	0.002
Spatial Lag	0.108***				
Time Lag	0.642***				
Space-Time Lag	-0.029**				
Log Likelihood	18565.72				
R^2	0.95				
$\tau + \rho + \eta$	0.72***				
Identification	Yes				

Notes: * Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 1000 simulated parameter combinations drawn from the variance-covariance matrix implied by the BCQML estimates.

In order to investigate how different factors affect government spending it is convenient to examine the information obtained with the simulation of the effects of the different control variables.

First, as regards the total effect of political factors such as political power and ideology, it can be seen that these controls are not statistically significant. These results are robust to different definitions of the variables. The use of Herfhindal Indexes for the political power and dummy variables for the ideology proxy, instead of the scaled variable from 0 to 10, did not changed the results. A plausible explanation for these findings could be that local governments are focused on solving people's needs with small influence of ideology or relative power on aggregate spending as explained by Travers (2009).[6] Local government's ideological alignment with regional dominating parties also presents an insignificant effect on government spending as obtained previously in Bastida *et al.* (2013) while the effect of alignment between local and national parties is positive and weakly significant. As hypothesized above, this positive and significant relationship could be due to the receipt of additional funding and grants.

Most of the economic controls, on the other hand, present the expected effects. The findings suggest that a higher level of per capita GDP increases per capita government spending. The direct simultaneous effect in Table (4.5) of GDP per capita is significant at the 1% significance level, the spillover effect is insignificant and the total effect is positive and significant at the 10% level. As to the effect of unemployment rate its overall impact on per capita government spending is observed to be not significant. The results for the effects of per capita taxes suggest that both the direct and indirect effects are relevant in increasing government spending. However, the effect of taxes is mainly driven by a strong spillover effect which accounts for the 66% of the total simultaneous effect. This implies that an increase in the taxes per capita in all other regions has a greater effect on own government spending than own tax movements. In a similar vein, transfers per capita received from upper government tiers, generate a strong positive and significant direct effect, a negative significant indirect effect and a net total positive and significant effect as expected. Interestingly, the quantitative result for transfers supports the fly-paper hypothesis, given that the elasticity of local government expenditures is greater with respect to transfers than to increases in per capita GDP.

The results for demographic factors show a significant and negative total effect of population density and net migration. The negative impact found for the population density goes in line with previous findings obtained by Solé-Ollé (2006) and Hortas-Rico and Salinas (2014) suggesting the existence of agglomeration economies that help to reduce per capita expenditure. The net migration rate, on the other hand, displays a negative and significant total effect. This result suggests that the increase in local spending per capita failed to keep pace with the intense migration process occurred in Spain during the sample period. Note, however, that this result also could reflect the fact that municipalities with a more dynamic private sector, where public intervention is not so relevant, are precisely those that receive more immigrants. Finally, as to the share of population above 65 years old, a statistically insignificant effect is observed.

[6] A more in depth analysis of the effect of ideology on each of the different functional categories reveals that right-wing governments tend to reduce average spending in education but raise spending in public safety and water provision while it does not affect housing, culture or residual collection. The results have not been included for the sake of brevity but are available upon request.

To study the dynamic responses of government spending to changes in the different determinants, the model is used to perform impulse-response analysis following Debarsy *et al.* (2012). Impulse-response functions in a dynamic spatial panel context contain both, temporal dynamic effects and spatial diffusion effects which correspond to exogenous changes that propagate across space. Figures (4.3) and (4.4) below display the adjustment path of government spending to transitory and permanent changes (respectively) for the various groups of variables considered for DSDM, DSLM and DLM specifications. As can be observed, the different model specifications tend to generate quantitative and qualitatively similar results for most of the regressors with the sole exception of the net migration effect. This divergent result could be due to omitted variable bias of the non-spatial specification. Differences between the impulse responses obtained with the DSDM and the DSLM are caused by exogenous diffusion effects while differences in the impulse-response functions between the DSLM and DLM, where spatial interactions do not exist, should be attributed to endogenous diffusion effects. As it is observed by comparing DSLM and DSDM impulse-responses, the omission of exogenous interactions effects underestimates the dynamic trajectory of government spending to regional alignment, taxes, population density and migratory shocks.

Table (4.6), reports the long results of the simulated direct, indirect and total effects which are displayed in columns 1, 2 and 3 respectively. As can be seen, most of the variables introduced in this analysis generate qualitatively similar short term and in the long term effects. Nevertheless, the most striking difference between the obtained results for long-run relationships is that of indirect (spillover) effects are now significant at the 5% level for most of the covariates. This result could be due to the fact that the transmission of shocks from neighboring municipalities needs some time to produce a visible effect. The positive differences between the relative relevance of indirect effects in the long run and the short run imply that, apart from the first period where interaction effects are mainly pure spatial feedbacks effects, space-time feedbacks passing from one municipality to another seem to be relevant in order to explain municipal government spending movements. Moreover, long-term effects associated with changes in any of the variables are considerably higher than those observed simultaneously which is consistent with macroeconomic theory.

Figure 4.3: Impulse Responses.

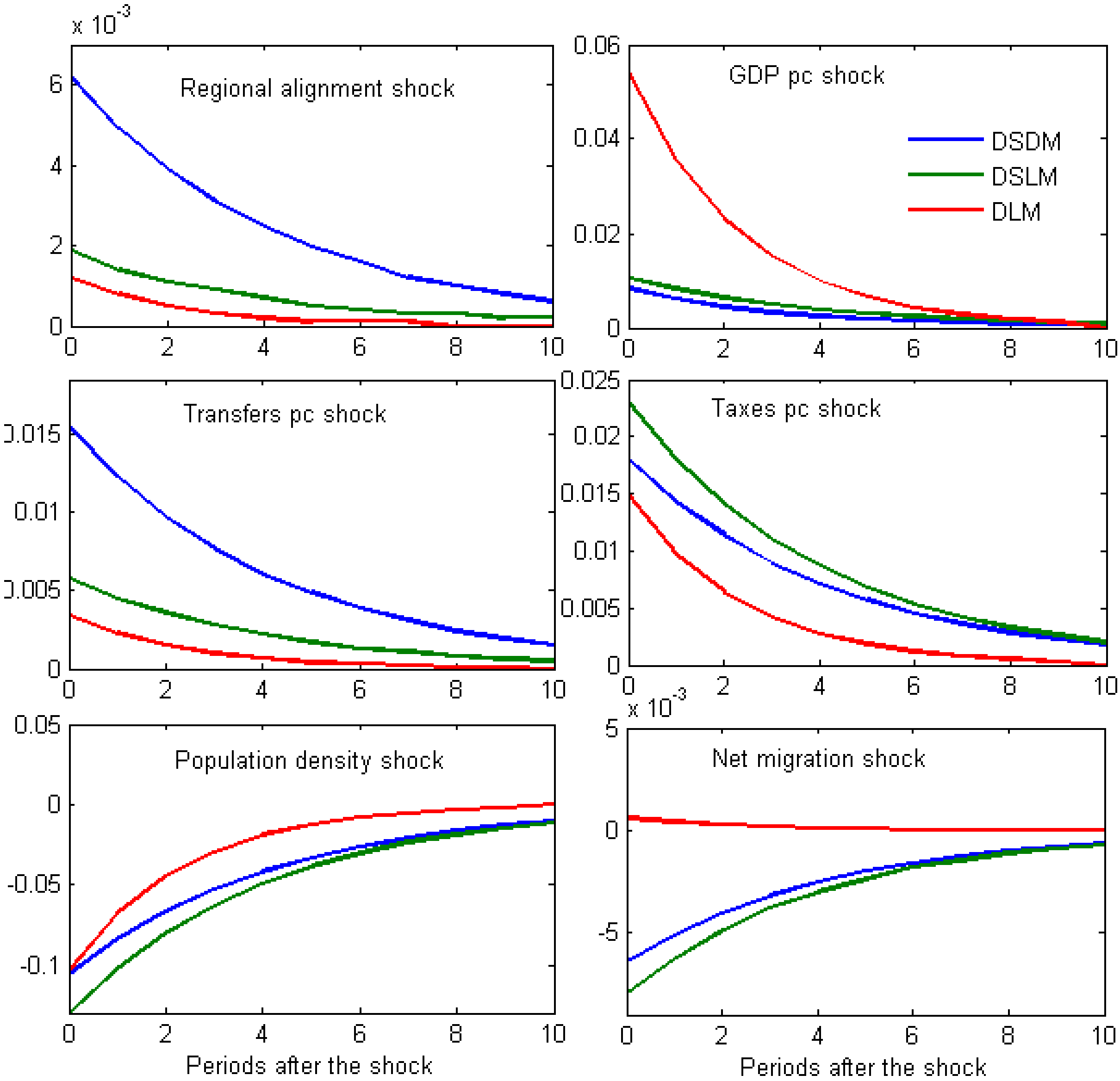


Figure 4.4: Accumulated Impulse Responses.

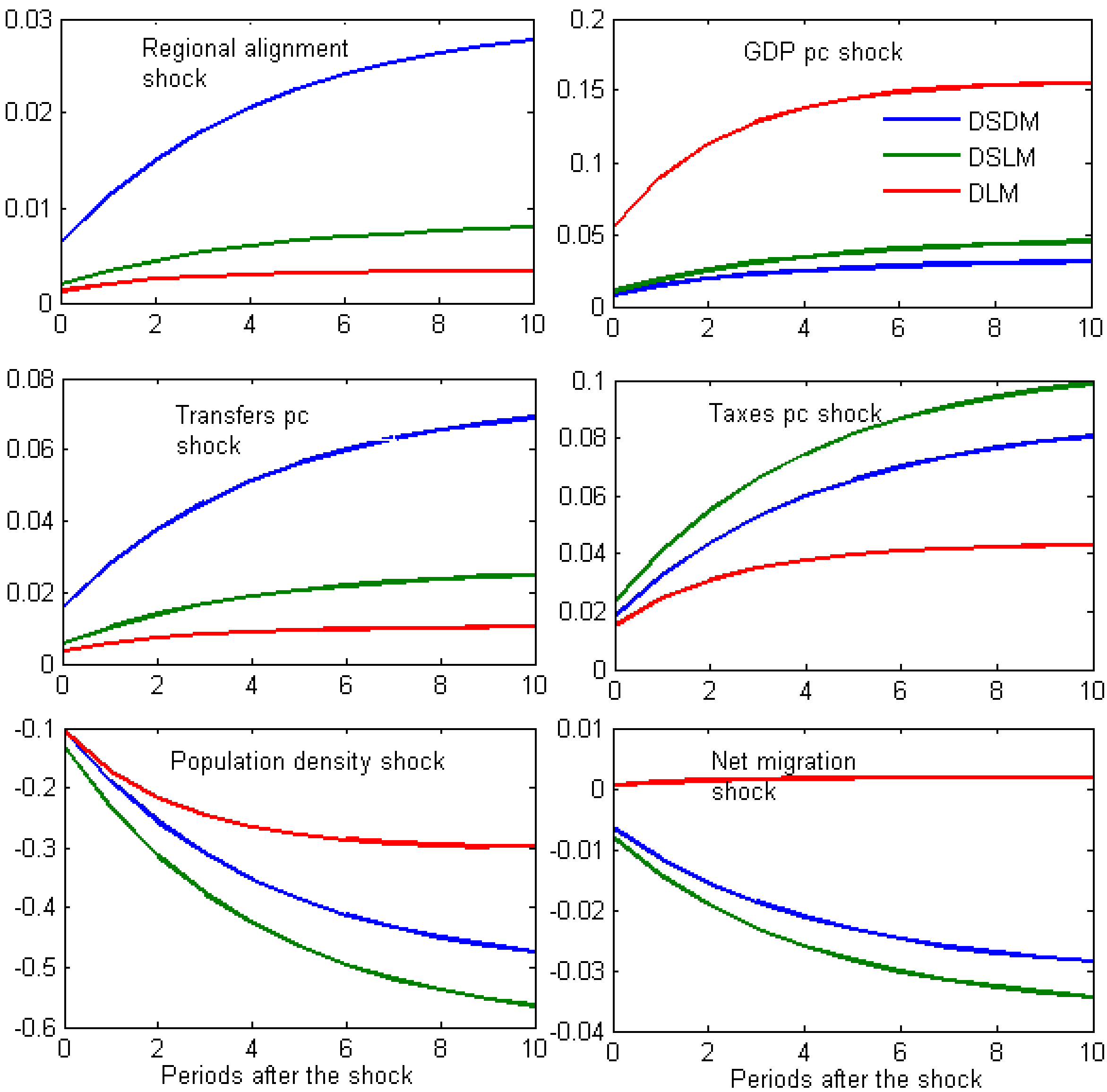


Table 4.6: Long Run Effects.

	Direct Effect	Indirect Effect	Total Effect
A. Political Factors			
Political Power	0.018	-0.062	-0.044
Ideology	-0.001	-0.004	-0.005
Nat Alignment	-0.009***	-0.003	-0.012
Reg Alignment	0.006	0.030*	0.036*
B. Economic Factors			
log GDP pc	0.037***	-0.004	0.033*
Unemployment	-0.011	-0.011	-0.023
log Tax pc	0.021***	0.069**	0.090***
log Transfers pc	0.086***	0.066***	0.152***
C. Demographic Factors			
Population density	-0.521***	-0.398*	-0.918***
Net Migration	-0.0296***	-0.0232***	-0.0528***
Population > 65	0.004	0.007	0.012

Notes:*Significant at 10% level, ** significant at 5% level, *** significant at 1% level. Inferences regarding the statistical significance of these effects are based on the variation of 1000 simulated parameter combinations drawn from the variance-covariance matrix implied by the BCQML estimates.

4.6.2 Relative Importance Analysis

Previous estimates inform us about the sign and significance of the relationship between the different covariates and the level of government per capita spending. Nevertheless, when the exogenous regressors are correlated among themselves, simulated effects may not accurately adress the relative contributions of the regressors driving government spending disparities. As one of the aims of this study is to explore the relative importance of the various factors explaining government spending, the relative contribution of the various factors is calculated with the LMG method (Lindeman *et al.*, 1980; Groemping, 2007). This metric performs a R^2 decomposition by averaging the marginal contributions of independent variables over all orderings of variables and using sequential sums of squares from the linear model, the size of which depends on the order of the regressors in the model.[7] GENIZI and CAR measures (Genizi, 1993; Zuber and Strimmer, 2010, 2011) are also employed to assess the robustness of the results. The R^2 decomposition results are shown in Table (4.7) below.

[7]This is a powerful technique that allows to take into account all the possible data generating causal schemes. This proposal has not found its way in econometric analysis for two main reasons. Firstly, its properties are not well understood and it is computationally challenging given that it requires the researcher to estimate 2^{p-1} models where p is the number of regressors. Given that all model orders with the same length can be summarized in one summand, the computational burden is reduced from $p!$ summands to 2^{p-1}. In this specific case where $p = 25$, 16.777.216 models are estimated.

As shown in Table (4.7), the different metrics generated similar results in the decomposition of the relative importance of the factors determining government spending. Therefore, in the discussion below the average of the different metrics is employed. First, it can be observed that the level of spending in the past year explains a 73.07% of the spending level in the present. This result reinforces contributions of political science, considering incrementalism as the most plausible hypothesis to explain municipal budget's evolution. In a second place, it is observed that spatial spillovers and spatio-temporal diffusion explain a 3.33 % and 1.58 % respectively. For its part, the set of controls explains 22.01% of government spending. This 22.01% can also be decomposed into own and neighbor's determinants relative importance. Specifically, 80.99% of government spending levels are associated to own municipal outcomes while only the 19.01% of the evolution of government spending is related to neighboring attributes.

Table 4.7: Model R^2 Decomposition.

Control Variable	Final Effect	Expected Effect	LMG (%)	CAR (%)	GEN (%)	Average (%)
Spatial Spillover	+	?	3.19	3.50	3.30	3.33
Time Lag	+	?	71.18	76.15	71.88	73.07
Space-Time Lag	-	?	1.88	0.90	1.957	1.58
Controls			23.74	19.44	22.862	22.01
X			78.37	86.05	78.58	81.00
WX			21.63	13.95	21.42	19.00
Total			100	100	100	100

Notes: The values correspond to percentage (%) contributions to $R^2 = 0.95$ of the fitted model of government spending.

Table (4.8) below shows that within the 22.01% of explanatory power related to the set of covariates, the group of economic factors explain 54.89% of government expenditure variability among Spanish municipalities during 2000-2012, while demographic factors explain 43.05%. Among these variables, the most relevant drivers of government spending are GDP per capita and the population density, explaining a 36.78% and 36.03% respectively. On a second level of importance, it is observed that the transfers received from upper tier government levels account for a 9.2% of government variability while taxes per capita account for a 6.7%. As observed above, the set of political variables do not seem to be a relevant driver of aggregate government spending in Spanish municipalities given that they do not explain more than a 2% of government expenditure municipal disparities.

Table 4.8: Government Spending Drivers Decomposition.

	Final Effect	Expected Effect	LMG (%)	CAR (%)	GEN (%)	Average (%)
A. Political Factors			2.04	1.89	2.25	2.06
Political Power	NS	?	1.12	1.03	1.21	1.12
Ideology	NS	-	0.04	0.02	0.052	0.04
Reg. Alignment	NS	?	0.70	0.66	0.80	0.72
Nat. Alignment	+	?	0.156	0.17	0.18	0.17
B. Economic Factors			54.84	54.99	54.83	54.89
log GDP pc	+	+	37.87	36.85	35.63	36.78
Unemployment	NS	?	1.95	2.21	2.21	2.12
log Tax pc	+	+	6.39	5.93	7.79	6.71
log Transfers pc	+	+	8.62	9.99	9.18	9.26
C. Demographic Factors			43.11	43.11	42.90	43.04
log Pop density	-	-	35.77	37.55	34.67	36.03
Net Migration	-	?	5.40	5.05	6.37	5.60
Population > 65	NS	?	1.94	0.49	1.86	1.43

Notes: The values denote the percentage (%) of the contributions to the R^2 implied by the set of controls.

4.6.3 Spillovers Effects by Functional Category

The results reported above are based on analysis of a sample of 1,230 municipalities, using total per capita expenditure as the dependent variable. In this section, as a further test for the presence of spatial spillovers in public spending, the previous exercise is carried out for different population sizes and different functional categories. Specifically, two additional samples including municipalities with populations over 10,000 inhabitants and 20,000 are considered. Therefore, the model selection for the W matrix and the fixed and time effects specification is performed for each of the population samples and spending categories. Table (4.9) below shows the optimal W for the different population thresholds. As observed, the optimal spatial connectivity structures are dependent on the various functional categories and samples of municipalities.

Employing the set of optimal spatial weight matrixes obtained above and re-estimating the model for a variety of public spending functionalities and test the existence of spatial spillovers among neighboring municipalities yields the results reported in the Table (4.10) below.

As shown in Table (4.10), for the sample including all municipalities with population above 5,000 inhabitants there is robust evidence on the existence of simultaneous significant and positive spillover in all the spending items considered. Overall, these findings support previous evidence in Bastida *et al.* (2013), who also find positive and significant spillovers for the various

Table 4.9: Optimal W by Spending Category.

Type of Spending	Population $> 5K$	Population $> 10K$	Population $> 20K$
Total	$W_{ij} = W(KNN = 4)$	$W_{ij} = exp\,(-0.03d_{ij})$	$W_{ij} = exp\,(-0.03d_{ij})$
Education	$W_{ij} = exp\,(-0.015d_{ij})$	$W_{ij} = exp\,(-0.02d_{ij})$	Cut-off 250 km
Culture	$W_{ij} = exp\,(-0.02d_{ij})$	$W_{ij} = exp\,(-0.02d_{ij})$	$W_{ij} = 1/d_{ij}^{1.5}$
Water	$W_{ij} = exp\,(-0.03d_{ij})$	$W_{ij} = exp\,(-0.005d_{ij})$	$W_{ij} = exp\,(-0.03d_{ij})$
Security	$W_{ij} = W(KNN = 10)$	$W_{ij} = W(KNN = 10)$	$W_{ij} = W(KNN = 8)$
Housing	$W_{ij} = exp\,(-0.015d_{ij})$	$W_{ij} = exp\,(-0.015d_{ij})$	Cut off 75 km
Residuals	$W_{ij} = W(KNN = 10)$	$W_{ij} = 1/d_{ij}^{1.5}$	$W_{ij} = 1/d_{ij}^{1.25}$

Notes:These results correspond to the specification of the DSDM with spatial and time-period fixed effects. $W_{ij} = W(KNN)$ denotes k-nearest neighbors matrices.

Table 4.10: Spillover Strength by Municipality and Spending Category.

	Population > 5.000		Population > 10.000		Population > 20.000	
Spillover	ρ	η	ρ	η	ρ	η
Total	0.108***	-0.029**	0.299***	-0.126***	0.049***	-0.048***
Education	0.332***	-0.241***	0.230***	-0.173***	0.183***	-0.165***
Culture	0.356***	-0.384***	0.295***	-0.203***	0.143***	-0.200***
Water	0.216**	-0.004	0.006	-0.018	0.039	-0.107**
Security	0.073***	-0.037*	0.100***	0.002	0.032	0.043
Housing	0.501***	-0.495***	0.325***	-0.357***	0.096***	-0.127***
Residuals	0.043**	0.044**	0.014	0.056***	0.006	0.069

Notes: *Significant at 10% level, ** significant at 5% level, *** significant at 1% level. The results are obtained using the optimal W matrix for each population sample and spending functionality spending categories in their exercise. Nevertheless, two novel results stemming from this analysis are that *(i)* the intensity of government spending spillovers of this study are higher than in Bastida *et al.* (2013) and that *(ii)* the effect of an increase in spending in $t-1$ in a municipality j, causes a decrease in spending on t in the municipality i.

Importantly, when looking at the sample with municipalities above 10,000 inhabitants it is observed that in most cases simultaneous positive spillovers exist. The only exceptions are found in the case of spending in solid waste residuals and water. Finally, in the sample of municipalities with population sizes above 20,000 only education, culture and housing categories generate significant spatial spillovers. In the water provision, residue disposal and public safety categories, the spillover effects are no longer statistically significant. This result could be due to the higher degree of joint provision and outsourcing of these services vs others.

Finally, previous results allow for a comparison with similar studies performed in other countries. This should be undertaken with caution, however, as there are significant differences in the structural characteristics and provisional responsibilities at local level, and in the classification of expenditures. The evidence for the effect of local expenditure in culture is somewhat mixed. While Lundberg (2006) and Akai and Suhara (2013) find a negative spatial relationship in Sweden and Japan, Werck *et al.* (2008) and Stastna (2009) find a positive effect of expenditures for Belgium and the Czech Republic. Therefore, the sign of the empirical results on cultural expenditure spillovers in Spain is in line with the findings of the two latter studies. Other authors such as Case *et al.* (1993) and Ermini and Santolini (2007, 2010) find the effect of spending in education generates positive spillovers in the US and insignificant effects in Italy, respectively. Therefore the evidence obtained on the behavior of educational spending is similar to that of the US. The other category for which comparisons can be made, is that of the security expenditures. At this regard, Ermini and Santolini (2007, 2010) find a negative spillover, while Hanes (2002) finds a positive spillover effect. Thus, the pattern of local interaction effects in public safety spending for Spain resembles that reported for Italy.

4.7 Conclusions

This paper has examined the empirical effect of political, economic and demographic factors in local government expenditure. This issue is analyzed in a sample of 1,230 Spanish municipalities with population over 5,000 in the period 2000-2012. The analysis relies on the estimation of a dynamic spatial panel data model using recently developed spatial econometric techniques that take into account the relevance of spatial and time effects in budgetary processes.

The results obtained in this analysis support political science contributions such as the incremental hypothesis as it is observed that temporal inertia is the key driver of budget processes. This result suggest that previous contributions on the literature of local governments interactions in Spain that omitted serial dynamic effects suffer from miss-specification and the estimated coefficients may be biased. Specifically, time lags explain a 73% of government spending variability among municipalities. However, another finding is that of positive and significant spillovers in total government spending per capita, although its relative relevance, about 3.3%, is considerably lower when compared to that of the time inertia. Given that the slope of the reaction function of government spending when neighboring jurisdictions change its spending is positive, it is possible to conjecture that this effect may be due to the existing complementarities in local public good provision.

Among the set of regressors included in the model to explain the evolution of government spending it is found that political factors are not relevant as they do not explain more than a 0.44% of government spending variability. On the other hand, economic and demographic factors explain a 12.07% and 9.46% of government spending respectively. In particular, the most relevant variables explaining spending disparities are the GDP and the population density. GDP explains 8.01% while population density explains a 7.92%. Finally, in order to test the robustness of the results, other functional categories and different type of municipalities are considered. The empirical findings suggest there are strong positive spatial spillovers in water and housing public provision. These are relatively stronger when compared to other categories such as security or waste management.

The results of this paper pose some policy implications. First, the positive estimated effect of taxes and grants suggests that with greater financial capacity local governments can play a more active role in financing local public good provision, thereby acting as agents of socio-economic development. Second, the estimated positive spatial spending spillover suggests that local governments tend to increase by 10.8 euro cents their spending per capita in response to a rise of

1 euro in spending in neighboring municipalities. This result implies that local governments in Spain could rapidly engage in races to the top or bottom, increasing fiscal policy instability. Furthermore, the existence of positive spatial spillovers suggests that some form of fiscal policy coordination should be placed in order to internalize decentralized actions and minimize inefficiencies. Additionally, the fact that government spending reacts more strongly to upper-tier level government transfers than to equivalent local output increases, suggests that some degree of fiscal illusion exists in Spanish municipalities. If revenue sources are not completely transparent and are not fully perceived by taxpayers, then, the cost of local government spending is seen to be less expensive than it actually is, providing incentives to overspending. Although the share of local expenditure accounts for a small fraction in the overall national budget, this issue should not be overlooked. Thus, additional efforts on increasing transparency and accountability are needed to improve the functioning of local budgeting.

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Directions of Future Research

Given that the results and conclusions of the various studies carried out in this thesis are provided at the end of each chapter, this section reviews possible extensions of the work performed here. What follows, therefore, are some brief remarks on different possible lines for future research to address some of the current challenges in dynamic spatial panel modeling.

1. Spatial Heterogeneity and Apparent Contagion

One of the key implications of the work performed here is that spatial spillovers and contagion dynamics play a significant role in many economic circumstances. However, there is room for improvement in the proper identification of the size of spatial spillovers. A first challenge facing future research in the field of spatial econometrics is to find adequate means to separate spatial heterogeneity from spatial dependence. As Anselin (2010) points out, the task of establishing a distinction between true and apparent contagion is truly daunting. The essence of the problem is that, in many cases, spatial data allow the identification of clusters and patterns but often fail to provide sufficient information to identify the processes leading up to the observed patterns. As a result, it is sometimes impossible to distinguish between the case where the clusters just reflect structural parameter instability over space or constitute a true contagious process. This is because of spatial diffusion tends to yield positive spatial auto-correlation, but the reverse is not necessary.

A promising approach to solve this issue that requires investigation in future research, is the endogenous identification of the various spatial regimes and clusters in the economic data, which should precede any analysis involving spatial spillover effects. As suggested by Billé *et al.* (2015), geographically weighted regressions and locally iterative geographically weighted regressions could be used as diagnostic tools for the initial determination of whether a spatial unit belongs to a concrete cluster or spatial regime. Similarly, spatial filtering techniques (Getis and Griffith, 2002) and AMOEBA techniques (Alstadt and Gettis, 2006) may be helpful to isolate spatially heterogeneous components in the sample data.

The additional information on spatial regimes could help the researcher to split the apparent contagion into two parts: that due to the presence of spatial heterogeneity and that (which is true contagion) due to endogenous and exogenous interactions. This type of analysis would confer greater robustness to the results obtained in Chapter 1 and Chapter 2, by enabling consideration of the possible presence of structural breaks in space. In particular, it would help to confirm findings indicating that volatility spillovers reduce economic growth rates, and the interpretation of spillovers arising from technological capital, employment growth and infrastructures enhancing a virtuous cycle towards a knowledge-based-economy.

From a policy-making perspective, moreover, it might be interesting to investigate more thoroughly the heterogeneous effects of regional policy variables such as Structural Funds as a driver of RLI or economic growth rates. Instead of averaging over the $K \times N \times N$ dimensional matrices of direct, indirect and total effects, as throughout this thesis, exploration of heterogeneity of such effects will provide new insights on the efficiency of regional policy and the optimality Structural Funds allocation, because feedback effects are not the same across all regions. Therefore, the contagion dynamics for the rest of the system are potentially highly heterogeneous. This interesting issue needs further attention in applied research and policy design given that, by exploring effect heterogeneity, for instance, the researcher could find that providing funds to regions of medium development generating strong spillover effects towards low developed neighbors is more effective (in redistributive terms) than directly targeting less developed regions. In this regard, empirical research taking into account the existence of spillovers suggests that productivity growth of the targeted regions (Fiaschi *et al.*, 2011) has positively benefited from Structural Funds, but that the size of spillover effects is very small in peripheral and under-developed regions (Dall'erba and Le Gallo, 2008). However, to the best of our knowledge, only Le Gallo *et al.* (2005) have explored spatial diffusion heterogeneity. By following this strand of research, in principle, it could be possible to evaluate whether policies aimed at reducing spatial disparities should be based on spatial inequality criteria or spatial competitiveness, which is the dichotomy currently pervading EU regional policy design (Capello, 2015).

2. Identifying the sources of interactions in W

A second issue to further investigate is related to the form of dependence between sample units. Along this thesis, exogenous and non-time varying geographical distance matrices based on different functional forms are used to model the interaction between neighboring regions. However, space and geography are only one part of the interface that connects economic events. Indeed, space is more than geography and the issue of how something happening in spatial unit i at time t ends up affecting spatial unit j at time $t+n$ should be examined in terms of overall connectedness (Fiaschi and Parenti, 2015).

For a W matrix to capture the key channels of interactions that give rise to connectivity between sample units, it is worth taking a closer look at the performance of hybrid W matrices, containing a richer set of information based on a variety of distance measures. This is because interregional spillovers might be something more than a function of spatial proximity (Fingleton and Le Gallo, 2008). Corrado and Fingleton (2012) suggest to use relative economic distances (i.e, in an economic distance space, big towns and cities are less remote than their geographical separation would imply, whereas small locations are often isolated from one another). However, it would be even more realistic to analyze spillover process based on a combination of spatial distance, the intensity of trade relations, the de-synchronization of cyclical output phases, institutional and cultural or linguistic similarities. Interesting applications in this line are Eff Anthon (2008) and Plaigin (2009) among others. Nevertheless, this raises the issue of working with endogenous spatial matrices.

A possible way to overcome the potential endogeneity problem is to construct the global W matrix by averaging over matrices based on spatial distance s and other type distance matrices $z = 1, \ldots, Z$, the latter ones, including only information that is out of the sample period (i.e, at period $t = 0$) so that:

$$W = \begin{cases} w_{ij} = 0 \quad if \quad i = j \\ w_{ij} = \left[\phi_s \left(\frac{f(d_{ij}^s)}{\sum_j f(d_{ij}^s)} \right) \right] + \left[\sum_z \phi_z \left(\frac{g(d_{ij}^z)}{\sum_j g(d_{ij}^z)} \right) \right] \quad if \quad i \neq j \end{cases} \tag{4.23}$$

where f is a functional form of the geographical distance metric d_{ij}^s, g is a functional form of the other distance metrics d_{ij}^z, ϕ_s measures how much weight the researcher attributes to geography in the hybrid W matrix and ϕ_z measures is the weight assigned to each non-geographical matrix such that $\sum_z \phi_z + \phi_s = 1$.

Importantly, by proceeding in this way there is no need to consider the endogeneity of the various components W_z, as the use of start of period values minimizes feedbacks from other model variables ensuring the overall exogeneity of W. The alternative is to allow for endogenous and time varying W matrices. However, if a weighting matrix in a spatial model is endogenous, typical model specifications will no longer be appropriate. Similarly, regression parameter estimators which do not account for the endogeneity of the weighting matrix will typically be inconsistent. At this regard, interesting insights for future research are provided by Kelejian and Piras (2014) who suggest the employment of IV estimators, while Lee and Yu (2015) suggest the use of QML estimators if the W is time-varying but exogenous.

The specification of alternative W matrices may affect the findings of the spatial econometric analysis in this thesis. For example, as regards the forms of interaction between regional labor markets in Chapter 3 the use of alternative matrices other than geography can provide interesting information. In relation to the design of appropiate matrices to capture labor-market connectivity, some distance metrics appear to be promising for future research. An interesting option is to use matrices based on travel times between regions, which may better at capturing infrastructure connectivity impediments: road times and conditions, speed limits, mountainous areas, public transport schedules, etc (Vega and Elhorst, 2014). Nevertheless, the issue of travel times raises the question of what travel time to use, as it is dependent on the transportation mean under consideration (cars, trains, ships, airplanes). Additionally, it is not clear whether researchers should use averages of them if for instance, most of the commuting between two regions is based on a concrete mean of transport. However, the use of row-normalized weights implies that weights are interpreted as the fraction of all spatial influence on unit i attributable to unit

j. The use of relative time distances in the context of travel times makes comparisons is problematic. To see this, consider the following contiguity spatial scheme with units i, j and k:

$$W = \begin{pmatrix} 0 & w_{ij} & w_{ik} \\ w_{ji} & 0 & w_{jk} \\ w_{ki} & w_{kj} & 0 \end{pmatrix} = \begin{pmatrix} 0 & 20 & 60 \\ 20 & 0 & 70 \\ 60 & 70 & 0 \end{pmatrix}$$

The effect of row-normalization will yield:

$$W = \begin{pmatrix} 0 & 0.25 & 0.75 \\ 0.22 & 0 & 0.78 \\ 0.46 & 0.54 & 0 \end{pmatrix}$$

The resulting interaction scheme after row-normalization has the drawback of diluting the interpretation of time-distance decay, because of the time-distance effect of unit k on unit i, 0.75, is not the same as that of unit i on unit k, 0.46. A procedure that has not been explore in this thesis is that of max-eigenvalue normalizations, which provides a normalization with the advantages of (i) ensuring that the resulting spatial weights are all between 0 and 1 so that we can still interpret them as relative influence intensities while at the same time and (ii) preserving data relations between all rows. Nevertheless, it should be noted that this normalization approach has the shortcoming of not working well in the context of dynamic panels (Lee and Yu, 2010).

It might also be useful to explore the possibilities of alternative W matrices with a view to examining the sources of spatial interaction among municipalities, and thereby extend the conclusions obtained in Chapter 4. Two hypotheses could be tested as alternatives to that of the presence of spatial spillovers. One is the political yardstick-competition hypothesis, the other is the social interaction hypothesis. The key prediction of the yardstick-competition hypothesis is that weak local governments will have a stronger tendency to mimic the policies implemented by neighboring municipalities. In order to test for this possibility, and following the approach used by Elhorst and Freret (2009), it would be necessary to adjust the BC-QML estimator for dynamic spatial panels developed by Lee and Yu (2010) in order to accommodate two spatial regimes in the endogenous variable. However, an alternative relying on the development of hybrid W matrices would involve extending the notion of neighborhood to those municipalities that have similar degrees of concentration of political power. Alternatively, the social interaction hypothesis of Santolini (2009), which suggests that interactions are stronger if municipalities are governed by parties of the same ideology, could be explored in depth by constructing spatial weight matrices based on a mix of ideological and economic distances.

3. Spatial Panel Vector Auto-regressions

One frontier in applied spatial econometric models is that of the estimation of dynamic multivariate spatial systems where every variable might be endogenous and where bidirectional relationships of causality are the interesting point of the modeling exercise. Currently, the economic analysis is restricted to models with only one dependent variable, which precludes the researcher to model the wide set of endogenous interactions and transmission channels between variables that arise in many multivariate contexts. This issue is potentially relevant in the modeling of growth and labor markets where not only different variables affect to each other but also where changes in the variables of one region affect other regions variables. Thus, future research aiming at modeling dynamic multivariate spatial systems, beyond the context of dynamic spatial panels and implicit equations such as those employed for economic growth in Chapter 1 or unemployment in Chapter 3, should take into account the existence of endogenous and simultaneous relationships among the set of variables and regions and shift its attention to the context of a Spatial Panel Vector Autoregression models (SPVAR).

In the time-series literature, vector autoregression analysis (VAR), originally developed by Sims (1980), has been recently augmented to include panel data VAR models (PVAR) (Canova and Cicarelli, 2013; Koop and Korobilis, 2016). These studies explore growth spillovers and financial contagions but no structural analysis has been carried out yet, because, in a multi-country/regional environment, such analysis would require specification of the way in which pulses propagate not only across variables, but also across spatial units. Indeed, to date, no structural multi-country/region analysis of labor market shock diffusion has been undertaken, and there are also few studies of non-structural SPVARs. Mutl (2009) explores the estimation of SPVAR-SEM processes; Beenstock and Felsenstein (2007) use a three-stage procedure to analyze Israel's regional housing sector; Di Giacinto (2011) uses ML to estimate the keynesian multiplier in Italian regions; and Mayor and Patuelli (2014) analyze deterioration in predictive ability as the forecast horizon increases. In Di Giacinto (2010) and Beenstock and Felsenstein (2007), estimation and identification issues are discussed. They demonstrate that the inclusion of spatially and temporally correlated disturbances is problematic because the structural parameters are not fully identified. Furthermore, another challenging issue when employing PVARs or SPVARs is the huge number of parameters and the low number of degrees of freedom.

As an example, in a very small PVAR model describing the labor market functioning with just 3 variables in a sample of 3 countries or regions and 2 lags (with no constant), the model already contains 182 parameters. Moreover, the use of recursive structural shock identification schemes typically employed in time-series, might not be enough to disentangle the sources of regional labor market fluctuations as they impose unrealistic assumptions. This is because when using recursive identification schemes, the recursivity is applied not only to the variables (which is by itself problematic), but also to the spatial units. As shown below, this procedure will impose unrealistic patterns on the different variables of the various regions by implying that shocks 1, 2 and 3 of region 1 are transmitted to all variables of both region 2 and region 3 and that region 2 transmits shocks to all variables of region 3, whereas, shocks originated in region 3 are confined to its boundaries. This type of spatial causal chain is unidirectional and very difficult to justify in light of the bi-directionality of effects that prevails in the spatial econometrics literature.

To solve these challenges in multivariate space-time labor market or growth model, three elements are worth mentioning. The first one is the employment of a mix of zero and sign restrictions since it is the most promising line of research to identify labor market structural shocks with independence of whether the spatial context is considered or not in the PVAR. Zero and sign restrictions impose different types of information on the model. Zero restrictions specify that some variables are not affected by a shock, while sign restrictions incorporate information on how some macroeconomic indicators are expected

Recursive Identification S-PVAR

Variables	Shocks								
	$S_{1,1}$	$S_{2,1}$	$S_{3,1}$	$S_{1,2}$	$S_{2,2}$	$S_{3,2}$	$S_{1,3}$	$S_{2,3}$	$S_{3,3}$
$x_{1,1}$	x	0	0	0	0	0	0	0	0
$x_{2,1}$	x	x	0	0	0	0	0	0	0
$x_{3,1}$	x	x	x	0	0	0	0	0	0
$x_{1,2}$	x	x	x	x	0	0	0	0	0
$x_{2,2}$	x	x	x	x	x	0	0	0	0
$x_{3,2}$	x	x	x	x	x	x	0	0	0
$x_{1,3}$	x	x	x	x	x	x	x	0	0
$x_{2,3}$	x	x	x	x	x	x	x	x	0
$x_{3,3}$	x	x	x	x	x	x	x	x	x

Notes:"0" denotes a zero response of the variable to the shock while "x" means the response of the variable is left unrestricted. The shock $S_{i,j}$ stands for the shock i originated in region/country j On the other hand, $x_{h,k}$ denotes the effect of $S_{i,j}$ on variable h of region/country k.

to react to a structural disturbance (Rubio-Ramírez *et al.*, 2010). Until recently, the standard methodologies used for imposing such restrictions were difficult to implement simultaneously. Examples of early attempts to jointly implement zero and sign restrictions in the context of non spatial macro-econometrics are Mountford and Uhlig (2009), Baumeister and Benati (2010), Benati (2013). Binning (2013) and Arias *et al.* (2014) later developed algorithms combining sign and zero restrictions. Nevertheless, unlike previous methods and studies, the algorithm by Arias *et al.* (2014) has been proven to draw from the correct posterior of the structural parameters. An example of how to extend the core of the theoretical model presented in Chapter 3 including wages, migration, unemployment, participation rates and the demographic structure disentangling structural shocks from each other is shown below.

Zero and Sign Restrictions Labor Market VAR

Variables	Shocks				
	Labor Supply	Labor Demand	Migration	Wage Bargaining	Demographic Aging
Wages	-	+	x	+	x
Unemployment	+	-	x	+	x
Participation	+	+	x	x	x
Migration Rate	x	x	+	x	x
Population > 55	0	0	-	0	+

Notes: "+" denotes a positive response of the variable to the shock, while "-" denotes a negative response of the variable to the shock. Also "0" denotes a zero response of the variable to the shock, while "x" means the response of the variable is left unrestricted.

Second, the employment of variables expressed in relative rates (either with respect to the country or to the EU average) may substantially simplify the identification of shocks and propagation patterns in the case of S-SPVARs. This is because if, for example, a shock produces an increase in labor supply in a given region, it will also, in relative terms, reduce labor supply in other regions within the system. However, working with variables expressed in relative terms may not always be satisfactory. In many situations, the researcher may be interested in working directly with the original data values. In this case, the problem of specifying the way in which the shocks are transmitted from one spatial unit to another can be solved (i) by employing non-neighborhood zero restrictions if two spatial units are not neighbors and (ii) by leaving the propagation pattern among neighbors unidentified. Note that this approach goes in line with the spirit of the spatial priors for VAR models developed by LeSage and Krivelyova (2002). However, additional efforts in prior-shrinkage design to overcome the curse of over-parametrization are crucial and will become increasingly necessary as the number of parameters in SPVARs grows with the square of the product of spatial units and variables. This issue, moreover, requires careful handling, given that the employment of priors affects the identification performance through sign-restrictions (Baumeister and Hamilton, 2014).

In this line, the design of suitable space-time Granger tests extending the work of Hurlin (2004a,b) to determine causal relations in space and time might help to identify which variables should be left as exogenous controls, as this may have a considerable impact on the results stemming from variance decompositions exercises, counter-factual analysis, etc. which are the key sources from which policy conclusions can be derived.

4. Integrated Spatial Bayesian Model Averaging

A final and important issue that has not been considered yet in the context of spatial econometrics is that of taking into account the whole set of sources of uncertainty to perform inference. These sources of uncertainty are: (i) regressors (X), (ii) spatial weight matrices (W) and (iii) spatial spillover/functional forms (S). Along this thesis, Chapters 1, 2 and Chapter 4, explored the issue of model uncertainty with respect W. In Chapter 3, the issue was moved an step further by taking into account uncertainty with respect both,

W and S. On the other hand, studies of LeSage and Fisher (2008), Crespo-Cuaresma and Feldkircher (2013) and Crespo-Cuaresma *et al.* (2014) have previously performed Spatial Bayesian Model Averaging (SBMA) and explored the issue of model uncertainty with respect X and W. This shows the existence of an unfilled gap in order to take into account of uncertainty with respect the three different dimensions from which uncertainty emerges in a spatial context. The later two studies adapt the (MC^3) algorithm developed by Madigan and York (1995) and Fernandez, Ley and Steel (2001a, b) to the context of spatial models. Nevertheless, it is possible to add some additional Metropolis-Hasting steps in the MC^3 sampler in order to perform inference over the three dimensions of uncertainty. Pseudo-code for implementing a more general algorithm consists on the following steps:

[**Step 1**] Draw a initial set of regressors X, a W and a functional form s to form a model M. Compute $p\left(M|y, X, W, s\right)$ and define neighborhood of model $nbd\left(M|y, X, W, s\right)$ which consists in M itself and models with +/-1 regressors not included in it, holding fixed W and s

[**Step 2**] Compare M with an alternative $M' \in nbd\left(M\right)$ and reject M' if $\alpha = \frac{p(M'|y,X',W,s)}{p(M|y,X,W,s)} < 1$, otherwise, accept it.

[**Step 3**] Flip a three-faced coin and use the outcome 1 to 3 to determine the following changes in M:

if $[o = 1]$ Add an explanatory variable chosen at random from those not included in the model (birth step), $X' \mapsto X''_{+}$

if $[o = 2]$ Eliminate an explanatory variable chosen at random from those currently (death step) $X' \mapsto X''_{-}$

if $[o = 3]$ Eliminate one variable randomly and replaced it randomly from the set of variables not included (move step) $X' \mapsto X''$

[**Step 4**] Flip a two-faced coin and use the outcome 1 to 2 to determine the following changes in M:

if $[o = 1]$ Chose at random another $W' \neq W$, to form $M(y, X'', W', s$. Accept it if $\alpha = \frac{p(M|y,X'',W,s)}{p(M|y,X'',W',s)} > 1$

if $[o = 2]$ Stay with W

[Step 5] Flip a two-faced coin and use the outcome 1 to 2 to determine the following changes in M:

if $[o = 1]$ Chose at random another $s' \neq s$, to form $M(y, X'', W', s')$. Accept it $\alpha = \frac{p(M|y,X'',W,s')}{p(M|y,X'',W',s)} > 1$

if $[o = 2]$ Stay with s

[Step 6] Go back to Step 2 and repeat the process n times, with n very large.

Defining a spatial model as an object $M_i^{s,z}$ where $s = 1, \ldots, S$ is the number of spatial functional forms, $W_z = 1, \ldots, Z$ is the set of candidate W matrices and $i \in [1, 2^k]$ is the total number of possible combinations of regressors, employing the previous algorithm will allow to compute key bayesian inference metrics:

(i) The Posterior Mean

$$E(\beta|y, X) = \sum_{s=1}^{S} \sum_{z=1}^{Z} \sum_{i=1}^{2k} E(\beta_i | M_i^{s,z}, y, X)\, p(M_i^{s,z}|y, X) \tag{4.24}$$

(ii) The Posterior Variance

$$\begin{aligned} Var(\beta|y, X) = & \sum_{s=1}^{S} \sum_{z=1}^{Z} \sum_{i=1}^{2k} Var(\beta_i | M_i^{s,z}, y, X)\, p(M_i^{s,z}|y, X) + \\ & \sum_{s=1}^{S} \sum_{z=1}^{Z} \sum_{i=1}^{2k} \left(E(\beta_i | M_i^{s,z}, y, X) - E(\beta|y, X)\right)^2 p(M_i^{s,z}|y, X) \end{aligned} \tag{4.25}$$

(iii) Posterior Inclusion Probability

$$PIP = p(\beta_k \geq 0|y, X) = \sum_{s=1}^{S} \sum_{z=1}^{Z} \sum_{i=1}^{2k} p(\beta_{ik} | M_i^{s,z}, y, X)\, p(M_i|y, X) \tag{4.26}$$

This type of integrated spatial model averaging analysis is promising given that it can be applied to further extend our knowledge about issues where uncertainty on the regressors, interaction schemes or spillover processes is relatively high. This is the case of growth processes, unemployment disparities, the efficiency of local governments, urban inequalities, social conflicts or other research topics.

References Directions of Future Research

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Appendix A

Frequentist Spatial Panel Estimation

This appendix section presents the algorithmic procedures associated with the employment of the different estimators employed along this research.

Estimation of Static Spatial Panels

In Chapters 1 and 2, SDM, SDEM, SLM, SEM and SLX specifications including spatial fixed-effects and time-period fixed effects are estimated in order to analyze the relationship between volatility and growth. These specifications are nested in the General Nesting Spatial Model (GNSM):

$$
\begin{aligned}
Y_t =& \mu + \iota_n \alpha_t + \rho W Y_t + X_t \beta_1 + W X_t \beta_2 + \epsilon_t \\
\epsilon_t =& \lambda W \epsilon_t + \upsilon_t
\end{aligned}
\tag{A.1}
$$

where Y_t denotes a $n \times 1$ vector consisting of observations for dependent variable of each spatial unit $i = 1, \dots, n$ at a particular point in time $t = 1, \dots, T$, X_t and WX_t are $n \times K$ matrix of own and neighbors exogenous covariates with associated β_1 and β_2 response parameters contained in $K \times 1$ vectors that are assumed to influence the dependent variable. $\upsilon_t = (\upsilon_{1t}, \dots, \upsilon_{nT})^{'}$ is a vector of i.i.d disturbances whose elements have zero mean and finite variance σ^2. The variable WY_t denote contemporaneous endogenous interaction effects among the dependent variable while $W\epsilon_t$ denotes spatially correlated disturbances. The parameter ρ is called the spatial autoregressive coefficient while λ is the spatial error diffusion parameter. W is a $n \times n$ matrix of known constants describing the spatial arrangement of the spatial units in the sample. $\mu = (\mu_1, \dots, \mu_N)^{'}$ is a vector with individual fixed effects, $\alpha_t = (\alpha_1, \dots, \alpha_T)^{'}$ denotes time specific effects and ι_n is a $n \times 1$ vector of ones.

Equation (A.1) converges to the various specifications employed in Chapters 1 and 2 depending on the restrictions imposed over the different parameters of the SAC model. In particular, it converges to a SDM specification if $\lambda = 0$ to a SLX specification if $\rho = \lambda = 0$ and to SLM specification if $\lambda = 0$ and $\beta_2 = 0$, to a SDEM specification if $\rho = 0$ and finally, to a SEM specification if $\rho = 0$ and $\beta_2 = 0$.

As noted by Lee and Yu (2010a), estimation of spatial panel data models with individual effects is likely to suffer from the incidental parameter problem when the time dimension is fixed because of the introduction of fixed effects increases the number of parameters. They conclude that direct maximum likelihood optimization will yield bias parameter estimates and using asymptotic theory they analytically derive the size of these biases. If the model contains spatial fixed effects (μ), but not time-period fixed effects (α_t), the parameter estimate of σ^2 will be biased if n is large and T is fixed. If the model contains spatial fixed effects (μ) and time-period fixed effects (α_t) all the parameter estimates will be biased if n is large and T is large. By contrast if T is fixed, the time-period effects can be regarded as a finite number of additional regression coefficients similar to the role of the parameter β. As a solution to this problem and in order to estimate previous static spatial panels consistently, Lee and Yu (2010a) propose to apply a bias correction procedure to the direct maximum likelihood estimation of the model. As an alternative estimation method, they propose to apply a data transformation procedure and establish the consistency and asymptotic distribution of the QML estimator of that approach.

The assumptions made for the maximum likelihood estimation of the spatial panels described above are:

A1. W is a $n \times n$ non-stochastic spatial weight matrix with zeros in the diagonal. This assumption helps the interpretation of the spatial effect as self influence shall be excluded in practice.

A2. The disturbances υ_t follow a normal distribution $\upsilon_t \sim N[0, \sigma^2]$ and $E|\upsilon_t^{4+\eta}| < \infty$ for some $\eta > 0$. This provides regularity conditions.

A3. $R(\rho) = I_n - \rho W$ and $D(\lambda) = I_n - \lambda W$ are invertible for all $\rho, \lambda \in P$ where P is a compact interval and ρ, λ fall in the interior of P.

A4. The elements of X are non-stochastic and bounded uniformly in n and T. Also the limit $\frac{1}{nT}\sum_{t=1}^{T} \tilde{X}_t' R(\rho)' D(\lambda) \tilde{X}_t$ exists and is non-singular.

A5. W is uniformly bounded (UB) in both row and column sums in absolute value. Also $R(\rho)^{-1}$ is UB. This assumption limits the spatial correlation to a manageable degree.

A6. n is large, and T can be finite or large.

As in Chapter 1 and Chapter 2, inferences are based on the SDM in what follows, the derivation of the estimator used to process the data will focus on this concrete spatial specification. Let $X = [x, Wx]$, let the vector of parameters of the SDM be $\zeta = [\rho, \beta_1, \beta_2]$ and $\eta = (\zeta, \sigma)$, then the direct approach for a SDM with just fixed effects, consists on the optimization of the following function:

$$\ln L(\eta, \mu) = \frac{nT}{2} \ln\left(2\pi\sigma^2\right) + T \ln|R(\rho)| - \frac{1}{2\sigma^2} \sum_{t=1}^{T} \tilde{\upsilon}_t'(\zeta, \mu)\, \tilde{\upsilon}_t(\zeta, \mu) \tag{A.2}$$

where $\upsilon_t'(\zeta, \mu) = R(\rho) Y_t - X_t\beta - \mu$. We can estimate directly μ and have the estimator of η via the concentrated log likelihood with μ concentrated out:

$$\ln L(\eta) = \frac{nT}{2} \ln\left(2\pi\sigma^2\right) + T \ln|R(\rho)| - \frac{1}{2\sigma^2} \sum_{t} \tilde{\upsilon}_t'(\zeta)\, \tilde{\upsilon}_t(\zeta) \tag{A.3}$$

where $\tilde{\upsilon}_t(\zeta) = R(\rho)\tilde{Y}_t - \tilde{X}_t\beta$ where $\tilde{Y}_t = Y_t - \bar{Y}_t$, $\bar{Y}_t = \frac{1}{T}\sum_t Y_t$ and $\tilde{X}_t = X_t - \bar{X}_t$ with $\bar{X}_t = \frac{1}{T}\sum_t X_t$ denote the time-demeaned endogenous and exogenous variables. The first order and second order derivatives of Equation (A.3) are given by:

$$\frac{\partial \ln L(\eta)}{\partial \eta} = \begin{bmatrix} \frac{1}{\sigma^2}\left[\sum_t \tilde{X}_t'\tilde{\upsilon}_t(\zeta)\right] \\ \frac{1}{\sigma^2}\left[\sum_t \left(W\tilde{Y}_t\right)' \tilde{\upsilon}_t(\zeta) - \sigma^2 trG_n(\rho)\right] \\ \frac{1}{2\sigma^4}\left[\sum_t \tilde{\upsilon}_t'(\zeta)\,\tilde{\upsilon}_t(\zeta) - n\sigma^2\right] \end{bmatrix} \tag{A.4}$$

and

$$\frac{\partial^2 \ln L(\eta)}{\partial\eta\partial\eta'} = -\begin{pmatrix} \frac{1}{\sigma^2}\left[\sum_t \tilde{X}_t'\tilde{X}_t\right] & * & * \\ \frac{1}{\sigma^2}\left[\sum_t \left(W\tilde{Y}_t\right)'\tilde{X}_t\right] & \frac{1}{\sigma^2}\left[\sum_t \left(W\tilde{Y}_t\right)'\left(W\tilde{Y}_t\right) + TtrG^2(\rho)\right] & * \\ \frac{1}{\sigma^4}\left[\sum_t \tilde{\upsilon}_t'(\zeta)\tilde{X}_t\right] & \frac{1}{\sigma^4}\left[\sum_t \left(W\tilde{Y}_t\right)'\tilde{\upsilon}_t(\zeta)\right] & 0 \end{pmatrix} - \begin{pmatrix} 0_{2k\times 2k} & 0_{2k\times 1} & 0_{2k\times 1} \\ 0_{1\times 2k} & 0 & 0 \\ 0_{1\times 2k} & 0 & -\frac{nT}{2\sigma^4} + \frac{1}{\sigma^6}\sum_t \tilde{\upsilon}_t'(\zeta)\,\tilde{\upsilon}_t(\zeta) \end{pmatrix} \tag{A.5}$$

where $G(\rho) = WR(\rho)^{-1}$ and tr denotes the trace of a matrix. The parameter estimates obtained optimizing Equation (A.3) are given by:

$$\hat{\beta}(\rho) = \left[\sum_t \tilde{X}_t' \tilde{X}_t\right]^{-1} \left[\sum_t \tilde{X}_t' R(\rho) \tilde{Y}_t\right] \tag{A.6}$$

and

$$\hat{\sigma^2}(\rho) = \frac{1}{nT} \left[\sum_t R(\rho) \tilde{Y}_t - \tilde{X}_t \beta(\rho)\right]' \left[\sum_t R(\rho) \tilde{Y}_t - \tilde{X}_t \beta(\rho) \tilde{Y}_t\right] \tag{A.7}$$

Note that, operationally, it is first necessary to obtain ρ. This is accomplished by recursively running the following OLS regressions to get estimates of $\tilde{\upsilon}_{o,t}$ and $\tilde{\upsilon}_{l,t}$:

$$\begin{aligned} \tilde{Y}_t &= \tilde{X}_t \beta_o + \tilde{\upsilon}_{o,t} \\ W\tilde{Y}_t &= \tilde{X}_t \beta_l + \tilde{\upsilon}_{l,t} \end{aligned} \tag{A.8}$$

Then, one can compute the maximum likelihood estimate of ρ optimizing the concentrated likelihood of Equation (A.9) feeded with the estimates of $\tilde{\upsilon}_{o,t}$ and $\tilde{\upsilon}_{l,t}$.

$$\ln L = C - \frac{nT}{2} \ln \left[\sum_t (\tilde{\upsilon}_{o,t} - \tilde{\upsilon}_{l,t})' (\tilde{\upsilon}_{o,t} - \tilde{\upsilon}_{l,t})\right] + T \ln |R(\rho)| \tag{A.9}$$

which is equivalent to the following expression:

$$\ln L = C - \frac{nT}{2} \ln [(S(\rho))] + T \ln |R(\rho)| \tag{A.10}$$

where C is a constant not depending on ρ and $S(\rho) = \sum_t \frac{\upsilon_{o,t}' \upsilon_{o,t} - 2\rho \upsilon_{o,t} \upsilon_{l,t} + \rho^2 \upsilon_{l,t}' \upsilon_{l,t}}{nT}$. Unfortunately, this maximization problem can only be solved numerically, since a closed-form solution for ρ does not exist. However, since the log-likelihood function of Equation (A.10) is concave in ρ the solution is unique. For the models with just fixed effects, the only parameter that is biased is σ. In order to correct for this bias, the correction just requires to apply the factor $\frac{T}{T-1}$ to the original estimate such that:

$$\sigma_{bc}^2 = \hat{\sigma}^2 \frac{T}{T-1} \tag{A.11}$$

Conversely, for static spatial panels including only time-period effects the parameter estimate of $\hat{\sigma}^2$ obtained by the direct approach can be corrected by:

$$\sigma_{bc}^2 = \hat{\sigma}^2 \frac{n}{n-1} \tag{A.12}$$

For static spatial panels including both spatial fixed and time-period effects the direct approach also requires a bias correction procedure. The log likelihood function with both μ and α_t concentrated out is:

$$\ln L(\eta) = \frac{nT}{2} \ln\left(2\pi\sigma^2\right) + T \ln|R(\rho)| - \frac{1}{2\sigma^2} \sum_t \tilde{\upsilon}_t'(\zeta) J_n \tilde{\upsilon}_t(\zeta) \tag{A.13}$$

where $\tilde{\upsilon}_t(\zeta) = R(\rho)\tilde{Y}_t - \tilde{X}_t\beta$, $\beta = [\beta_1, \beta_2]$ and $J_n = I_n - \frac{1}{n}\iota_n\iota_n'$ is the deviation from the group mean transformation over spatial units. The first and second order derivatives are given by:

$$\frac{\partial \ln L(\eta)}{\partial \eta} = \begin{bmatrix} \frac{1}{\sigma^2}\left[\sum_t \tilde{X}_t{}' J_n \tilde{\upsilon}_t(\zeta)\right] \\ \frac{1}{\sigma^2}\left[\sum_t \left(W\tilde{Y}\right)' J_n \tilde{\upsilon}_t(\zeta) - TtrG(\rho)\right] \\ \frac{1}{2\sigma^4}\left[\sum_t \tilde{\upsilon}_t'(\zeta) J_n \tilde{\upsilon}_t(\zeta) - n\sigma^2\right] \end{bmatrix} \tag{A.14}$$

and

$$-\frac{\partial^2 \ln L(\eta)}{\partial\eta\partial\eta'} =$$

$$\begin{pmatrix} \frac{1}{\sigma^2}\left[\sum_t \tilde{X}_t' J_n \tilde{X}_t\right] & * & * \\ \frac{1}{\sigma^2}\left[\sum_t \left(W\tilde{Y}_t\right)' J_n \tilde{X}_t\right] & \frac{1}{\sigma^2}\left[\sum_t \left(W\tilde{Y}_t\right)' J_n \left(W\tilde{Y}_t\right) + (T-1)\, tr\left(J_n G^2(\rho)\right)\right] & * \\ \frac{1}{\sigma^4}\left[\sum_t \tilde{\upsilon}_t'(\zeta) J_n \tilde{X}_t\right] & \frac{1}{\sigma^4}\left[\sum_t \left(W\tilde{Y}_t\right)' J_n \tilde{\upsilon}_t'(\zeta)\right] & 0 \end{pmatrix} \tag{A.15}$$

$$+ \begin{pmatrix} 0_{2k\times 2k} & 0_{2k\times 1} & 0_{2k\times 1} \\ 0_{1\times 2k} & 0 & 0 \\ 0_{1\times 2k} & 0 & -\frac{nT}{2\sigma^4} + \frac{1}{\sigma^6}\sum_t \tilde{\upsilon}_t(\zeta) J_n \tilde{\upsilon}_t(\zeta) \end{pmatrix}$$

The parameter estimates obtained optimizing Equation (A.13) are given by:

$$\hat{\beta}(\rho) = \left[\sum_t \tilde{X}_t' J_n \tilde{X}_t\right]^{-1} \left[\sum_t \tilde{X}_t J_n' R(\rho) \tilde{Y}_t\right] \tag{A.16}$$

and

$$\hat{\sigma^2}(\rho) = \frac{1}{nT}\left[\sum_t R(\rho)\tilde{Y}_t - \tilde{X}_t\beta(\rho)\right]' J_n \left[\sum_t R(\rho)\tilde{Y}_t - \tilde{X}_t\beta(\rho)\right] \tag{A.17}$$

As in the previous case with just spatial fixed effects, numerical procedures are employed to obtain the maximum likelihood estimate of ρ. In particular, the quick procedure developed by Pace and Barry (1997) to exploit sparsity of the W matrix is used. This approach consists on evaluating the log-likelihood using a $q \times 1$ vector of values for ρ in the interval $[\rho_{min}, \rho_{max}]$ such that:

$$\begin{pmatrix} \ln L(\rho_1) \\ \ln L(\rho_1) \\ \dots \\ \ln L(\rho_q) \end{pmatrix} = \kappa + T \begin{pmatrix} \ln |R(\rho_1)| \\ \ln |R(\rho_2)| \\ \vdots \\ \ln |R(\rho_q)| \end{pmatrix} - \left(\frac{nT}{2}\right) \begin{pmatrix} \ln(S(\rho_1)) \\ \ln(S(\rho_2)) \\ \vdots \\ \ln(S(\rho_q)) \end{pmatrix} \tag{A.18}$$

Note that given a sufficiently fine grid of q values for the log-likelihood, interpolation can supply intervening points to any desired accuracy. Usually, the interval $[\rho_{min}, \rho_{max}]$ is [-1,1].

Finally, the bias correction applied to the direct ML estimates of the SDM with both spatial fixed and time-period fixed effects takes the following form:

$$\begin{pmatrix} \beta_{1,bc} \\ \beta_{2,bc} \\ \rho_{bc} \\ \sigma_{bc} \end{pmatrix} = \begin{pmatrix} 1_K \\ 1_K \\ 1 \\ \frac{T}{T-1} \end{pmatrix} \circ \begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\rho} \\ \hat{\sigma} \end{pmatrix} \left(-\frac{1}{n}\right) \left(-\frac{1}{nT}\frac{\partial^2 \ln L(\eta)}{\partial\eta\partial\eta'}\right)^{-1} \begin{pmatrix} 0_k \\ 0_k \\ \frac{1}{1-\hat{\rho}} \\ \frac{1}{2\hat{\sigma}^2} \end{pmatrix} \tag{A.19}$$

Estimation of Dynamic Spatial Panels

In Chapters 3 and 4 Dynamic Spatial Durbin Model (DSDM) specification with both fixed and time effects are estimated employing the Bias-Corrected Quasi-Maximum Likelihood (BCQML) estimator developed by Lee and Yu (2010b). The model reads as:

$$Y_t = \mu + \iota_n \alpha_t + \tau Y_{t-1} + \rho W Y_t + \eta W Y_{t-1} + X_t \beta + W X_t \theta + \upsilon_t \tag{A.20}$$

The assumptions made for the estimation of the dynamic spatial panel above are:

A1. W is a $n \times n$ non-stochastic spatial weight matrix with zeros in the diagonal. This assumption helps the interpretation of the spatial effect as self influence shall be excluded in practice.

A2. The disturbances υ_t are i.i.d across i an with zero mean and variance σ^2, and $E|\upsilon_t^{4+\eta}| < \infty$ for some $\eta > 0$. This provides regularity conditions.

A3. $R(\rho)$ is invertible for all $\rho \in P$ where P is a compact interval and ρ falls in the interior of P.

A4. The elements of X are non-stochastic and bounded uniformly in n and T. Also the limit $\frac{1}{nT}\sum_{t=1}^{T} \tilde{X}_t' R' R \tilde{X}_t$ exists and is non-singular.

A5. W is uniformly bounded (UB) in both row and column sums in absolute value. Also $R(\rho)^{-1}$ is UB. This assumption limits the spatial correlation to a manageable degree.

A6. $\sum_{h=1}^{\infty} abs\left(A_n^h\right)$ is UB where $abs\left(A_n\right)_{ij} = |A_{n,ij}|$ where $A = \left(I_n - \rho W\right)^{-1}\left(\tau I_n + \eta W\right)$. This assumption rules out the case of space-time co-integration.

A7. n is a non-decreasing function of T and T goes to infinity.

One way to estimate Equation (A.20) is to directly estimate all the parameters including the time effects and individual effects in the model which will yield a bias of the order $O\left(max\left(n^{-1}, T^{-1}\right)\right)$ for the common parameters that can be corrected with a bias-correction procedure. However, in this research the transformed approach which consists on a transformation of the data that eliminates the time-period fixed effects in order to avoid the bias $O\left(n^{-1}\right)$ is used. Recall the definition of the deviation from the individual mean transformation where $J_n = I_n - \frac{1}{n}\iota_n\iota_n'$ and $W\iota_n = \iota_n$ so that

$J_nW = J_nW\left(J_n + \frac{1}{n}\iota_n\iota_n'\right) = J_nWJ_n$ because $J_nW\iota_n = 0$. Hence we have:

$$J_nY_t = \tau\left(J_nY_{t-1}\right)+\rho\left(J_nW\right)\left(J_nY_t\right)+\eta\left(J_nW\right)\left(J_nY_{t-1}\right)+\left(J_nX_t\right)\beta_1'+\left(J_nW\right)\left(J_nX_t\right)\beta_2'+\left(J_n\mu\right)+\left(J_n\upsilon_t\right) \tag{A.21}$$

which does not involve the time effects α_t and the term $J_n\mu$ can be regarded as the transformed individual effects. Thus, we can estimate $\theta = (\tau, \eta, \beta, \rho, \sigma)$, $\beta = (\beta_1, \beta_2)$ and $J_n\mu$ basing on the transformed equation where relevant variables are pre-multiplied by J_n. A special feature of the transformed Equation (A.21) is that the variance matrix of $J_n\upsilon_t$ is equal to $\sigma^2 J_n$ so that the elements of $J_n\upsilon_t$ are correlated. Also, J_n is singular with rank $(n-1)$ as J_n is an orthogonal projector with trace $(n-1)$. Hence, there is linear dependence among the elements of $J_n\upsilon_t$. An effective procedure to estimate the model requires to eliminate such dependence. As proposed by Lee and Yu (2010b) this can be done with the eigenvalues and eigenvectors decomposition of J_n . Let $\left[F_{n,n-1}, \frac{\iota_n}{\sqrt{n}}\right]$ be the orthonormal matrix of eigenvectors of J_n where $F_{n,n-1}$ is the matrix of eigenvalues of ones and $\frac{\iota_n}{\sqrt{n}}$ corresponds to the eigenvalue zero. The transformation of J_nY_t to $Y_t^* = F_{n,n-1}J_nY_t$ is of dimension $n-1$ gives:

$$Y_t^* = \rho W^* Y_t^* + \tau Y_{t-1}^* + \eta W^* Y_{jt-1}^* + X_t^*\beta_1 + \beta_2 W^* X_t^* + +\mu_i^* + \upsilon_t^* \tag{A.22}$$

where $W^* = F_{n,n-1}'WF_{n,n-1}$, $Y_t^* = F_{n,n-1}J_nY_t = F_{n,n-1}'Y_t$, $X_t^* = F_{n,n-1}X_t$, $X_t^* = F_{n,n-1}X_{jt}$, $\mu^* = F_{n,n-1}'J_n\mu = F_{n,n-1}'\mu$ and $\upsilon_t^* = F_{n,n-1}'\upsilon_t$ is an $n-1$ dimensional disturbance with zero mean an variance matrix $\sigma^2 I_{n-1}$. The log-likelihood function of Equation (A.22) is given by:

$$\ln L\left(\theta, \mu*\right) = -\frac{(n-1)\,T}{2}\ln 2\pi - \frac{(n-1)\,T}{2}\ln\sigma^2 - T\ln|I_{(n-1)} - \rho W^*| - \frac{1}{2\sigma^2}\sum_t \ln\left(\upsilon_t^{*'}\left(\theta\right)\upsilon_t^*\left(\theta\right)\right) \tag{A.23}$$

where $\upsilon_t^{*'}\left(\theta\right) = \left(I_{(n-1)} - \rho W^*\right)Y_t^* - \delta Z_t^* - \mu^*$, $Z_t^* = \left[Y_{t-1}^*, W^*Y_{t-1}^*, X_t^*, W^*X_t^*\right]$ and $\delta = (\tau, \eta, \beta)$. Notice that $|I_{n-1} - \rho W^*| = \frac{1}{1-\rho}|I_n - \rho W|$ and that $\upsilon_t^{*'}\left(\theta\right) = \left(I_{(n-1)} - \rho W^*\right)Y_t^* - \delta Z_t^* - \mu^*$ can be expressed as:

$$\begin{aligned} \upsilon_t^{*'}\left(\theta\right) = &\quad \left(I_{(n-1)} - \rho W^*\right)Y_t^* - \delta Z_t^* - \mu^* \\ &= F_{n,n-1}'\left(I_n - \rho W\right)Y_t - \delta Z_t - \mu \end{aligned} \tag{A.24}$$

because $F'_{n,n-1}W\iota n = F'_{n,n-1}\iota_n = 0$. Thus, taking into account that $F'_{n,n-1}F_{n,n-1} = J_n$ we can express the variance of the disturbances as:

$$\upsilon_t^{*\prime}(\theta)\,\upsilon_t^{*}(\theta) = \left[(I_n - \rho W)\,Y_t - \delta Z_t - \mu\right]' J_n \left[(I_n - \rho W)\,Y_t - \delta Z_t - \mu\right] \tag{A.25}$$

Therefore, it is possible can re-write the log-likelihood in Equation (A.23) as:

$$\begin{aligned} \ln L(\theta,\mu) = \quad & -\tfrac{(n-1)T}{2}\ln 2\pi - T\ln(1-\rho) - \tfrac{(n-1)T}{2}\ln\sigma^2 \\ & +T\ln|I_n - \rho W| - \tfrac{1}{2\sigma^2}\textstyle\sum_t \ln\left(\upsilon_t'(\theta)\,J_n\upsilon_t(\theta)\right) \end{aligned} \tag{A.26}$$

where J_n is the inverse of $\sigma^{-2}Var\,(J_n\upsilon_t)$. Therefore, data is transformed from Y_t to $Y_t^* = F'_{n,n-1}Y_t$ and then Equation (A.23) is maximized by searching over the parameter space. This is equivalent to the estimation of the spatial dynamic panel data model with only individual effects with (n-1) cross-section units and T time periods. Alternatively, one can maximize Equation (A.27) instead. However, although the components of υ_t are i.i.d in the model, the elements υ_t^* even if they are uncorrelated might not be independent. Concentrating μ out from previous expression yields:

$$\begin{aligned} \ln L(\theta) = \quad & -\tfrac{(n-1)T}{2}\ln 2\pi - \tfrac{(n-1)T}{2}\ln\sigma^2 - T\ln(1-\rho) + T\ln|I_n - \rho W| \\ & -\tfrac{1}{2\sigma^2}\textstyle\sum_t \left(\tilde{\upsilon}_t'(\theta)\,J_n\tilde{\upsilon}_t(\theta)\right) \end{aligned} \tag{A.27}$$

where $\tilde{\upsilon}_t(\theta) = (I_n - \rho W)\,\tilde{Y}_t - \tilde{Z}_t\delta$ and $J_n\tilde{\upsilon}_t(\theta) = J_n\left[(I_n - \rho W)\,\tilde{Y}_t - \tilde{Z}_t\delta - \alpha_t\iota_n\right]$ because $J_n\iota_n = 0$. The previous log likelihood function divided by the effective sample size $(n-1)T$ yields the corresponding quasi-likelihood function:

$$\begin{aligned} Q(\theta) = \quad & \tfrac{1}{(n-1)T}E\ln L(\theta) = -\tfrac{1}{2}\ln 2\pi - \tfrac{1}{2}\ln\sigma^2 - \tfrac{1}{n-1}\ln(1-\rho) \\ & -\tfrac{1}{n-1}\ln|R(\rho)| - \tfrac{1}{2\sigma^2}\tfrac{1}{(n-1)T}E\textstyle\sum_t \left(\tilde{\upsilon}_t'(\theta)\,J_n\tilde{\upsilon}_t(\theta)\right) \end{aligned} \tag{A.28}$$

The first and second order derivatives from which parameter estimates of $\hat{\theta}$ can be obtained are given by:

$$\frac{1}{(n-1)T}\frac{\partial \ln L(\theta)}{\partial\theta} = \frac{1}{(n-1)T}\begin{bmatrix} \frac{1}{\sigma^2}\sum_t \left(J_n\tilde{Z}_t\right)'\tilde{\upsilon}_t(\theta) \\ \frac{1}{\sigma^2}\sum_t \left(J_nW\tilde{Y}_t\right)' J_n\tilde{\upsilon}_t(\theta) - TtrG_n(\rho) + \frac{T}{1-\rho} \\ \frac{1}{2\sigma^4}\sum_t \tilde{\upsilon}_t(\theta) J_n\tilde{\upsilon}_t(\theta) - (n-1)\sigma^2 \end{bmatrix} \quad (A.29)$$

where $G(\rho) = WR(\rho)^{-1}$ and tr denotes the trace of a matrix and:

$$\frac{1}{(n-1)T}\frac{\partial^2 \ln L(\theta)}{\partial\theta\partial\theta'} = -\frac{1}{(n-1)T} \quad (A.30)$$

$$\begin{pmatrix} \frac{1}{\sigma^2}\sum_t \tilde{Z}_t' J_n\tilde{Z}_t & \frac{1}{\sigma^2}\sum_t \tilde{Z}_t' J_n W\tilde{Y}_t & \frac{1}{\sigma^4}\sum_t \tilde{Z}_t' J_n \upsilon_t \\ * & \frac{1}{\sigma^2}\sum_t \left(\left(W\tilde{Y}_t\right)' J_nW\tilde{Y}_t\right) + Ttr\left(G^2(\rho)^2\right) - \frac{T}{(1-\rho)^2} & \frac{1}{\sigma^4}\sum_t \left(W\tilde{Y}_t\right)' J_n\upsilon_t \\ * & * & -\frac{(n-1)T}{2\sigma^4} + \frac{1}{\sigma^6}\sum_t \tilde{\upsilon}_t(\theta) J_n\tilde{\upsilon}_t \end{pmatrix}$$

Lee and Yu (2010b) by means of a rigorous asymptotic distribution analysis show that the QML estimator has the bias B given by:

$$B = -\frac{1}{T}\Sigma^{-1}(\theta)\,\alpha(\theta) \quad (A.31)$$

that needs to be corrected so that $\theta_{bc}^1 = \hat{\theta} - B$ where size of the bias B is given by:

$$\Sigma^{-1}(\theta) = \frac{1}{\sigma^2}\begin{pmatrix} E[H] & 0 \\ 0 & 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 \\ 0 & \frac{1}{n-1}\left[tr\left(G_n' J_n G_n\right) + tr\left(G_nJ_n\right)^2\right] & \frac{1}{\sigma^2(n-1)}tr\left(J_nG_n\right) \\ 0 & \frac{1}{\sigma^2(n-1)} & \frac{1}{2\sigma^4} \end{pmatrix} + O\left(\frac{1}{T}\right) \quad (A.32)$$

where $H = \frac{1}{(n-1)T}\sum_t \left(Z_t, G_n\tilde{Z}_t\delta\right)' J_n \left(\tilde{Z}_t, G_n\tilde{Z}_t\delta\right)$ and the term $\alpha(\theta)$ is:

$$\alpha(\theta) = \begin{pmatrix} \frac{1}{n-1}tr\left(\left(J_n\sum_{h=0}^{\infty} A^h\right) R(\rho)\right)^{-1} \\ \frac{1}{n-1}tr\left(W\left(J_n\sum_{h=0}^{\infty} A^h\right) R(\rho)^{-1}\right) \\ 0_{2k} \\ \frac{1}{n-1}\tau tr\left(W\left(J_n\sum_{h=0}^{\infty} A^h\right) R(\rho)^{-1}\right) + \frac{1}{n-1}\eta tr\left(GW\left(J_n\sum_{h=0}^{\infty} A^h\right) R(\rho)^{-1}\right) + \frac{1}{n-1}trJ_nG_n \end{pmatrix} \quad (A.33)$$

Appendix B

Bayesian Spatial Panel Estimation

This subsection explains the use Bayesian estimation methods along this thesis, which draws heavily from previous work of Lesage and Pace (2009) and Lesage (2014a). Application of Bayesian estimation methods to spatial econometrics models presents some advantages with respect maximum likelihood. First, they solve the problem of inference in maximum likelihood computed using numerical hessians, which are not always very good. Second, they can be used to relax the assumption of constant variance normal disturbances. Third, they can be used to formally solve model comparison problems. Specifically, they can be used to (i) compare models based on different weight matrices W, (ii) different explanatory variables X or (iii) different specifications (SAR, SEM, SLX, SDM, SDEM).

Along the different chapters of this research, Bayesian Estimation have been applied in order to perform model selection and comparison with respect the spatial weight matrix W. Note, however, that in Chapter 3, this methodology has been used to select among spatial specifications and with respect the W matrix. The choice of the W matrix is important because it determines the rest of the analysis. Therefore, taking a Bayesian perspective on model uncertainty about the W matrix in the context of static and dynamic spatial panel data modeling simplifies considerably the task of selecting an appropriate model.

An implication of Bayesian econometrics is that inferences drawn on how suitable is the use of alternative W matrices, depends on prior distributions assigned to the model parameters. Often, Bayesian analysis tries to avoid situations where the conclusions depend heavily on subjective prior information by relying on diffuse or non-informative prior distributions. As parameters governing the prior distributions such as the prior variance increase, the prior distributions become more vague or diffuse and often tend to uniform distributions. However, as noted by Zellner (1971), uniform distributions are improper since they can reflect a situation where no defined limits exist for the integral of the prior distribution, leaving these undefined. Impropriety can be a problem in some model comparison contexts and not in others. If the improper priors for the various models are different, they will not cancel each other properly, or if the models being compared have a different number of parameters, the ratio of model probabilities may become zero or infinite depending on the specific model in the numerator versus denominator (Koop, 2003). Given that in each of the chapters the explanatory variables are the same and what varies is W, Bayesian estimations performed in this research rely safely on non-informative priors for the model parameters parameters. In Chapter 3, where dynamic spatial models with different number of variables are estimated, the integration constant is adjusted according to the corresponding degrees of freedom (see Lesage (2014a) routines for a similar treatment in the context of static spatial panels and Elhorst *et al.* (2015) in the context of dynamic spatial panels).

A further point that should not be overlooked, is that in the empirical analysis carried out along this thesis, data exhibits wide variation across regions or municipalities. As explained by Lesage and Pace (2009) in the cases where the number of sample observations is small, the posterior distribution places more emphasis on prior parameters than the distribution implied by the small sample of observable data and model contained in the likelihood. Nevertheless, this is not the case in the studies performed here, where prior experience (information) was very limited and on the contrary, a great deal of sample data was used. Hence, the posterior distribution along the various chapters used to select among alternative W and specifications, placed more emphasis on the model and sample data information, embodied in the likelihood.

Bayesian Model Comparison

In this subsection, the basics of Bayesian model comparison are described. The underlying idea of Bayesian W selection and model comparison is to consider a finite set of alternative models $M = M_1, M_2, .., M_N$ based on different spatial weight matrices holding the other model aspects constant (i.e, the explanatory variables) and select the model M_i that is more likely to be the true model given the data by looking at the posterior distribution.

Denote by $\Theta = [\beta, \sigma, \rho]$ the vector of parameters of the model (in the case of static panels) or $\Theta = [\beta, \sigma, \tau, \eta, \rho]$ in dynamic space-time panels. Then, the joint probability of the set of N models, parameters and observations correspond to:

$$p(M, \Theta, y) = \pi(M)\,\pi(\Theta|M)\,L(y|\Theta, M) \tag{B.1}$$

where $\pi(M)$ is the prior probability assigned to the model, $\pi(\Theta|M)$ reflects the priors of the vector of conditional parameters to the model and $L(y|\Theta, M)$ is the likelihood of the data conditioned on the parameters and models. In order to make each model M_i equally likely a priori, the same prior probability $\pi(M_i) = 1/N$ is assigned to each model under consideration. As shown in equation B.2 below, it is possible to use the Bayes rule to derive the posterior probability of model i:

$$p\left(M^i, \Theta^i|y\right) = \frac{p(M^i, \Theta^i, y)}{p(y)} = \frac{\pi(M^i)\,\pi(\Theta^i|M^i)\,L(y|\Theta^i, M^i)}{p(y)} \tag{B.2}$$

Integrating with respect Θ^i we get the marginal likelihood, the key quantity used to compare the various models based on different spatial weight matrixes.

$$p(y|M_i) = \int p\left(y|\Theta^i, M_i\right) p\left(\Theta^i|M_i\right) d\Theta^i \tag{B.3}$$

For example, for the case of two models, M_1 and M_2 with parameter vectors Θ_1; Θ_2 and data denoted by Y, it is possible to use Bayes' theorem to calculate the posterior probability that M_1 is the correct model (conditional on the fact that the correct model is in the set $\{M_1, M_2\}$. This is given by:

$$p(M_1|y) = \frac{p(y|M_1)}{p(y|M_1) + p(y|M_2)} \frac{p(M_1)}{p(M_2)} \tag{B.4}$$

where $p(y|M_k)$ is the marginal likelihood of the data given M_k and $p(M_k)$ is the prior probability of the model M_k $(k = 1; 2)$. Notice that in the case of a W matrix selection between two models the sum of the posteriors adds up to 1 so that $p(M_1|y) + p(M_2|y) = 1$. Notice that in order to convert previous expressions into scalars useful for model comparison purposes, the use of priors for the model parameters $\pi(\Theta|M)$ and likelihood functions $p(y|\Theta^i, M_i)$ is required. These topics are discussed in the subsection of model estimation.

Data Transformation

An important issue in the context of Bayesian Spatial Panels estimation, is the treatment of the data and the fixed and time-period fixed effects. Note that Bayesian Markov Monte Carlo (MCMC) routines for spatial panels required to compute Bayesian posterior model probabilities do not exist yet in traditional econometric software packages. As an alternative, all cross-sectional arguments of James LeSage routines, were replaced by their spatial panel counterparts, for example a block-diagonal $NT \times NT$ matrix, $diag(W, ..., W)$ as argument for W. Similarly, the T matrices X_t, Y_t of size $n \times K$ and $n \times 1$ are stacked into a $nT \times K$ and $nT \times 1$ matrices respectively.

Regarding the treatment of the effects and depending on the specification, two different procedures are implemented in order to match the frequentist estimation procedures developed by Lee and Yu (2010). For models including solely regional fixed effects as in Chapter 1, the time mean operator $J_T = I_t - (\frac{1}{t})(\iota_t \iota_t^{'})$ is applied to the data, which is equivalent to time-demeaning and working with $\tilde{Z} = [\tilde{Y}, W\tilde{Y}, \tilde{X}, W\tilde{X}]$ as in the section of Static Spatial Panel Estimators. For models including fixed and time-period fixed effects, as it is the case of models estimated the rest of chapters, the data transformation requires two steps. First, the spatial mean operator $J_n = I_n - (\frac{1}{n})(\iota_n \iota_n^{'})$ is applied to the endogenous and exogenous variables $Z = [Y, WY, X, WX]$. Then, the orthonormal matrix F of eigenvectors of J_t corresponding to eigenvalues of 1 is used to transform matrices Z, $[Z_1, Z_2, ..., Z_T]F$ of size $n \times T$ into $[Z_1^*, Z_2^*, ..., Z_T^*]$ which removes regional and time effects and reduces the model dimension to $(n-1)\,T$. Similarly, in these scenarios, the W matrix is transformed so that $\tilde{W} = FWF$ is of size $n - 1 \times n - 1$

In the mathematical development that follows, the procedure to perform Bayesian Estimation for static panels as in equations B.5 and B.7 are described below:

$$Y_t = \mu + \rho W Y_t + X_t \beta_1 + W X_t \beta_2 + \upsilon_t \tag{B.5}$$

where $\upsilon_t \sim N[0, \sigma^2 I_n]$. After the data transformation equation B.5 becomes:

$$\tilde{Y}_t = R^{-1}(\rho)\left(\tilde{X}_t \beta_1 + W\tilde{X}_t \beta_2 + \tilde{\upsilon}_t\right) \tag{B.6}$$

where $R(\rho) = I_{nT} - \rho\,(I_T \otimes W)$, $\tilde{Y}_t = Y_t - \bar{Y}$, $\bar{Y} = \frac{1}{T}\sum Y_t$, $\tilde{X}_t = X_t - \bar{X}$, $\bar{X} = \frac{1}{T}\sum X_t$ and $\tilde{\upsilon}_t = \upsilon_t - \bar{\upsilon}_{it} = \upsilon_T$. For a model including both spatial fixed and time-period fixed effects as in equation (B.7) below:

$$Y_t = \mu + \iota_n \alpha_t + \rho W Y_t + X_t \beta_1 + W X_t \beta_2 + \upsilon_t \tag{B.7}$$

the corresponding data transformation yields:

$$Y_t^* = R^{-1}(\rho)\left(X_t^* \beta_1 + W X_t^* \beta_2 + \upsilon_t\right) \tag{B.8}$$

where in this case $R(\rho) = I_{(n-1)T} - \rho\left(I_{(n-1)T} \otimes \tilde{W}\right)$. In order to avoid an excess of notation, the corresponding star or the tilde, is deleted from now onwards, but the reader should keep in mind that, in the next steps, the data employed has been transformed as in Equations (B.8) and (B.6).

Bayesian Model Estimation

To perform Bayesian inference researchers need to combine prior distributions with the likelihood of the model to estimate the parameters β_1, β_2, ρ and σ^2. For the case of the SDM specification of Equation (B.8) including spatial fixed and time-period fixed effects above, the likelihood is given by:

$$L\left(\beta, \sigma, \rho, Y, \tilde{X}\right) = \left(2\pi\sigma^2\right)^{\frac{(n-1)T}{2}} \left|R(\rho)\right| exp - \left[\left(\frac{1}{2\sigma^2}\right)\left(R(\rho)Y - X\beta\right)\left(R(\rho)Y - X\beta\right)\right] \tag{B.9}$$

where $\tilde{X} = [X, WX]$ and $\beta = [\beta_1, \beta_2]$ denote the $(n-1)T \times 2K$ and $2K \times 1$ matrices of variables and parameters respectively. To perform the derivations for models including only spatial fixed effects as in Chapter 1, it is sufficient to substitute $(n-1)T$ by nT in the corresponding terms of the likelihood.

The prior distributions for the model parameters employed in Chapters 1 to 3, are a normal-inverse-gamma conjugate prior for β and σ and a uniform prior for ρ based on the beta distribution. The prior distributions indicated using π:

$$\begin{aligned} &\pi(\beta) \sim N(c, T) \\ &\pi\left(\frac{1}{\sigma^2}\right) \sim \Gamma(d, v) \\ &\pi(\rho) \sim \frac{1}{Beta(a_0, a_0)} \frac{(1+\rho)^{a_0-1}(1-\rho)^{a_0-1}}{2^{2a_0-1}} \end{aligned} \tag{B.10}$$

In order these prior distributions to be diffuse, c is to zero and T to a very large number (1e+12). Diffuse priors for σ are obtained setting $d = 0$ and $v = 0$. The configuration of the prior distribution of the spatial autoregressive is obtained by setting $a_0 = 1.01$. The use this type of prior is recommended in empirical applications as it does not require subjective information on the part of the practitioner given that it relies on the defined dependence parameter space for these models (Lesage, 2014). The only difference regarding prior specification in the model estimation procedure implemented in Chapters 1 and 2, and that of Chapters 3 and 4, is that the parameter vector β is extended to include time and space-time lags such that: $\beta = [\beta_1, \beta_2, \tau, \eta,]$, which implies that a diffuse prior $\pi(\tau, \eta) \sim N(c, T)$ is also applied to the time Y_{t-1} and space-time lag WY_{t-1}. Bayesian estimation methodology focuses on distributions involving data and parameters, which has the effect of structuring estimation problems in such a way as to produce a posterior distribution that can be decomposed into a sequence of conditional distributions. The conditional distribution for β that follows from the maximum likelihood model in Equation (B.9) is given by:

$$\begin{aligned}
p\left(\beta|\rho, \sigma, Y, \tilde{X}, W\right) &\sim N\left(\bar{b}, \sigma^2 B\right) \\
\bar{b} &= A\left(\tilde{X}' R|\left(\rho\right)|Y + \sigma^2 T^{-1} c\right) \\
B &= \sigma^2 A \\
A &= \left(\tilde{X}'\tilde{X} + \sigma^2 T^{-1}\right)^{-1}
\end{aligned} \tag{B.11}$$

Thus, the conditional posterior distribution for β follows a multivariate normal distribution. On the other hand, the conditional distribution for σ given β parameters takes the form:

$$\begin{aligned}
p\left(\sigma^2|\beta, \rho, Y, X, W\right) &\propto \left(\sigma^2\right)^{\frac{N(T-1)}{2}+d+1} \exp\left[-\upsilon'\upsilon + \frac{2v}{2\sigma^2}\right] \\
\upsilon &= R|\left(\rho\right)|Y - \tilde{X}\beta
\end{aligned} \tag{B.12}$$

Finally, the posterior distribution of ρ is given by:

$$\begin{aligned}
&\pi\left(\rho|\beta,\sigma,Y,\tilde{X},W\right)\propto|R\left(\rho\right)|\left[s^{2}\left(\rho\right)^{\frac{(n-1)t-2K}{2}}\right]\pi\left(\rho\right)\\
&b\left(\rho\right)=\left(\tilde{X}'\tilde{X}\right)\tilde{X}'RY\\
&s^{2}\left(\rho\right)=\frac{\left(R|\left(\rho\right)|Y-\tilde{X}\beta\left(\rho\right)\right)\left(R|\left(\rho\right)|Y-\tilde{X}\beta\left(\rho\right)\right)}{\left(n-1\right)T-2K}
\end{aligned} \tag{B.13}$$

To carry out the estimation of the posterior distribution a sampling method is required. This is achieved by means of Markov Chain Monte Carlo (MCMC) sampling techniques. The underlying idea of the MCMC is that instead of working with the posterior density of our parameters, the same goal could be achieved by examining a large random sample from the posterior distribution. As shown by Gelfand and Smith (1990), MCMC sampling from the sequence of complete conditional distributions for all parameters in a model produces a set of estimates that converge in the limit with the true (joint) posterior distribution of the parameters. The approach to perform MCMC relies on the Metropolis-Hasting (MH) algorithm, due to Hastings (1970) which generalizes the method of Metropolis *et al.* (1953). MCMC estimation schemes involve starting with an arbitrary state or initial values for the parameters denoted by $\theta^0=[\rho^0\beta^0,\sigma^0]$ from which we can construct a chain, by recognizing that any Markov chain that has found its way to state θ^t can be completely characterized by the probability distribution for time $t+1$. This algorithm relies on a proposal distribution $f\left(\theta|\theta^t\right)$ for time $t+1$ given that we have θ^t. A candidate point θ^* is sampled from the proposal distribution and:

[**1**]. This point θ^* is accepted as $\theta^{t+1}=\theta^*$ with probability:
$\psi\left(\theta^t,\theta^*\right)=min\left[1,\frac{p(\theta^*|y,X,W)f\left(\theta^t|\theta^*\right)}{p(\theta^t|y,X,W)f(\theta^*|\theta^t)}\right]$

[**2**] otherwise $\theta^{t+1}=\theta^t$, that is, we stay in the current value of θ.

In particular starting with $\theta^0=\rho^0\beta^0,\sigma^0$ the algorithm involves the repetition of the following steps a great number of times:

Step (a) Generate draws of β from the conditional multivariate distribution $p\left(\beta|\rho^0,\sigma^0,Y,\tilde{X},W\right)$ with mean and variance as in Equation (B.11) and use the MH rule to update the chain. This updated value for the parameter vector β is labeled β^1.

Step (b) Generate draws of σ from the conditional chi-squared distribution $p\left(\sigma|\rho^0,\beta^1,Y,\tilde{X},W\right)$ with $(n\,(T-1))$ degrees of freedom. Notice that we rely on the updated value of the parameter vector $\beta=\beta^1$ when evaluating this conditional density. Using the MH rule to update the chain with respect σ, the updated parameter is labeled as σ^1.

Step (c) Generate draws of ρ from the conditional distribution $p\left(\rho|\beta^1,\sigma^1,Y,\tilde{X},W\right)$ which takes the form of $p\left(\rho|\beta^1,\sigma^1,Y,\tilde{X},W\right) \propto |R(\rho)|\exp\left(\frac{1}{2\sigma^2}(R(\rho)y-X\beta)'(R(\rho)y-X\beta)\right.$. This conditional distribution has not a known form. To generate samples of ρ the MH sampling is combined with the griddy Gibbs method. The griddy Gibbs is a faster procedure that consists on taking logs on Equation (B.13), constructing a vector of associated with a grid of q values for ρ in the feasible interval using the Barry and Pace (1999) approach. Pace and Barry (1999) proposed to accelerate the base of the estimator for $\ln|R(\rho)|$ relying on an asymptotic 95% confidence interval, $\left(\bar{V}-F,\bar{V}+F\right)$ constructed using the mean $\bar{V}$ of p generated independent random variables taking the form:

$$V_i=-(n-1)\,t\sum_{k=1}^{m}\frac{x_i'Wx_i}{x_i'x_i}\frac{\rho^k}{k},i=1,\ldots,p \tag{B.14}$$

where $x_i\sim N(0,1)$, x_i independent of x_j if $i\neq j$ and

$$V_i=-n(T-1)\sum_{k=1}^{m}\frac{n(T-1)\rho^{m+1}}{(m+1)\,(1-\rho)}+1.96\sqrt{\frac{s^2\,(V_1,\ldots,V_p)}{p}} \tag{B.15}$$

where s^2 is the estimated variance of the generated V_i and m and p are chosen to provide the desired accuracy. This approach to compute $\ln|R(\rho)|$, along with the vectorized expression of $s(\rho)^2=\varphi(\rho_i)=\upsilon_0'\upsilon_0-2\rho_i\upsilon_d'\upsilon_0+\rho_i^2\upsilon_d'\upsilon_d$, produces a simple numerical integration problem that can be solved using Simpson's or Trapezoid rules. Notice that integration is repeated in each step as the value of $s(\rho)^2$ changes with each pass through the MCMC sampler. As in the previous steps, MH accepts ρ_* as a candidate point for ρ^1 with probability:

$$\psi(\rho,\rho^*)=min\left[1,\frac{p(\rho^*|\beta^1,\sigma^1,Y,X,W)\,f(\rho|\rho*)}{p(\rho|\beta^1,\sigma^1,Y,X,W)\,f(\rho|\rho^*)}\right] \tag{B.16}$$

otherwise $\rho^1=\rho$, which implies the value of ρ does not change.

Appendix C

Relative Importance Metrics

Assigning shares of relative importance to each or to a set of regressors is one of the key goals of researchers in applied studies and in sciences that work with observational data. Advances in computational capabilities have led to increased applications of computer-intensive methods like averaging over orderings that enable a reasonable decomposition of the model variance. Along this thesis metrics of relative importance are employed in Chapters 3 and 4.

Let the DSDM of Equation (C.1):

$$Y_t = \rho W Y_t + \tau Y_{t-1} + \eta W Y_{t-1} + X_t \beta + \theta W X_t + \upsilon_t \tag{C.1}$$

be re-written in compact form as $Y = Z\Pi + \upsilon$ where $Z = [WY_t, Y_{t-1}, WY_{t-1}, X_t, WX_t]$ and $\Pi = [\rho, \tau, \eta, \beta, \theta]$. If all regressors are uncorrelated, there is a simple and unique answer to the relative importance question of any regressor k. In particular, by computing $(\Pi^2)_{k+1} \times \upsilon_{k+1,i}$, with $\upsilon_{k+1,i}$ denoting the regressor k and the error term variance in the spatial unit i, gives a measure of the contribution of the regressor k to the model fit.

However, as explained by Groemping (2007) in case of correlated Z's is no longer obvious how the model's variability can be decomposed. In order explore the relative importance of the various factors explaining unemployment disparities or municipal government spending in Chapters 3 and 4, I study relative contribution of the various factors with the LMG method (Lindeman *et al.*, 1980; Groemping, 2007) and the Genizi and CAR scores (Genizi, 1993; Zuber and Strimmer, 2010; 2011). The decomposition procedures are detailed below:

Let the variance of the dependent variable Y be given by σ_y^2, the variance of the set of regressors contained in Z be denoted by Σ and the covariance of Y and the covariates by Σ_{yZ}. Let $\mathbf{P}$ denote the correlations among regressors and $\mathbf{P}_{yZ}$ marginal correlations between regressors and Y, such that:

$$\Sigma = V^{\frac{1}{2}}\mathbf{P}V^{\frac{1}{2}} \tag{C.2}$$

and

$$\Sigma_{yZ} = V^{\frac{1}{2}}\mathbf{P}_{yZ}V^{\frac{1}{2}} \tag{C.3}$$

where $V = diag\,(Var(Z_1, \ldots, Var(Z_p)$. Defining the correlation between the model estimates and Y as $\Omega = corr\left(Y, \widehat{Y}\right)$, then the squared multiple correlation coefficient is expressed as:

$$R^2 = \Omega^2 = \mathbf{P}_{yZ}\mathbf{P}^{-1}P_{Zy} \tag{C.4}$$

Then, the unexplained variance can be written as $\sigma_Y^2\,(1-\Omega)$ and the explained variance of a model with Z_k regresors with indices in the set S as $evar_S = [\sigma_Y^2\Omega]_{Z_k, k\in S}$. Finally, the sequential added explained variance when adding the regressors with indices in M to a model that already contains the regressors with indices in S as $svar = \left[\sigma_y^2\Omega\right]_{M\cup S} - [\sigma_Y^2\Omega]_S$. This implies that the true coefficient of determination is given by:

$$R^2 = \Omega^2 = \frac{evar_{(S)}}{\sigma_y^2} \tag{C.5}$$

With these definitions in hand, and for a model $Y = Z\Pi + \upsilon$ with p regressors:

$$R^2 = \Omega^2 = \sum_{k=1}^{p} \phi^m X(k) \tag{C.6}$$

where m denotes the decomposition method. The LMG method assigns to each regressor Z_k the following share:

$$\phi^{LMG} Z(k) = \frac{1}{p}\sum_{i=0}^{p-1}\left(\sum_{S\subseteq k+1,\ldots,p,n(S)=i} \frac{svar\left(\{k\}\,|S\right)}{\binom{p-k}{i}}\right) \tag{C.7}$$

where $svar$ denotes the sequentially added explained variance as defined above. Thus the share ϕ_k assigned to regresor k is the average over model sizes i of average improvements in explained variance when adding regressor k to a model of size i without k. Thus, the LMG metric performs a R^2 decomposition by averaging marginal contributions of independent variables over all orderings of variables and using sequential sums of squares from the linear model, the size of which depends on the order of the regressors in the model.This proposal has not found its way in econometric analysis for two main reasons. Firstly, its properties are not well understood and it is computationally challenging given that it requires the researcher to estimate 2^{p-1} models where p is the number of regressors.

Importantly LMG measure satisfies desirable criteria for the decomposition of the model R^2: *i)* proper decomposition (the sum of all shares is the model variance), *ii)* non-negativity (all shares have to be non-negative) and *iii)* inclusion (a regressor Z_k with $\beta_k \neq 0$ should receive a nonzero share). Groemping (2007) argues that these are the relevant criteria for empirical analysis while the *iv)* exclusion criteria $\beta_k = 0$ should receive a 0 weight, is a less convincing requirement if the study has a causal interpretation in mind.

Finally, the weights associated to the GENIZI and CAR measures are given by:

$$\phi^{GEN} Z(k) = \sum_{p=1}^{p} \left[\left(\mathbf{P}^{\frac{1}{2}} \right)_{kp} \left(\mathbf{P}^{\frac{-1}{2}} \mathbf{P}_{Zy} \right)_{p} \right]^2 \tag{C.8}$$

and

$$\phi^{CAR} Z(k) = \omega_k^2 \tag{C.9}$$

with $\omega = \mathbf{P}^{\frac{-1}{2}} \mathbf{P}_{Zy}$.

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