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What drives regional unemployment rate disparities in European regions?

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What Drives Regional Unemployment Rate Disparities in European Regions?

Vicente Rios

July 2014

Abstract

This paper investigates the evolution of the geographical distribution of unemployment rates in a sample of 258 NUTS-2 European regions between 2000 and 2011. In particular, I explore the role played by market equilibrium, disequilibrium and institutional factors shaping regional unemployment disparities. To that end, the present analysis uses recently developed spatial panel econometric techniques that integrate spatial and temporal dynamics. 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. In conjunction with spatio-temporal panel data regression model estimates, stochastic kernels are used to analyze the effect of the various factors in the shape of the whole distribution of unemployment rate. Empirical results suggest that regional unemployment rate differences have decreased and that such regional convergence process has been driven by regional market equilibrium factors.

1 Introduction

Over the last two decades there have been numerous studies analyzing the causes of unemployment in European regions using a variety of different approaches and methods (see Elhorst (2003) for a detailed review). This increasing interest has to do with the fact that unemployment rate is a key indicator of the socio-economic well-being in a region. Rising unemployment not only results in a loss of income for individuals and increased pressure with respect to government spending on social benefits but also reflects unused labor capacity in the economy. At this regard, the rise of unemployment in Europe and the failure of labor markets to achieve full employment are generally regarded as 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 of both, the aggregate level of unemployment and regional inequality among regions have become crucial issues for policy analysis and intervention in the European Union (European Commission, 2010a). Moreover, attaining acceptable levels of unemployment is nowadays a top priority on the European Unions policy agenda (European Commission, 2010b) ¹ being the destination of European funds strongly influenced by regional disparities in the unemployment rate.

From an academic perspective, there are three important reasons to analyze 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). Furthermore, not only the magnitude of unemployment disparities among regions is as large as it is between countries (Taylor and

¹Europes 2020 strategy, building on the previous planning synthesized in Lisbon Strategy goals, sets again employment and social cohesion goals in order to track regional development performance and the assessment of Regional Policy outcomes.

Bradley, 1997; OECD, 2009², Zeilstra and Elhorst, 2012) but also regions within a country may have different sources and structures of unemployment and may need different policies to mitigate it. A second reason is that macroeconomic studies performed at the country level (Bean, 1994; Scarpetta, 1996) give no explanation for the existence of regional unemployment disparities. This strand of 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. At this regard, Zeilstra and Elhorst (2012) have shown by means of a hierarchical modeling exercise that regional unemployment differentials depend on a combination of national and regional-level variables. Third, in a world characterized by the absence of frictions (in line with the neoclassical theoretical framework), unemployment differentials among regions should not exist which suggests that regional disparities may reflect an overall inefficient regional economic system (Taylor, 1996).

Economic theory provides two different explanations on the nature and significance of regional unemployment disparities. The first one is related to equilibrium mechanisms while the second one is related to a disequilibrium view. According to the equilibrium view, long run differentials represent an equilibrium where factors such as favorable climatic conditions or an attractive social environment encourage people to stay in regions where unemployment rates are high (Marston, 1985). Within this conceptual framework each region tends to its own equilibrium unemployment rate which is determined by regional demand and supply factors, amenities and endowments. In other words, the spatial distribution of unemployment under the equilibrium interpretation is characterized by constant utility across areas. 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 second view considers that all regions tend to a competitive equi-

²OECD (2009) reports that the differences in unemployment rates within OECD countries were almost twice as high as those between countries in 2006.

librium 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 adjustment processes to asymmetric shocks (i.e, a shortage of labor demand). The adjustment process may be faster or slower and depending on its speed differences in unemployment across areas could persist for a long time. However, in the long run, differences will disappear through migration and factor mobility between regions. This view stems from neoclassical theory which suggests that with increased economic integration and the removal of impediments to the free flow of production factors unemployment rates should converge given the convergence in factor returns.

In this sense, empirical studies are crucial given that they provide a more profound understanding about the unemployment phenomenon by confronting the plausibility of the competing theories and the explanatory power of the variables involved in them with the data (i.e, Basile and Benedictis, 2009; Basile et al., 2009; Niebur, 2003; Hewartz and Niebuhr, 2013). Up to now, the empirical observation of the economic landscape in Europe has revealed the existence of persistent disparities in unemployment rates in Spain and Italy (Lopez-Bazo et al, 2005; Cracolici et al, 2007). These findings may suggest the nature of regional unemployment disparities in south Europe would be the result of a long-run equilibrium rather than a short-term disequilibrium caused by temporary shocks. Nevertheless, the study of the nature of unemployment regional disparities at the aggregate European level has received hardly any attention in this context. Indeed, to the best of my knowledge only Zeilstra and Elhorst (2012) have analyzed the joint impact of regional and national factors on regional disparities in a sample of 9 countries (135 NUTS2 + 11 UK NUTS1 regions) for the period ranging from 1983-1997. However, their analysis focuses on the behavior of a representative region instead of the whole geographical distribution. On the other hand, studies analyzing the behavior of the whole European unemployment distribution are almost inexistent and only Overman and Puga (2002) in a pioneering study have analyzed this issue with

1986-1996 data for 150 NUTS2 regions. The lack of more recent analysis on the nature of unemployment in the context of the European integration setting with a greater cross-sectional sample is especially remarkable in view of the relevance of theoretical arguments and the policy implications related to them. As Marston (1985) points out: *‘If unemployment is of equilibrium nature, any policy oriented to reduce regional disparities is useless since it cannot reduce unemployment anywhere for long’*.

An additional striking feature of unemployment rates in European regions that has been overlooked by the literature is that they exhibit both positive spatial and temporal correlations. As Elhorst (2003) point out, previous studies explaining the evolution of unemployment rates that did not take into account spatial and serial dynamic effects may have been misspecified. Regarding this issue, only Pattachini and Zenou (2007) estimated a time-space recursive model (in the terminology of Anselin et al.(2008)) of unemployment rates for UK regions while Vega and Elhorst (2013) estimated a dynamic spatial durbin for 182 NUTS2 regions. Lee and Yu (2013) by using asymptotic theory provide conditions for the identification of spatial dynamic durbin models. However, if the focus of the analysis are the spillover effects, dynamic spatial durbin models may suffer from serious identification problems as shown by Gibbons and Overman (2012). This paper is an attempt to overcome shortcomings in previous empirical papers by applying recently developed spatial econometric tools that allow the researcher to take into account the spatial and temporal correlations in a general dynamic spatial lag panel data model.

In this research, I directly integrate spatial and serial dynamic effects within a dynamic spatial lag model of the regional European unemployment rates, combining both regional and national factors for a sample of 258 NUTS2 regions belonging to 27 countries ranging from 2000 to 2011. In a first step, I employ the dynamic spatial lag estimation techniques developed by Lee and Yu (2008; 2010) to obtain the average total effects of the factors driving unemployment rate differentials in European regions. Important

methodological issues such as the inclusion of region-specific and time-specific fixed effects, the estimation methods and the specification and selection of the spatial matrix will be addressed. However, the focus of this analysis is to explore the effect of the various factors on the whole distribution of unemployment rates and learn about the nature of the unemployment phenomenon in Europe. This is the reason why I do not restrict the analysis to a traditional regression approach. In a second step, I analyze how much of the features observed in the geographical distribution of the unemployment rates can be explained by some factors that can potentially affect unemployment by comparing the entire observed distribution to the conditional distribution obtained once the effects of the various determinants have been removed following Lopez-Bazo et al. (2005). To that end, non-parametric methods to explore the evolution of the dynamic distribution of unemployment rates are applied in line with Quah (1996) and Magrini (2007).

The paper is organized as follows. The next section analyses the geographical distribution of regional unemployment rates in Europe between 2000 and 2011. The third section presents the dynamic spatial lag model employed to capture the effect of different factors and the estimation procedure. The fourth section presents the regressions results and the analysis of the effects of the explanatory factors on the whole distribution. The final sections section summarizes the main results and concludes.

2 Data and Preliminary Evidence

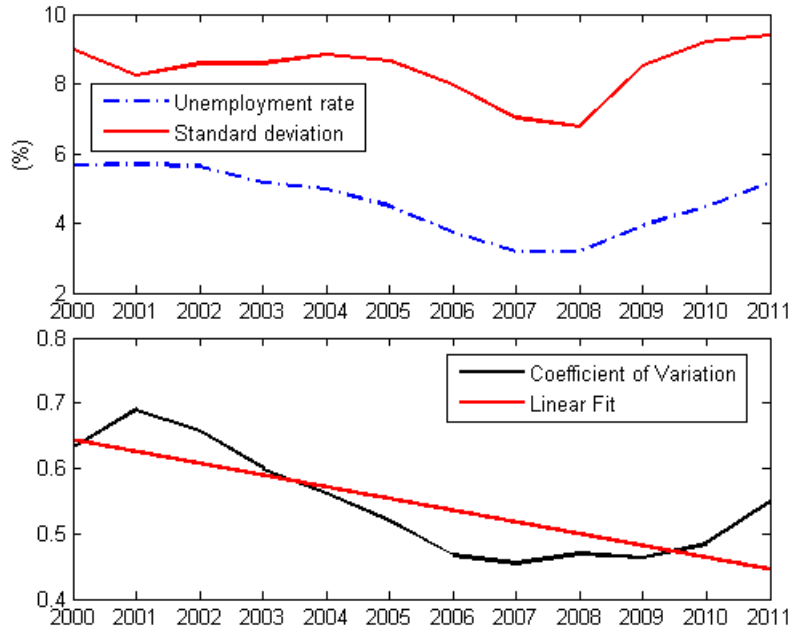
The data used in this study are drawn from different databases ³. The sample covers a total of 258 NUTS-2 ⁴ regions belonging of 27 EU states. The study period goes from 2000 to 2011. The key variable throughout the paper is the regional unemployment rate in the various regions between 2000 and 2011. Changes in aggregate European unemployment rates are reported in Figure 1a below. As it is observed, at the beginning of the decade the average unemployment rate was 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 in the subsequent years it reached the 9.4% level in 2011. As it is observed in Figure 1b, the coefficient of variation -as a first proxy of unemployment differentials in European regions- displayed a similar evolution: it decreased until 2008 and hiked from 2008 to 2011. However, the linear fit shows that the overall pattern is that unemployment differentials between regions have decreased.

With the aim of providing a deeper insight into the regional pattern of unemployment in Europe, I estimate the density function associated with the distribution of unemployment rates in 2000 and 2011. Figure 2 plots the distribution of regional unemployment rates relative to the average of all regions, what is called the EU relative unemployment rates. To read 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

³A detailed explanation of the data sources and the construction of the variables used in the modeling exercise is attached in Appendix A

⁴NUTS is the French acronym for Nomenclature of Territorial Units for Statistics, a hierarchical classification of subnational spatial units established by Eurostat. In this classification NUTS-0 corresponds to country level and increasing numbers indicate increasing levels of subnational disaggregation. NUTS-2 level 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 regional economic issues in Europe, which facilitates the comparison of our results with those obtained in previous papers. Second, NUTS-2 regions are particularly relevant in terms of EU regional policy provided that cohesion and regional policy funds are assigned at this level.

Figure 1: Unemployment Dynamics

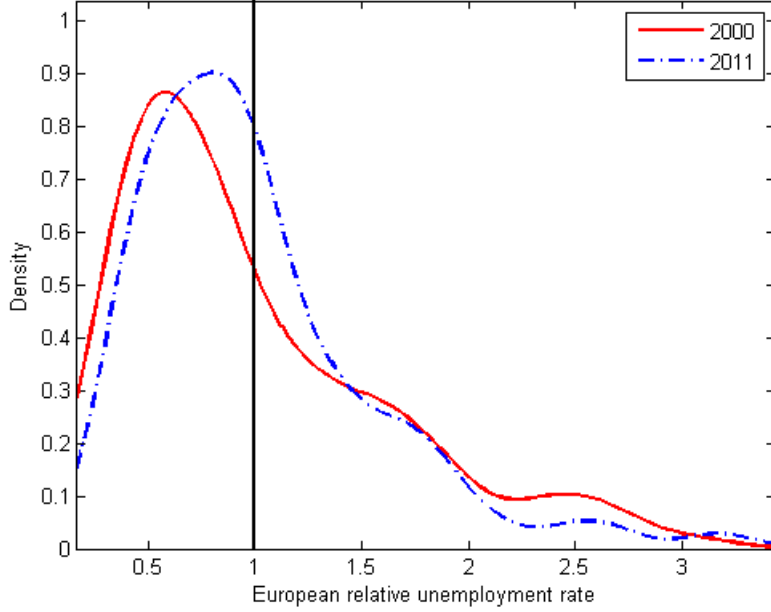


any particular region i will have that relative rate of unemployment. As it is shown in Figure 2, the probability mass of any region to be allocated around the European wide average was higher in 2011 (80%) than in 2000 (55%). Furthermore, the probability mass in the left side of the distribution which corresponds to regions with an unemployment rate about 1.5 or 2 times above the European average has decreased. Thus, Figure 2 hints at a decrease in inequality of Europe's regional unemployment rates.

In order to explore whether Figure 2 indicates a structural process of convergence I track the evolution of each region's relative unemployment rate over time with a continuous transition matrix, that is, a stochastic kernel. As defined by Magrini (2007) a stochastic kernel provides the likelihood of transiting from one place in the range of values of relative unemployment rates to the others. Hence, it provides evidence about the shape of and the mobility within the dynamic distribution⁵. Figure 3 presents the

⁵Gaussian kernel functions were used, while the smoothing parameters were selected according the procedure described in Magrini (2007). For a detailed explanation see Appendix B.

Figure 2: Unemployment Relative Distribution

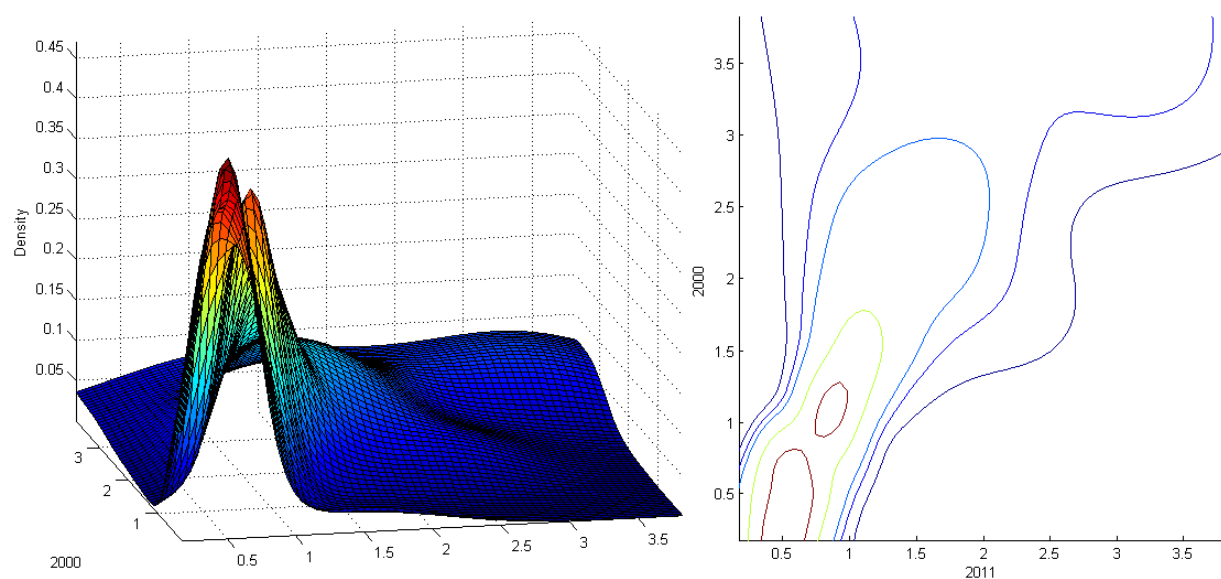


non-parametric estimate of the stochastic kernel for the cross-regional distribution of unemployment between 2000 and 2011. The z-axis in the three dimensional, plot measures the probability of transiting from the corresponding point in the t axis to any other point. The right side of the Figure 3 shows the corresponding contour plot, on which the lines connect points at the same height on the three dimensional kernel.

The key issue is to explore whether or not the stochastic kernel has clear peaks. Specifically, our estimates show the presence of two different peaks, the first one which is the highest is centered near the value of 0.5 times the average while the second one is centered above the value of 1 times the average of the horizontal axis. Therefore, the highest peak is formed by regions with unemployment rates below the European average while the second cluster consists on regions with unemployment levels close to the European average. A remarkable feature of Figure 3 is that the probability mass flows along the main diagonal, which implies suggests the distribution of relative unemployment rates has remained stable. Nevertheless, as it is shown in the contour plot,

the level of uncertainty in the linkages between the relative distributions of 2000 and 2011 appears to be higher in regions that were above 1.5 times the average unemployment rate than in the rest of the distribution. Specifically, amongst the regions with the highest unemployment rates (above 1.5 times the European average in 2000), I find that 35.2% of them moved to the range between 1 to 1.5 times the European average while a 27.8% experienced movements to the range between 0.5 and 1 times the European average. These results show that although the distribution of unemployment rates remained stable, in 2011 there were more regions with unemployment rates close to the average.

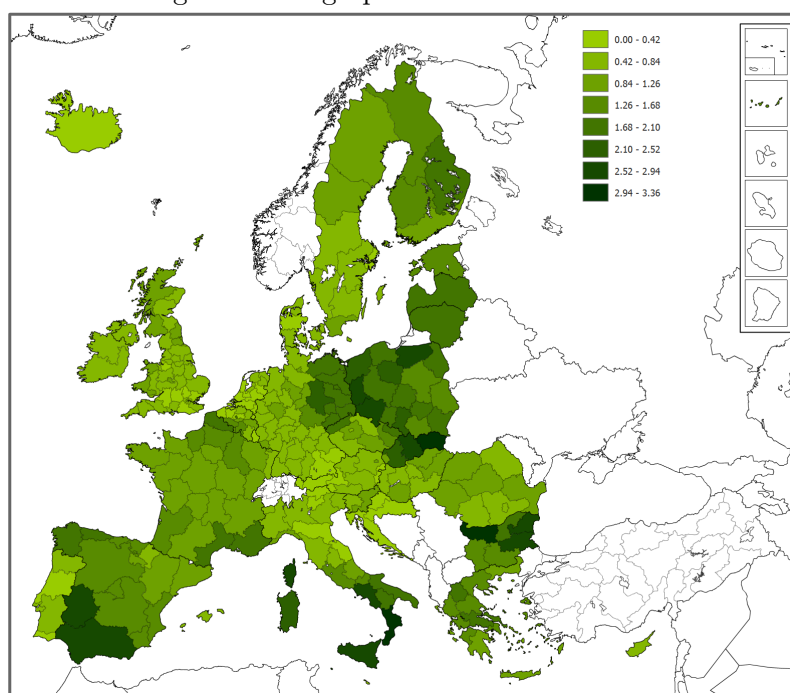
Figure 3: Stochastic Kernel Unemployment Rates



The observed behavior in previous Figures is due to both: *i*) the catching-up behavior of the eastern European regional economies such as Poland, Slovenia, Bulgaria, East-Germany or Latvia and *ii*) the lagging behavior of northern Europe regional economies who started with relatively low levels of unemployment and worsened their position. This is corroborated when looking at the geographical dimension of unemployment in Figures 4 and 5, that display relative unemployment rates in 2000 and 2011 respectively. Specially successful is the case of Polish (Bulgarian) regions that starting from a level

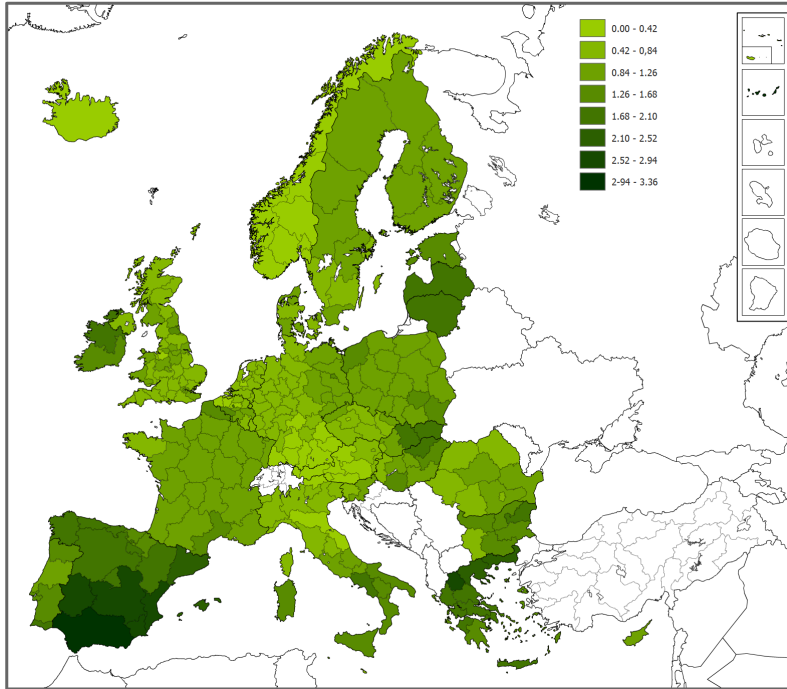
1.9 times the EU average have converged to a level just 1.2 (1.3) times above the EU average. On the other hand, the bad performance of labor markets in northern regions has produced an increase in the relative unemployment position in Sweden, Ireland or Denmark, who have approached to EU average. Nevertheless, this aggregate pattern of convergence hides some degree of heterogeneity given that some regions that were initially in a bad position have worsened it even more. The worst results are obtained in the periphery of Europe. Starting from relatively high unemployment levels, Spanish regions have increased on average its distance with respect the EU average moving from 1.5 times to 2.3 times above it. Similarly, Greece has also displayed a bad performance given that starting from a level close to the EU average it diverged to a level 1.6 times above it.

Figure 4: Grogographical Distribution 2000



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 regional disparities I follow an approach

Figure 5: Grogographical Distribution 2011

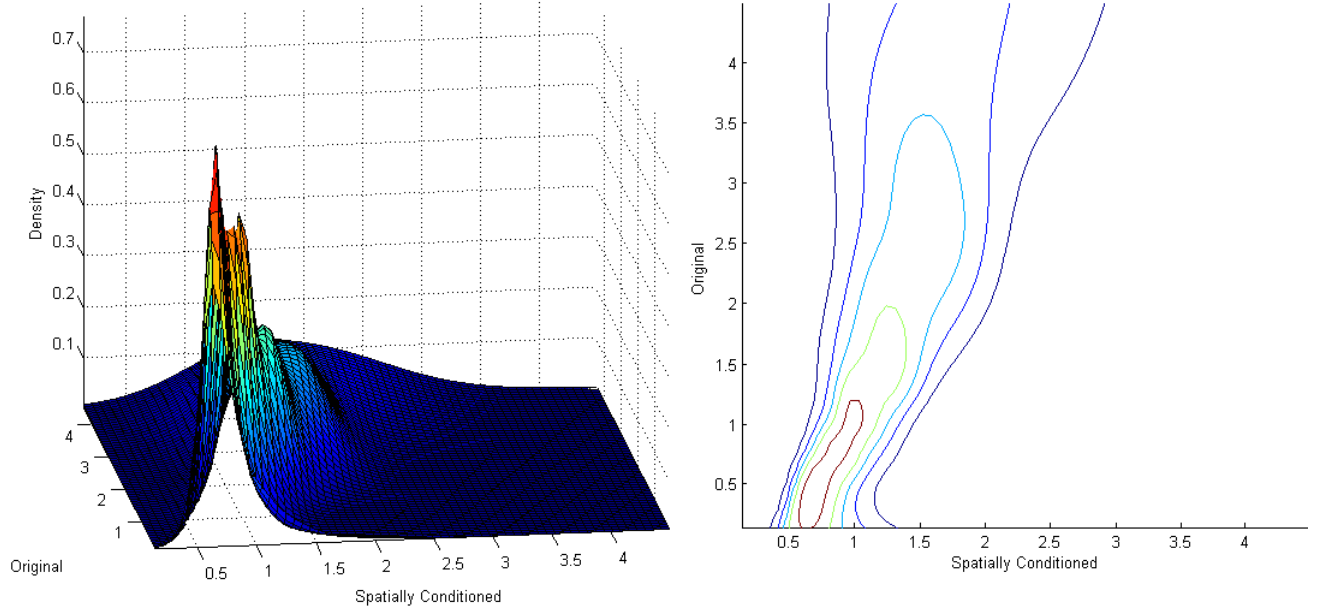


based on the pioneer work of Quah (1996). I construct a conditioned distribution in which each region's unemployment rate is expressed relative to the average of its neighboring regions. Specifically, the weighted average relative unemployment rate of neighboring regions is given by WU_t where W is a spatial weight matrix describing the spatial interdependences among the sample regions and U_t is the Europeans relative unemployment level. The spatial weight matrix used in the analysis is defined as:

$$W = \begin{cases} w_{ij} = 0 & \text{if } i = j \\ w_{ij} = \frac{1/d_{ij}^2}{\sum_j 1/d_{ij}^2} & \text{if } i \neq j \end{cases} \quad (1)$$

where d_{ij} is the great-circle distance between the centroids of regions i and j . I use the inverse of the squared distance, in order to reflect a gravity function. W is row standardized so that is the relative and not the absolute distance which 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

Figure 6: Spatially Conditioned



location I estimate a stochastic kernel capturing the transitions between the original distribution and the neighbor-relative unemployment distribution, using the information available for the study period as a whole. The results are depicted in Figure 6. As it can be observed, neighboring effects are relevant in this context, provided that the probability mass is not centered around the main diagonal. 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. This implies that neighboring regions are characterized by registering similar levels of European relative unemployment rate. Accordingly, spatial effects are a relevant factor explaining observed variations in unemployment rates. Further evidence 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.

3 Methodology

3.1 The Model.

In line with the findings obtained in Section 2, recent papers have shown that regional unemployment rates may be driven both by intra-regional factors and by extra-regional factors affecting nearby regions (Zeilstra and Elhorst, 2012; Vega and Elhorst, 2013). To investigate unemployment rate disparities in European regions I propose an extension of the theoretical model developed by Zeilstra and Elhorst (2012) which builds on the Blanchard and Katz (1992) framework. Originally, the model of Blanchard and Katz (1992) ignored the spatial characteristics of the data and the potential role of neighboring effects in shaping unemployment outcomes. However, this does not seem a very realistic assumption in the context of European integration, characterized by growing interregional trade, migratory movements and technology and knowledge transfer. In the model presented here, 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 neighbouring regions. With increasing economic interdependence, the induced changes of unemployment in neighbouring areas spill over again to adjacent labor markets, including the location where the shock originated. The model reads as:

$$n_{it} = -\alpha_1 (w_{it} - p_{it}) + \alpha_2 u_{it} - \beta_n X_{n,it} - \gamma_n Z_{n,it} - \delta_1 W_{ij} u_{jt} + \epsilon_{it}^d \quad (2)$$

$$(w_{it} - p_{it}) = -\beta_w X_{w,it} - \gamma_w Z_{w,it} - \alpha_3 u_{it} - \alpha_4 \Delta u_{it} - \alpha_4 \Delta \zeta - \delta_2 W_{ij} u_{jt} - \Delta \delta_3 W_{ij} u_{jt} + \epsilon_{it}^w \quad (3)$$

$$l_{it} = \alpha_6 (w_{it} - p_{it}) - \alpha_7 u_{it} - \delta_4 W_{ij} u_{jt} + \beta_l X_{l,it} + \gamma_l Z_{l,it} + \epsilon_{it}^s \quad (4)$$

$$u_{it} = n_{it} - l_{it} \quad (5)$$

where n_{it} is labor demand; l_{it} is labor supply; u_{it} is unemployment; w_{it} is gross wage; p_{it} is price level in region i at time t , u_{jt} denotes the unemployment rate in neighboring regions j and W_{ij} is spatial weight matrix that represent the spatial interdependence between regions i and j . 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 $i = j$. We also suppose that $\sum_{j \neq i}^N w_{ij} = 1$ for $i = 1, \dots, N$, in order to avoid scale affects. Both wages and price levels are expressed in logarithms. The α_i and δ_i parameters are positive, β and γ are unknown and the terms, ϵ_{it}^d , ϵ_{it}^w , ϵ_{it}^s , denote labor demand, wage and labor supply shocks respectively.

Equation (2) is the labor demand equation where labor demand is assumed to depend on real wages, unemployment, regional labor market factors ($X_{n,it}$, ie, GDP gap) and institutional factors ($Z_{n,it}$, i.e, employment protection legislation). Real wages have a negative effect on labor demand within a region given that a lower wage makes a region more attractive to firms. The effect of the unemployment rate is uncertain because of on one hand a higher unemployment rate implies a larger pool of workers from which to choose but on the other a shortage in the labour demand induces an outward migration of the most mobile workers. Equation (3) is a wage setting equation where real wages depend positively on the various labor market factors ($X_{w,it}$, i.e,) and institutional conditions ($Z_{w,it}$, i.e, coordination, union density, coverage, etc) affecting worker bargaining positions and negatively on the unemployment level and unemployment growth. As in Zeilstra and Elhorst (2012) the variable $\Delta\zeta$ reflects the change in wage inflation. Finally, equation (4) expresses labour supply as a function of real wages, regional labour market conditions ($X_{l,it}$, demographic composition and education of the population), and institutional factors ($Z_{l,it}$ unemployment benefits).

Substituting (2), (3) and (4) into (5) one can obtain:

$$u_{it} = \tau u_{it-1} + \rho W u_{jt} + \eta W u_{jt-1} + \tilde{\beta}' \tilde{X}_{it} + \tilde{\gamma}' \tilde{Z}_{it} + \kappa \Delta\zeta + \psi (\epsilon^d - \epsilon^s) + \rho \epsilon^w \quad (6)$$

where $\tau = \frac{\Theta\alpha_4}{\Phi}$, $\rho = \frac{\Theta(\delta_2+\delta_3)+\delta_4-\delta_1}{\Phi}$, $\eta = \Theta\delta_3$, $\tilde{\beta}' = [\frac{\beta_n}{\Phi}, \frac{\Theta\beta_w}{\Phi}, \frac{\beta_l}{\Phi}]'$, $\tilde{\gamma}' = [\gamma_l, \gamma_w, \gamma_n]'$, $\tilde{X}_{it} = [X_n, X_w, X_l]$, $\tilde{Z}_{it} = [Z_n, Z_w, Z_l]$, $\kappa = \frac{\alpha_5\Theta}{\Phi}$, $\psi = \frac{1}{\Phi}$, $\rho = \frac{\Theta}{\Phi}$, $\Phi = [1 + \alpha_7 - \alpha_2 + \Theta(\alpha_3 + \alpha_4)]$, and $\Theta = (\alpha_1 + \alpha_6)$.

Additionally, one can rewrite Equation (6) in the short form of a two-way fixed effects Dynamic Spatial Lag model, as follows:

$$u_t = \tau u_{t-1} + \rho W u_t + \eta W u_{t-1} + X_t \beta + \mu_i + \lambda_t + \epsilon_t \quad (7)$$

where u_t denotes a $N \times 1$ vector consisting of observations for the unemployment rate measured in percentages for every region $i = 1, 2, \dots, N$ at a particular point in time $t = 1, 2, \dots, T$, X_{it} , 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 unemployment. τ , the response parameter of the lagged dependent variable u_{t-1} is assumed to be restricted to the interval $(-1, 1)$ and $\epsilon_t = (\epsilon_{1t}, \dots, \epsilon_{Nt})^T$ is a vector of i.i.d disturbances whose elements have zero mean and finite variance σ^2 . The variables $W u_t$ and $W u_{t-1}$ denote contemporaneous and lagged endogenous interaction effects among the dependent variable. In turn, ρ is called the spatial autoregressive coefficient. W is a $N \times N$ matrix of known constants describing the spatial arrangement of the regions in the sample. If W is row-normalized, ρ and τ are defined on the interval $(1/r_{min}, 1)$, where r_{min} equals the most negative purely real characteristic root of W . $\mu_i = (\mu_1, \dots, \mu_N)^T$ is a vector with region fixed effects, and $\lambda_t = (\lambda_1, \dots, \lambda_T)$ denotes time specific effects. 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).

3.2 The Empirical Specification.

Equations (6) and (7) show the unemployment rate is a reduced form function of a

variety of factors affecting the labor demand, supply and wages. According to the pioneering work of Partridge and Rickman (1997), these factors can be broadly categorized as disequilibrium factors (DEQ), market equilibrium factors (ME), demographic variables and characteristics of the workforce (DEM) and producer and consumer amenities (AMEN). Additionally, Equation (6) shows that institutional variables are relevant in this context. Thus following previous studies (see Boeri and Van Ours, 2008; Zeilstra and Elhorst, 2012) we include a variety of national-level institutional covariates (INST). The set of controls included in this research has been selected on the basis of the findings of existing studies on the determinants of unemployment disparities (Elhorst, 2003). However, 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 this study is focused. The various factors included in the empirical exercise are:

A) Disequilibrium Factors (DEQ). In order to account for regional disequilibrium labor market dynamics the percentage change in real wage growth (RWG)⁶, employment growth (EMP), cyclical output fluctuations (YGAP) and a structural change index (SC) are included. A primary factor driving unemployment differences is the rate of change of wages. A slow rate of wage adjustments explain why idiosyncratic shocks or asymmetric responses to common shocks might produce unemployment rates to differ across regions (Marston, 1985). 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 (Partridge and Rickman, 1997a,b). A second candidate 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 level⁷. According to Isserman (1986) this variable is

⁶I defined the wage rate as a ratio of the nominal compensation per employee with respect a country price index. As Elhorst(2003) points out this type of measure better approximates supply shocks

⁷Real GDP gap is computed by applying the Hedrick Prescott filter. Concretely the HP filter is presented as a solution to extract the trend of a time series from the following optimization problem: $\min \sum_{t=1}^T \{(y_t - \mu_t)^2 - \lambda [(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1})]^2\}$ where the parameter lambda defines the smoothnes of the obtained trend. For this study, given that the frequency of data is annual it takes a

the most widely used indicator of regional labor demand. If a region is growing faster than the European level, unemployment in that region should decrease relatively. A third factor determining disparities is employment growth. If a region creates employment at a faster rate the European average, unemployment in that region should decrease relatively (Diaz, 2011). Finally, the intensity of structural change may matter since (given labor market flexibility) regions characterized by more pronounced reallocation of jobs face higher adjustment burdens (Robson, 2009; Herwartz and Niebuhr, 2013). To proxy job re-allocation dynamics as a measure of structural change I include the Lilien Index (1982)⁸.

C) Equilibrium Labor Market Variables (ME). Sectoral diversification in a region may affect unemployment rate (Langhi et al., 2005). The more specialized a regional economy is, the less capability has 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. Diversity of employment is measured by one minus a two digit Herfindahl Index (HI)⁹. Additionally, differences in the industrial mix might impact the geographical distribution of unemployment (Overman and Puga 2002, Niebuhr 2003; Lopez-Bazo et al, 2005). Accordingly, the model also includes the regional employment shares in agriculture (AGR), manufacturing (MANU), construction (CONS), financial services (FS) and non-market services (NM). The employment share in the distribution sector is excluded in order to avoid collinearity problems. Regions specialized in declining industries such as agriculture and manufacturing are expected to exhibit higher unemployment rates than regions specialized in growing industries such

value of 100.

⁸This index is measured as $L = \left[\sum_{i=1}^N \left(\frac{x_{irt}}{x_{rt}} \right) (\Delta \log x_{irt} - \Delta \log x_{rt})^2 \right]^{\frac{1}{2}}$ where i is the industry, r is the region and t is time. Although it may be argued that structural change is a market equilibrium force given that time span of our sample is rather short the interpretation of job reallocation variable should be viewed as a disequilibrium or transitory determinant of regional disparities.

⁹This index is computed as: $H_{rt} = \left(\frac{x_{rit}}{\sum_i x_{rit}} \right)^2$ where r denotes the region, i denotes the sector and t time

as financial and public services. Finally I include the real wage level (RW). As real wages is supposed to exert a negative influence on labor demand and a positive effect on labor supply a positive relationship with unemployment is expected¹⁰

D) Equilibrium Demographic Factors (DEM). The structure of the population may have important influences on labor supply and labor demand. According to Groenewold(1997), a region faces a problem of unemployment if its natural population growth rate exceeds its employment growth rate. Eventhough these variations have no immediate effect, if birth rates are high the share of younger population tends to be large and the share of old small. I control for this issue by using the age structure of the population: the percentage of the working age population aged between 15 and 24 (YOUNG) and those between 54 and 64 years old (OLD). Participation rates of females are also likely to affect unemployment rates (FEM). As the survey of Elhorst (2003) documents, results of empirical studies at this respect virtually fit all possibilities finding support for a positive and negative signs for both female and male participation. Human capital variables (EDUC) are 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). In order to evaluate the effect of human capital on unemployment rates I use an index that combines both, the share of population with a low educational attainment and the share of population with a high educational attainment¹¹. As a final demographic equilibrium variable I include the net migration rate (MIG) which might be an important mechanism balancing labor market disparities.

E) Amenities (AMEN). Amenities may be considered as a compensating differential for the higher probability of unemployment. Variables used to proxy for producer and

¹⁰Following the suggestion of Elhorst(2003) the ratio of real wages with respect labor productivity was also considered. The results are very similar but are not presented for the sake of brevity.

¹¹I follow Bubbico and Dijkstra(2011) so that the education index mimics the EU Regional Human Development Indicator (HDI) methodology. I combine low and high education attainment for people aged 2564 as below: $EDUC = \frac{1}{3}(1 - L) + \frac{2}{3}H$ where L is the (%) of population with secondary education and H is the (%) of population with tertiary education.

consumer amenities were largely conditioned by the availability of data and I only included employment density (EMPD) as a proxy for urbanization following Lopez-Bazo et al. (2005) and Cracolici et al. (2007). 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 but 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 amenities is unknown. In addition, spatial fixed effects included in the model to measure time-invariant unobservable equilibrium effects are included in the category of amenities.

F) Institutions (INST). Following macroeconomic research I consider the role of labour market institutions, provided that they may be crucial determinants behind the evolution of unemployment (Hewartz and Niebuhr, 2013). In order to approximate institutional effects I introduce the employment protection legislation (EPL), a bargaining coverage index (COV) and a coordination index (COORD). The EPL indicator of the OECD, consists of rules and procedures that define the limits to the faculty of firms to hire and fire workers in private employment relationships. Historically, employment protection has been typically design to protect jobs and increase job stability by reducing job destruction (OECD, 2013) which in turn may help to avoid unemployment . A second institutional control is the Bargaining Coverage index (COV). This index is computed as the sum of the union density and the collective bargaining coverage indicators¹². Finally I analyze whether the characteristics of the different collective bargaining systems 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 characteristic is the degree of coordination between the bargaining partners in

¹²The reason for this choice is due to the relationship between union density and bargaining coverage. As Longhi et al. (2005) point out, 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. Hence, the higher the collective bargaining coverage the lower the union density and viceversa.

order to reach consensus. However, the differences between the degree of centralization and coordination are only minor. In order to capture country variations with respect these two dimensions I sum and aggregate these two variables in a coordination index (COORD).

Table 1 shows the mean, the standard deviation and the minimum and maximum values for the covariates used in the empirical analysis.

Table 1: Unemployment drivers: summary statistics

| Variable | Mean | Standard deviation | Minimum | Maximum |
|---------------------|--------|--------------------|---------|---------|
| Unemployment | 8.44 | 4.86 | 1.20 | 30.4 |
| Employment Growth | 0.59 | 3.26 | -31.47 | 80.43 |
| RGDP Gap | 0.12 | 3.20 | -27.03 | 20.55 |
| Migration | 2.98 | 6.26 | -76.09 | 34.30 |
| Real Wage Growth | 0.75 | 6.02 | -37.38 | 52.22 |
| Real Wage | 234.74 | 112.26 | 9.08 | 574.53 |
| Agriculture | 7.49 | 8.84 | 0.06 | 62.62 |
| Manufacture | 18.27 | 6.91 | 1.89 | 38.55 |
| Construction | 7.43 | 2.26 | 2.47 | 16.48 |
| Non Market Services | 29.07 | 6.74 | 8.43 | 63.35 |
| Financial Services | 12.35 | 5.85 | 1.40 | 33.86 |
| Old | 11.22 | 3.29 | 3.43 | 21.92 |
| Young | 11.93 | 3.01 | 3 | 24.25 |
| Female | 44.51 | 3.09 | 29.67 | 51.63 |
| Education | 37.77 | 8.51 | 8.93 | 63.17 |
| Emp. Density | 190.8 | 625.4 | 1.4 | 8152.4 |
| Diversity Index | 76.81 | 2.75 | 55.26 | 81.24 |
| Coverage Index | 92.91 | 31.9 | 21. 47 | 173.08 |
| Coordination Index | 5.29 | 2.31 | 2.00 | 10.00 |
| Structural Change | 36.50 | 34.26 | 1.78 | 758.91 |
| EPL | 2.39 | 0.64 | 1.20 | 4.58 |

3.3 Estimation and Interpretation.

To estimate the effect of the various covariates in Equation (7) I apply the bias correction procedure developed by Lee and Yu (2008, 2010) for a dynamic spatial panel data model with spatial and time period fixed effects. The estimator that is derived from this log-likelihood function is the Quasi Maximum Likelihood (QML) estimator. The term quasi is used here since the errors are not assumed to be normally distributed. However the QML estimator developed by Lee and Yu (2008) is biased when both the number of spatial units and the points in time in the sample go to infinity. 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, $\tau + \rho + \eta < 1$). Therefore, a Bias-Corrected Quasi Maximum Likelihood (BCML) estimator is used to estimate Equation (7)¹³. 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 cointegrated. Under explosive or spatially cointegration model scenarios, Lee and Yu(2010) and Yu et al. (2012), propose to transform the model in spatial first differences to get rid of possible unstable components in Y_t . Mathematically this is equivalent to:

$$BU_t = \tau BU_{t-1} + \rho BWU_t + \eta BWU_{t-1} + BX_t\beta + B\mu_i + \epsilon_t \quad (8)$$

where $B = (I - W)$. This transformation *i*) eliminates all time-period fixed effects since $\alpha_t(I - W) \iota_N = 0$, *ii*) reduces the number of observations by one for every time period and *iii*) changes the variance-covariance matrix from $\sigma^2 I$ to $\sigma^2 \Sigma$ where $\Sigma =$

¹³For this purpose I used MATLAB routines that have kindly been made available by Jihai Yu.

$(I - W)(I - W)'$. As Elhorst et al. (2013) point out, at least one eigenvalue of $(I - W)$ will be zero which reduces the rank of the matrix Σ . Hence, an additional transformation is required. Elhorst et al. (2013) propose to apply a transformation matrix to the model in order to get:

$$PBU_t = \tau PBU_{t-1} + \rho PBWU_t + \eta PBWU_{t-1} + PBX_t\beta + PB\mu_i + PB\epsilon_t \quad (9)$$

where $P = \Lambda_{N-1}^{-\frac{1}{2}} F'_{N,N-1}$ being $\Lambda_{N-1}^{-\frac{1}{2}}$ the matrix of non-zero eigenvalues of Σ and $F'_{N,N-1}$ the matrix of the corresponding eigenvectors. Notice that since $W^* \equiv PW(I - W) = \Lambda_{N-1}^{-\frac{1}{2}} F'_{N,N-1} W F_{N,N-1} \Lambda_{N-1}^{\frac{1}{2}}$ the model can be rewritten as:

$$U_t^* = \tau U_{t-1}^* + \rho WU_t^* + \eta WU_{t-1}^* + X_t^*\beta + \mu^* + \epsilon_t^* \quad (10)$$

whose parameters can be consistently estimated by the same bias corrected QML estimator. Yu et al. (2012) show that this transformed model is stable if $\tau + \omega_{max-1}(\rho + \eta) < 1$ where ω_{max-1} denotes the second largest eigenvalue of the spatial weights matrix W . Importantly the latter restriction is less exigent than the former.

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 represents a more valid basis for testing this hypothesis. The matrix of partial derivatives of U_t with respect to the k -th explanatory variable of X_t in region 1 up to region N (say x_{ik} for $i = 1, \dots, N$, respectively), both at a particular point in time t is:

$$\begin{bmatrix} \frac{\partial U_t}{\partial x_{1,k}} \\ \vdots \\ \frac{\partial U_t}{\partial x_{N,k}} \end{bmatrix} = \begin{bmatrix} \frac{\partial u_1}{\partial x_{1,k}} & \cdots & \frac{\partial u_1}{\partial x_{N,k}} \\ \vdots & \ddots & \vdots \\ \frac{\partial u_N}{\partial x_{1,k}} & \cdots & \frac{\partial u_N}{\partial x_{N,k}} \end{bmatrix} = (I - \rho W)^{-1} \beta_k \quad (11)$$

These partial derivatives have the following properties. First, if a particular explanatory variable in a particular region changes, not only unemployment rate in that region will change but also unemployment rates in other regions. Hence 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. Note that every diagonal element of the matrix of partial derivatives represents a direct effect and every non diagonal element of the matrix of partial derivatives represents an indirect effect. In this context, direct effects capture the average change on the unemployment rate caused in internal to region dynamics while the indirect effect can be interpreted as the global spillover effect that occur provided that $\rho \neq 0$. Representation of direct and indirect effects is difficult because they are different from one region to another because of the diagonal and off-diagonal elements of the so-called spatial multiplier matrix $(I - \rho W)^{-1}$ are also different between regions. Thus, I follow Lesage and Pace (2009) who propose to measure the direct effect by the average of the diagonal entries and the indirect effect by the average of non-diagonal elements¹⁴. Finally, the *total* effect, which is object of main interest, is the sum of the direct and indirect impacts.

¹⁴Le Sage and Pace (2009) show that the numerical magnitudes of these two calculations of the indirect effect are identical due to symmetries in computation

4 Results

This section reports and discusses the empirical findings. It is divided into two main subsections. Initially, I report the results from the dynamic spatial lag model estimation. I start by using a spatial weights matrix W that is based on the inverse squared distance between regions, which implies that spatial interactions among european regions are inversely proportional to the square of the geographical distance between them. Then, I test the robustness of the results with respect the spatial weight matrix definition using several selection criteria. Finally, I carry out a simulation exercise based on stochastic kernel conditioning following Lopez-Bazo et al. (2005) to assess the effect caused by the different set of factors on the whole unemployment rates distribution.

Table 2 reports the estimation results of the dynamic spatial lag model. However, before proceeding with the analysis of Table 2, it is important to determine the best specification of the empirical model in this context. Following Elhorst et al., (2013), I start by looking at the individual spatial and time effects in our data, since I need to ascertain whether regions are homogenous or heterogeneous. Column (1) shows the result of the bias corrected QML estimator applied to the model with fixed spatial effects and column (2) shows the result of the DSLM with both, spatial fixed effects and time-period fixed effects. The results of the corresponding F-test (0.74 with 10 degrees of freedom in the numerator and 2548 degrees of freedom in the denominator, $p = 0.68$) indicate that time-period fixed effects should not be included ¹⁵. To find out whether the model including spatial fixed effects is stable I calculated $\tau + \rho + \eta$ and carried out a two-sided Wald-test to investigate the null hypothesis $\tau + \rho + \eta = 1$. Since the Wald-test (2.25 with $p=0.13$) is not significant I cannot reject the null of spatial cointegration. Given that the model might be spatially cointegrated I consider its reformulation in spatial first differences as explained in section 3.3. The corresponding results are shown

¹⁵It should be stressed that I did not use the F-test for a standard panel data model here but for a dynamic spatial panel data model including the variables U_t, WU_t and WU_{t-1}

in Column (3).

Using the dynamic spatial lag model in spatial first differences, the direct, indirect and total effects are simulated. The results are shown in columns 4, 5 and 6 respectively. However, as shown by McMillen (2003, 2010) the DSLM model has the problem of imposing a unique ratio between the spillover and direct effects for every explanatory variable, which in this case is 2.5. Since the ratio between direct and spillover effects within the spatial lag framework is the same for all variables, I do not focus the attention on the analysis of indirect effects and I directly analyze the total effects.

As it is shown, the total effects of the different variables display the expected signs. We first look at the effects of the disequilibrium variables. The effect changes in growth rate of employment exerts a negative effect on unemployment. Meanwhile, the GDP gap and the wage inflation do not exert statistically significant effects on unemployment. Finally, it can be seen that the effect of structural reconfiguration, approximated by the Lilien index, has a positive effect on unemployment.

With respect to market equilibrium variables, we find that high levels of wages tend to increase the level of unemployment. Moreover, the total effects associated with the productive structure show that regions with a high share of employment in agriculture, manufacturing and construction tend to have lower levels of unemployment. The effect of employment in non-market services and services is not significant. Noting the positive effect of sectoral diversification in unemployment, we find that diversified production structures do not reduce unemployment. The variables that approximate the impact of demographic characteristics on unemployment show expected signs. Younger populations tend to suffer more unemployment problems than those with a proportion of older people. The education index that approximates the level of human capital in a region shows a negative and significant effect on unemployment which suggests that more educated populations tend to suffer less problems of unemployment because. The effect

Table 2: Dynamic Spatial Panel Model Results, $W = 1/d^\alpha$, $\alpha = 2$

| Variable | Fixed Effects Model | Fixed and Time Effects Model | Spatial First Differences | Direct Effects | Indirect Effects | Total Effects |
|----------------|----------------------|------------------------------|---------------------------|----------------------|---------------------|---------------------|
| U_{t-1} | 0.60*** (38.71) | 0.60*** (38.53) | 0.59*** (38.19) | 0.64*** (37.46) | 1.61*** (8.35) | 2.25*** (11.16) |
| WU_{t-1} | -0.39*** (-11.66) | -0.36*** (-9.52) | -0.39*** (-11.82) | -0.42*** (-11.32) | -1.06*** (-5.74) | -1.48*** (-6.82) |
| $EMPG_t$ | -0.09*** (-11.30) | -0.09*** (-10.80) | -0.09*** (-10.57) | -0.10*** (-11.40) | -0.25*** (-7.57) | -0.35*** (-9.04) |
| $YGAP_t$ | -0.03*** (-3.34) | -0.02 (-1.63) | -0.03*** (-3.30) | -0.01 (-0.99) | -0.02 (-0.97) | -0.03 (-0.98) |
| RWG_t | -0.00 (-0.51) | -0.00 (-0.26) | -0.00 (-0.56) | -0.00 (-0.13) | -0.00 (-0.12) | -0.00 (-0.13) |
| RW_t | 0.01*** (4.63) | 0.01*** (5.32) | 0.01*** (4.63) | 0.01*** (5.2) | 0.02*** (4.63) | 0.03*** (4.92) |
| $AGRI_t$ | -0.08*** (-2.84) | -0.07*** (-2.51) | -0.08*** (-2.87) | -0.07** (-2.34) | -0.19*** (-2.25) | -0.26** (-2.29) |
| $MANU_t$ | -0.26*** (-7.01) | -0.25*** (-6.62) | -0.26*** (-7.03) | -0.23*** (-5.55) | -0.59*** (-4.77) | -0.81*** (-5.12) |
| $CONS_t$ | -0.21** (-4.22) | -0.19** (-3.80) | -0.21** (-4.23) | -0.13** (-2.34) | -0.33** (-2.25) | -0.45** (-2.29) |
| NMS_t | 0.05 (1.46) | 0.05 (1.26) | 0.05 (1.46) | -0.01 (-0.30) | -0.03 (-0.30) | -0.04 (-0.30) |
| FS_t | -0.06 (-1.29) | -0.08 (-1.50) | -0.06 (-1.30) | -0.07 (-1.24) | -0.18 (-1.21) | -0.24 (-1.22) |
| DIV_t | 0.18*** (4.28) | 0.18*** (4.23) | 0.18*** (4.25) | 0.16*** (3.69) | 0.42*** (3.38) | 0.58 (3.51) |
| OLD_t | -0.18*** (7.42) | -0.20*** (-7.33) | -0.18*** (-7.43) | -0.17*** (-5.81) | -0.45*** (-4.90) | -0.62*** (-5.29) |
| $YOUNG_t$ | 0.07*** (3.22) | 0.08*** (3.26) | 0.07*** (3.24) | 0.07*** (2.70) | 0.17** (2.58) | 0.24*** (2.64) |
| FEM_t | 0.16*** (5.52) | 0.15*** (5.09) | 0.16*** (5.56) | 0.16*** (5.18) | 0.43*** (4.58) | 0.60*** (4.87) |
| $EDUC_t$ | -0.05*** (-3.17) | -0.06*** (-3.44) | -0.05*** (-3.19) | -0.05** (-2.63) | -0.13** (-2.52) | -0.19** (-2.57) |
| MIG_t | -0.35*** (-5.57) | -0.34*** (-5.43) | -0.34*** (-5.55) | -0.32*** (-4.77) | -0.84*** (-4.21) | -1.17*** (-4.46) |
| $EMPD_t$ | 0.01*** (3.67) | 0.01 (3.30) | 0.01*** (3.64) | 0.00*** (2.91) | 0.01*** (2.75) | 0.02*** (2.82) |
| $UDCOV_t$ | 0.00 (-0.25) | 0.00 (0.10) | 0.00 (-0.24) | 0.00 (0.04) | 0.00 (0.03) | 0.00 (0.03) |
| $COORD_t$ | -0.03 (-0.63) | 0.00 (-0.02) | -0.03 (-0.64) | 0.02 (0.53) | 0.06 (0.52) | 0.08 (0.52) |
| SC_t | 0.00** (1.97) | 0.00** (1.90) | 0.00** (1.93) | 0.00** (2.07) | 0.01** (2.01) | 0.01** (2.04) |
| EPL_t | -1.22*** (-3.12) | -1.10** (-2.77) | -1.22*** (-3.12) | -0.91** (-2.12) | -2.38** (-2.05) | -3.29*** (-2.08) |
| WU_t | 0.74*** (33.48) | 0.72*** (31.40) | 0.74*** (33.43) | | | |
| Corr R-squared | 0.69 | 0.66 | 0.67 | | | |
| Log-likelihood | -4654.22 | -4647.95 | -4617.07 | | | |
| Observations | 2838 | 2838 | 2827 | | | |

of net migration on unemployment is negative, suggesting that new jobs are created with the arrival of immigrants.

Finally, amenities, approximated by employment density, are positively related to unemployment suggesting that the effect of amenities is negatively related with the well functioning of the labor market. This might be due to the fact that congestions costs faced by the firms dominate the positive effect associated to an increasing probability of job matching. Regarding the effect of national institutional variables included in the model results show that neither the levels of coordination and coverage obtained through unions or collective agreements have a significant effect on unemployment levels. However, as expected, the effect of EPL on unemployment is negative.

The results that have been presented so far, depend strongly on the connectivity matrix W . An interesting and important question is whether the performance of the model will improve and the conclusions will change when other spatial weights matrices are used. Indeed, one of the most criticized aspects of spatial econometric models (Corrado and Fingleton, 2012) is that the spatial weights matrix cannot be estimated but needs to be specified in advance. 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. At this regard, the basic idea is to consider S alternative models based on different spatial weight matrices. The other model aspects (i.e, the explanatory variables) are held constant. The Bayesian model comparison approach requires assigning prior probabilities to each model s ($s = 1, 2, N$). In order to make each model equally likely a priori, the same prior probability $1/S$ is assigned to each model under consideration. Each model is estimated

by both frequentist and bayesian methods and then posterior probabilities are computed based on the data and the estimation results of the set of S models.

Table 3 reports the performance of DSLM model with spatial fixed for a broad range of alternative specifications of W and puts together the three previous selection procedures¹⁶. The first set of matrixes consists of different versions of the inverse distance matrixe with cutt-offs while the second set captures gravity-type matrixes whose off-diagonal elements are defined by $W_{ij} = \frac{1}{d_{i,j}^\alpha}$ for $\alpha = 1, 3$. The last group of spatial matrixes consists on exponential-decay matrixes, $W_{ij} = -exp(\theta d_{ij})$ for $\theta = 0.005, \dots, 0.03$ 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.

As it is observed the best matrix according to the various selection criteria is $W_{ij} = -exp(0.01d_{ij})$, which imposes an speed of decay in the intensity of spatial interactions of 1% as distance among regional units increases. Importantly, when using this matrix the model is stable and does not suffer from spatial cointegration (i.e, $\tau + \rho + \eta = 0.94$). At this regard, the Wald test display a statistic of 18.09 with p-value 0.00. Therefore, I use this model to perform inference on the effect of the different covariates. Table 4 shows both the estimated coefficients obtained with the BC-QML estimator and the direct, indirect and total effects.

¹⁶Estimations with the various spatial weight matrixes W have been performed in SDM models with regional and time effects and combines the three previous selection procedures. However, with $W_{ij} = -exp(0.01d_{ij})$ time-period fixed effects should not be included in the model as the F test on the joint significance of the time-period fixed effects with 10 d.o.f in the numerator and 2548 in the denomintator is 1.34, p-value of 0.20. Nevertheless, we find the results are robust in terms of qualitative and quantitative impacts within the set of exponential decays matrixes.

Table 3: Spatial Weights Model Comparison

| Spatial Weights Matrix | Log-likelihood Function Value | Bayesian Posterior Model Probability | σ^2 |
|------------------------------------|-------------------------------|--------------------------------------|------------|
| Cut-off 500 km | -4755.68 | 1.00 | 1.73 |
| Cut-off 1000 km | -4865.00 | 0.00 | 1.89 |
| Cut-off 1500 km | -4884.12 | 0.00 | 1.92 |
| Cut-off 2000 km | -4918.00 | 0.00 | 1.97 |
| Cut-off 3000 km | -4946.09 | 0.00 | 2.01 |
| $1/d^\alpha, \alpha = 1$ | -4750.07 | 0.00 | 1.73 |
| $1/d^\alpha, \alpha = 1.25$ | -4707.94 | 0.00 | 1.66 |
| $1/d^\alpha, \alpha = 1.5$ | -4677.42 | 0.00 | 1.61 |
| $1/d^\alpha, \alpha = 1.75$ | -4658.10 | 0.93 | 1.57 |
| $1/d^\alpha, \alpha = 2$ | -4654.22 | 0.00 | 1.55 |
| $1/d^\alpha, \alpha = 2.25$ | -4653.78 | 0.07 | 1.55 |
| $1/d^\alpha, \alpha = 2.5$ | -4663.14 | 0.00 | 1.55 |
| $exp - (\theta d), \theta = 0.005$ | -4619.26 | 0.00 | 1.55 |
| $exp - (\theta d), \theta = 0.01$ | -4576.97 | 1.00 | 1.48 |
| $exp - (\theta d), \theta = 0.015$ | -4593.77 | 0.00 | 1.49 |
| $exp - (\theta d), \theta = 0.02$ | -4620.23 | 0.00 | 1.52 |
| $exp - (\theta d), \theta = 0.03$ | -4663.83 | 0.00 | 1.56 |

Notes: Bayesian Markov Monte Carlo (MCMC) routines for spatial panels required to be able to compute Bayesian posterior model probabilities does not exist yet. As an alternative I have replaced all cross-sectional arguments of James Lesage routines by their spatial panel counterparts, for example a block-diagonal NTxNT matrix, $diag(W, \dots, W)$ as argument for W .

Table 4: Dynamic Spatial Panel Model Results, W ($\theta = 0.01$)

| Variable | Coefficient Estimates | Direct Effects | Indirect Effects | Total Effects |
|----------------|--------------------------|-----------------------|-----------------------|-----------------------|
| $U(t-1)$ | 0.55 *** (35.27) | 0.59 *** (34.06) | 0.51 *** (13.22) | 1.09 *** (21.88) |
| $WU(t-1)$ | -0.22 *** (-9.47) | -0.23 *** (-9.17) | -0.20 *** (-6.43) | -0.44 *** (-7.77) |
| $EMPG(t)$ | -0.10 *** (-12.45) | -0.11 *** (-12.60) | -0.09 *** (-10.19) | -0.20 *** (-12.12) |
| $YGAP(t)$ | -0.05 *** (-5.60) | -0.05 *** (-5.71) | -0.04 *** (-5.61) | -0.09 *** (-5.76) |
| $RWG(t)$ | 0.00 (-0.46) | 0.00 (-0.44) | 0.00 (-0.44) | 0.00 (-0.44) |
| $RW(t)$ | 0.001*** (3.05) | 0.01 *** (3.07) | 0.00 *** (3.02) | 0.01 *** (3.06) |
| $AGRI(t)$ | -0.07 ** (-2.43) | -0.07 ** (-2.45) | -0.06 ** (-2.42) | -0.13 ** (-2.44) |
| $MANU(t)$ | -0.26 *** (-7.08) | -0.28 *** (-7.13) | -0.24 *** (-6.60) | -0.52*** (-7.04) |
| $CONS(t)$ | -0.22*** (-4.47) | -0.24*** (-4.48) | -0.20*** (-4.33) | -0.44*** (-4.45) |
| $NMS(t)$ | 0.07** (2.05) | 0.08** (2.04) | 0.07** (2.02) | 0.14** (2.03) |
| $FS(t)$ | -0.10** (-2.09) | -0.11** (-2.08) | -0.09** (-2.06) | -0.20** (-2.07) |
| $DIV(t)$ | 0.19*** (4.77) | 0.21*** (4.75) | 0.18*** (4.51) | 0.39*** (4.69) |
| $OLD(t)$ | -0.16 *** (-6.97) | -0.18*** (-6.91) | -0.15*** (-6.33) | -0.33*** (-6.78) |
| $YOUNG(t)$ | 0.07*** (3.23) | 0.08*** (3.22) | 0.07*** (3.12) | 0.15*** (3.19) |
| $FEM(t)$ | 0.16*** (5.50) | 0.17*** (5.43) | 0.15*** (5.26) | 0.32*** (5.43) |
| $EDUC(t)$ | -0.03** (-1.97) | -0.03** (-1.97) | -0.03* (-1.95) | -0.06** (-1.97) |
| $MIG(t)$ | -0.29 *** (-4.72) | -0.31 *** (-4.73) | -0.27 *** (-4.57) | -0.58 *** (-4.71) |
| $EMPD(t)$ | 0.01*** (4.11) | 0.01*** (4.11) | 0.01*** (3.98) | 0.01*** (4.08) |
| $UDCOV(t)$ | 0.01 (1.01) | 0.01 (1.04) | 0.01 (1.03) | 0.02 (1.04) |
| $COORD(t)$ | 0.02 (0.45) | 0.02 (0.46) | 0.02 (0.46) | 0.04 (0.46) |
| $SC(t)$ | 0.00** (2.02) | 0.00** (2.02) | 0.00** (2.01) | 0.00** (2.02) |
| $EPL(t)$ | -1.09*** (-2.80) | -1.17*** (-2.85) | -1.01*** (-2.81) | -2.18*** (-2.85) |
| $W * U(t)$ | 0.50*** (27.82) | | | |
| Corr R-squared | 0.706 | 30 | | |
| Log-likelihood | -4576.97 | | | |
| Observations | 2838 | | | |

Notes: The dependent variable is in all cases the unemployment rate of the various regions. t-statistics in parentheses. * Significant at 10% level, ** significant at 5% level, *** significant

The direct effects shown in column (2) are different from the estimates of the response parameters shown in column (1) of Table 3. This is caused by the feedback effects that arise as a result of impacts passing through to other regions and back to the region itself. These feedback effects, however, turn out to be very small, ranging from 0 to 14% depending on the specific control. Overall, the qualitative results obtained with this W matrix are very similar to those obtained under the former matrix. However, this new spatial conditioning scheme shuts down spatial interactions at a faster rate than the inverse squared distance matrix, which restricts considerably the magnitude of the global spillovers in the system of regional economies. An additional important difference with respect to the results obtained using the former W matrix is that Table 3 displays significant effects for some market disequilibrium and market disequilibrium variables that in the previous model were not significant.

As for the disequilibrium variables, we obtain similar results for the effect of employment growth and structural change. I find that the effect employment growth decreases unemployment as in Zeilstra and Elhorst (2012) or Vega and Elhorst (2013). On the other hand, the effect of job reallocation through the structural change (SC) proxy is found to exert a positive impact in unemployment rates as in Herwartz and Niebuhr (2013). Additionally, output fluctuations impact negatively on unemployment presenting the expected sign. This result is similar to that obtained in Taylor and Bradley (1997).

Regarding the market equilibrium variables, some of the sectoral employment shares that with the former W were not significant became significant now. Interestingly, I find that non-market services affect positively the unemployment rate while financial services exert a negative effect. However, note that this result may also reflect the fact public sector could be creating more jobs in those regions with the highest unemployment rates. As before, agriculture and manufacture have a negative effect of unemployment. As explained by Elhorst (2003) this specific result might be associated to larger employment

multipliers in both agriculture or industry that in the service sector activities, which are largely dependent on the demand created by the other two sectors of the economy. Industry diversity impacts positively unemployment and its effects are significant while the coefficient of the real wages is also significant with the expected positive sign.

All of the demographic variables are significant and have the expected signs. The positive sign of female participation indicates that growth of the labor force is not fully compensated for by the growth of jobs and that it is translated into unemployment rates. The positive effect of the share of young population and negative effect of share of the old on unemployment rates supports previous findings (Molho, 1995). Skills and education appear to be inversely related to the unemployment rate which suggests there is a positive influence on regional labor demand of skills. As regards to the effect of migration I find a negative effect as in Lopez-Bazo et al (2005) or Basile et al (2009). When looking at the institutional factors I find that neither bargaining coverage nor coordination structures are statistically significant which supports previous evidence (see, Blanchard and Wolfers, 2000; Nickell et al., 2005). As in Zeilstra and Elhorst (2012), the EPL is negatively related with unemployment which suggests that differences in job protection matter in explaining differentials.

Notice that the regression analysis may not be entirely informative when analyzing a system of regional economies, because it concentrates on the behavior of a representative economy and is silent on what happens in the tails of the cross-sectional distribution of economies (Magrini, 2007). For this reason, I complement spatial econometric models with the estimation of stochastic kernels. The idea is to simulate virtual distributions under the assumption that all regions would have shown the same values for the variables defining each factor (i.e, conditioning out the effect of a given factor). If the factor had no effect on the distribution during the sample period then the real and virtual distribution should not differ. I follow Lopez-Bazo et al (2005) by using previous coefficient estimates and combining them with the variables considered in the empirical model. In contrast to

Overman and Puga (2002) I consider the effect of all the factors included in the analysis. This is at the cost of imposing some homogeneity, as the coefficients in the model are common to all regions regardless its precise value in each region. The effect of a factor X on the unemployment rate differential of region i in period t U_{Xi} is computed as:

$$U_{Xi} = (X_{i,t} - \bar{X}_t) \hat{\beta}_x \quad (12)$$

where $X_{i,t}$ is a vector with observations for the variables included in factor X for that province and that time period, \bar{X}_t is the vector of averages across provinces for those variables in period t and $\hat{\beta}_x$ is the vector of estimated coefficients associated to those variables. Second, conditional unemployment rate differentials are computed by subtracting the effect of the factor from the unemployment rate differentials:

$$UCONDi = (U_{i,t} - \bar{U}_t) - U_{Xi} \quad (13)$$

where \bar{U}_t is the average unemployment rate in period t . Using the information provided by the conditional unemployment distribution one can estimate its density and analyze its shape applying non parametric techniques. Changes between the actual and the virtual distribution can be analyzed with stochastic kernels in the same way as it is done in Section 2 above. Hence, the kernel density flows along the diagonal would indicate that specific factor does not affect the observed distribution while if the dispersion in the real distribution is mostly caused by a specific factor, the kernel will run in parallel to the axis that measure actual differentials. Conditional distributions and density functions were computed for the sample period for each factor but only the estimation of the stochastic kernel will be shown here. Stochastic kernels for the disequilibrium and market equilibrium conditioning exercises are shown in Figures 6 and 7. As expected, the disequilibrium variables in Figure (6) do not significantly affect the distribution given that density flows are allocated along the diagonal. As it is shown, disequilibrium

variables account for little part of the impact on the lower side of the unemployment distribution. On the contrary, the effect of market equilibrium variables seems a key driver of wide European unemployment distribution characteristics. When equilibrium components are conditioned out, the resulting distribution is much more concentrated and the density flows in parallel to the y axis. However, the contributions of different factors is far of homogenous. Most of demographic variables did no exert a significant influence (with the exception of the net migration rate) but market equilibrium factors such as the share of employment in the manufacture sector account for a large part of the characteristics of the distribution. Institutions and amenities seem to play a minor role on the whole spatial distribution. The latter result might be due to the short-time sample used in the analysis, given that the effect of these variables should be more identifiable in long-time samples. Taken together, these results suggest that the small reduction in unemployment rate differentials observed during the period 2000-2011 has been mainly driven by market equilibrium forces.

Figure 7: Disequilibrium Variables

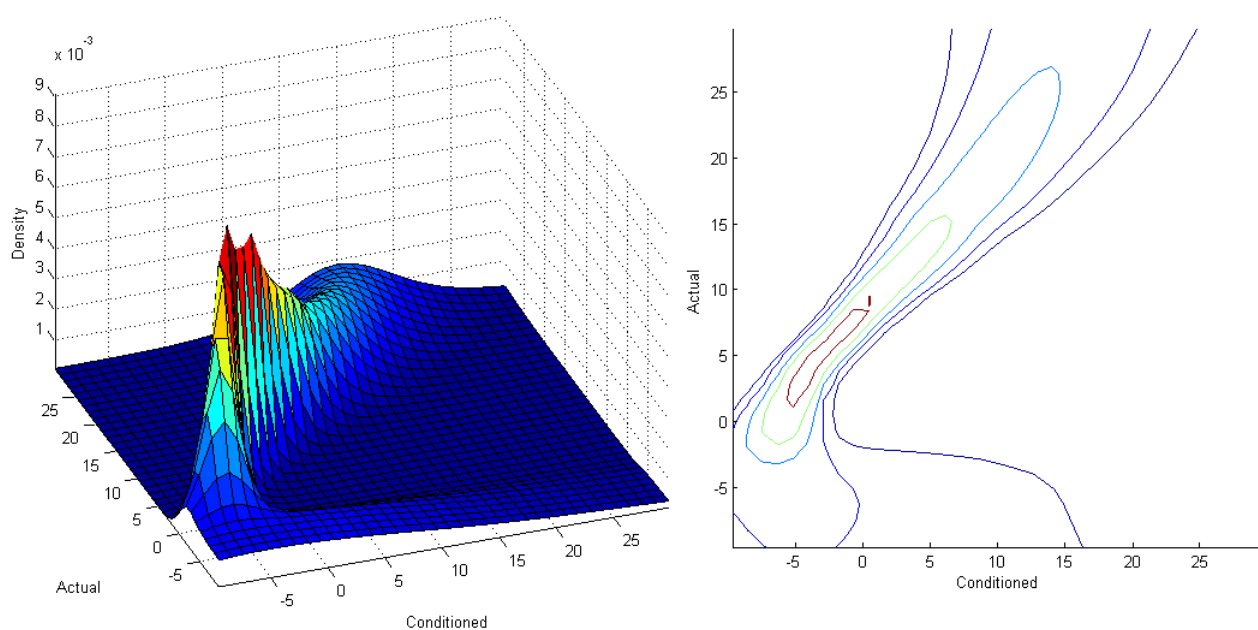
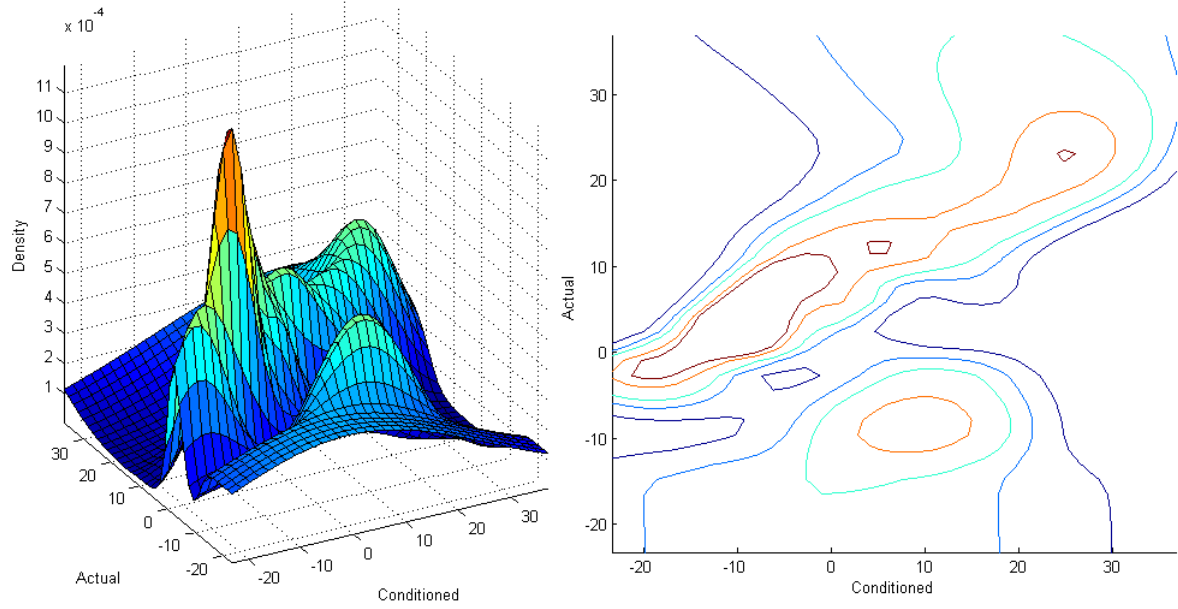


Figure 8: Market Equilibrium Variables



5 Conclusions

This paper applies recently developed spatial econometric tools to study changes over time in the distribution of European unemployment rates. The analysis of the dynamic distribution of unemployment rates during 2000-2011 suggests that regional disparities have decreased because of the catch-up process experienced by eastern European regions with relatively high unemployment rates at the beginning of the period. Nevertheless, regional unemployment gaps seem to be highly persistent as indicated by stochastic kernel estimates. The spatial distribution of unemployment rates indicates that spatial effects have been relevant shaping the evolution of unemployment differentials. In view of these facts, I augment the Blanchard and Katz (1992) theoretical framework and I derive a dynamic spatial lag model that integrates spatial and serial dynamic effects within a single equation. Within this framework, a region-specific shock will not only affect the respective labor market, but instead spill over to neighbouring regions. The empirical model also includes spatial and time effects to control for unobserved heterogeneity and a set of regional equilibrium and disequilibrium factors together with national labor market institutional covariates. In order to carry out the model estimation, the dynamic spatial panel model is estimated by means of the bias correction quasi-maximum likelihood estimator developed by Lee and Yu (2008; 2010).

The econometric analysis starts by using a spatial weight matrix based on the squared of the distance. However, I find that under such spatial dependence scheme regional unemployment rates turn out to be unstable in a dynamic spatial panel data model. In order to remove unstable components I follow Lee and Yu (2010) and reformulate the model in spatial first differences. By taking spatial first differences in the dynamic spatial panel data model, I show that the change in the regional unemployment rate of a particular region depends not only on the change in current and past unemployment rates of other regions but also on a set of exogenous explanatory variables relevant in the literature. However, model selection criteria such as Bayesian posterior probabilities,

likelihood values and error variance results indicate that the square distance matrix must be rejected in favor of an exponential decay distance matrix, where the connectivity between regions decreases with the distance at the 1% rate. Under this specific form of spatial dependence, most of disequilibrium, market equilibrium and demographic variables appear to have a significant effect on unemployment rates of the region itself but also a significant spillover effect on neighboring regions.

In order to complement the regression analysis I analyze by means of stochastic kernels how much of the features observed in the geographical distribution of the unemployment rates are explained by the each factor. Thus, by comparing the entire observed distribution to the one obtained once total estimated effects of the various determinants have been removed, I find that market equilibrium factors are the main driver of the slow convergence process in European unemployment rates. Although the limited-time frame and the nature of the study imply that any conclusions should be taken with caution, the non-parametric analysis suggests that the key factor is the share of employment in the manufacturing sector. Conversely, the evolution of regional unemployment rate differentials does not seem to be driven by regional disequilibrium factors, amenities or national-level labor market institutions. Therefore, the results obtained here support the view of Blanchard and Katz (1992) who consider that unemployment rate differentials are a temporary disequilibrium phenomenon which may vanish with increasing migration flows and economic integration.

The results of this study raise some policy implications. Isolated actions aimed at fostering the reduction of regional unemployment in regions facing high-unemployment should consider the possibility of important spillovers into the neighboring regions. Provided that policy outcomes might not be internalized at the regional level, coordinated industrial policies at the wide European level might be more successful than isolated actions, which is a possibility that has so far remained unexplored by the policy makers in charge of the design of the EU labor market policy. Finally, I would like to emphasize

that further research is needed to increase our understanding of the behavior of underlying spatial spillover mechanisms and spatio-temporal propagation processes, which play a relevant role in the observed decreasing unemployment disparities. I intend to pursue this issue in future research.

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Appendix A: Data Description

U: Unemployment Rate. The Unemployment Rate $UR_{i,t}$ data is obtained from Eurostat and it is defined as:

$$UR_{i,t} = 100 * \left(\frac{U_{i,t}}{LF_{i,t}} \right)$$

where $U_{i,t}$ is the number of unemployed and $LF_{i,t}$ is the labor force.

A. Disequilibrium Factors.

EMPG: Employment Growth. Employment Growth $\Delta EMP_{i,t}$ is obtained from Cambridge Econometrics and it is defined as the annual percentage rate of change:

$$\Delta EMP_{i,t} = 100 * \left(\frac{EMP_{i,t} - EMP_{i,t-1}}{EMP_{i,t-1}} \right)$$

YGAP: Real Gross Domestic Product Gap. The data sources for the YGAP calculation are the Cambridge Econometrics Database and Eurostat. YGAP is computed using the Hedrick Prescott filter in order to obtain the long run trend in a first place. Concretely, the HP filter is presented as a solution to extract the trend of a time series from the following optimization problem:

$$\hat{Y} = \underset{\mu_t}{\operatorname{argmin}} \sum_{t=1}^T \left\{ (y_t - \mu_t)^2 - \lambda [(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1})]^2 \right\}$$

where the parameter λ defines the smoothness of the obtained trend. For this study, given that the frequency of data is annual it takes a value of 100. Given the long run trend \hat{Y}_i , fluctuations are computed as:

$$\tilde{Y}_{i,t} = Y_{i,t} - \hat{Y}_i$$

where $Y_{i,t}$ is defined as $Y_{i,t} = \frac{RGDP_{i,t}}{POP_{i,t}}$ and $RGDP_{i,t}$ is the GDP level (constant prices 2000) and $POP_{i,t}$ is the total population. While GDP levels are obtained from

Cambridge Econometrics, price levels are obtained from Eurostat.

SC: Structural Change Index. The Structural Change proxy $SC_{i,t}$ is the Lilien Index:

$$SC_{i,t} = \left[\sum_{i=1}^N \left(\frac{x_{irt}}{x_{rt}} \right) (\Delta \log x_{irt} - \Delta \log x_{rt})^2 \right]^{\frac{1}{2}}$$

RWG: Real Wage Growth. Real Wage Growth is computed as the annual percentage change of the level of real wages:

$$RWG_{i,t} = 100 \frac{RW_{i,t} - RW_{i,t-1}}{RW_{i,t}}$$

B. Market Equilibrium Factors.

RW: Real Wages. Regional real wage calculation $RW_{i,t}$, combines Cambridge Econometrics and Eurostat databases. This variable is defined as:

$$RW_{i,t} = \frac{W_{i,t}}{P_{c,t}}$$

where $W_{i,t}$ denotes the nominal compensation per employee (Cambridge Econometrics) and $P_{c,t}$ is a country price index (Eurostat).

DIV: Diversity Index The Diversity Index is computed as:

$$DIV_{i,t} = 100 - 100 \left(\frac{x_{irt}}{\sum_r x_{irt}} \right)^2$$

where r denotes the sector and it is computed over all sectors in the Cambridge Econometrics Database.

INDUSTRY MIX. Industry mix data is taken from the Cambridge Econometrics database. The shares of employment in the various sectors are computed as:

$$AS_{i,t} = \text{Agriculture Share} = 100 \left(\frac{AGRI_{i,t}}{EMP_{i,t}} \right)$$

$$MANU_{i,t} = \text{Manufacture Share} = 100 \left(\frac{MANU_{i,t}}{EMP_{i,t}} \right)$$

$$CONS_{i,t} = \text{Construction Share} = 100 \left(\frac{CONS_{i,t}}{EMP_{i,t}} \right)$$

$$NMS_{i,t} = \text{Non Market Services Share} = 100 \left(\frac{NMS_{i,t}}{EMP_{i,t}} \right)$$

$$FS_{i,t} = \text{Financial Services Share} = 100 \left(\frac{FS_{i,t}}{EMP_{i,t}} \right)$$

where $AGRI_{i,t}$, $MANU_{i,t}$, $CONS_{i,t}$, $NMS_{i,t}$ and $FS_{i,t}$, denote the number of employed in the agriculture, manufacture, construction, non-market services and financial services sectors respectively. $EMP_{i,t}$ is the total number of employed workers in the regional economy.

C. Demographic Factors

OLD: Share of Population between 55-65 years. Data to compute the share of old population is taken from Eurostat. The share of old population are defined as:

$$OLD_{i,t} = 100 \left(\frac{POLD_{i,t}}{POP_{i,t}} \right)$$

where $POLD_{i,t}$ is the number of people between 55-65 years and $POP_{i,t}$ denotes the number of people between 15-65 years.

YOUNG: Share of Population between 15-25 years. Data to compute the share of young population is taken from Eurostat. The share of old population are defined as $YOUNG_{i,t} = 100 \left(\frac{PYOUNG_{i,t}}{POP_{i,t}} \right)$, where $PYOUNG_{i,t}$ is the number of people between 15-25 years and $POP_{i,t}$ denotes the number of people between 15-65 years.

FEM: Female Participation. Data to compute the share of female in the labor force is taken from Eurostat. The female participation rate is defined as:

$FEM_{i,t} = 100 \left(\frac{LF_{FEM_{i,t}}}{LF_{i,t}} \right)$, where $LF_{FEM_{i,t}}$ is the number of active females and $LF_{i,t}$ is the total active population.

EDUC: Education Index. In the definition of the education index I follow Bubbico and Dijkstra(2011) so that the education index mimics the Regional Human Development Indicator (HDI) for the EU. Thus, I combine low and high education attainment

for people aged 2564 as below:

$$EDUC = \frac{1}{3}(1 - L) + \frac{2}{3}H$$

where L is the (%) of population with secondary education and H is the (%) of population with tertiary education. The data for the education index are drawn from the Eurostat database.

MIG: Net Migration The data to approximate net migration is obtained from Eurostat. This variable is computed as the residual difference between the growth rate of the population and its natural change:

$$MIG_{i,t} = POP_{i,t+1} - POP_{i,t} + (B_{i,t} - D_{i,t})$$

where $B_{i,t}$ is the number of people born and $D_{i,t}$ is the number of people dead.

D. Amenities

EMPD: Employment Density. Employment Density data is drawn from Cambridge Econometrics. The variable is defined as:

$$EMPD_{i,t} = \frac{EMP_{i,t}}{Area_i}$$

where $EMP_{i,t}$ is the number of employed workers and Area is the surface in squared kilometers.

E. Labor Market National Institutions.

COV: Coverage Index The Coverage Index $COV_{i,t}$ is computed as the summation of the union density percentage $UD_{i,t}$ and the percentage of workers covered by collective bargaining agreements $COV_{i,t}$. The data is collected from the ICTWSS database.

COORD: Coordination Index The Coverage Index $COORD_{i,t}$ is computed as the summation of the coordination score $CO_{i,t}$ and centralization score $CENT_{i,t}$. The data is collected from the ICTWSS database.

EPL: Employment Protection Legislation The Employment Protection Legislation index $EPL_{i,t}$ from the OECD database.

Appendix B: Estimation Methods

1. Dynamic Spatial Panel Data Model Estimation

The model considered in this paper is:

$$Y_{nt} = \tau Y_{n,t-1} + \rho W_n Y_{n,t} + \eta W_n Y_{n,t-1} + X_{n,t} \beta + \mu_n + \lambda_t \iota_n + V_{nt} \quad (14)$$

where $Y_{nt} = (y_{1t}, y_{2t}, \dots, y_{nt})'$ and $V_{nt} = (v_{1t}, v_{2t}, \dots, v_{nt})'$ are $nx1$ column vectors and v_{it} is i.i.d across i and t with zero mean and variance σ^2 , W_n is known nxn spatial weights matrix which is nonstochastic and generates the spatial dependence between cross sectional units y_{it} , X_{nt} is an nxk_x matrix of nonstochastic regressors, μ_n is a $nx1$ column vector of fixed individual effects and λ_t is a scalar of time effect and ι_n is a $nx1$ column vector of ones.

As shown in Lee and Yu (2010), when both n and T go to infinity, one way to estimate the model above is to estimate all the parameters including both the time effects and individual effects which will yield a bias of the order $O(\max(n^{-1}, T^{-1}))$ for the common parameters. Denote $\theta = (\delta', \rho, \sigma^2)'$ and $\alpha_T = (\alpha_1, \alpha_2, \dots, \alpha_t)$. The log-likelihood of the model is:

$$\ln L_{n,T}^d(\theta, \mu_n, \alpha_T) = -\frac{nT}{2} \ln \pi - \frac{nT}{2} \ln \sigma^2 + T \ln |S_n(\rho)| \quad (15)$$

$$- \frac{1}{2\sigma^2} \sum_{t=1}^T [V_{nt}(\theta, \mu_n, \alpha_T)]' [V_{nt}(\theta, \mu_n, \alpha_T)] \quad (16)$$

where $V_{nt}(\theta, \mu_n, \alpha_T) = S_n(\rho) Y_{nt} - Z_{nt} \delta - \mu_n - \alpha_t \iota_n$, $S_n = I_n - \rho W_n$, $\delta = (\tau, \eta, \beta)'$ and

$Z_{nt} = (Y_{n,t-1}, W_n Y_{n,t-1}, X_{n,t})$. By concentrating out the individual fixed effects μ_n and the time-period fixed effects α_T , one can rewrite previous model log-likelihood as:

$$\ln L_{n,T}^d(\theta) = -\frac{nT}{2} \ln \pi - \frac{nT}{2} \ln \sigma^2 + T \ln |S_n(\rho)| \quad (17)$$

$$-\frac{1}{2\sigma^2} \sum_{t=1}^T [\tilde{V}_{nt}(\theta)]' J_n [\tilde{V}_{nt}(\theta)] \quad (18)$$

where $\tilde{V}_{nt} = S_n(\rho) Y_{nt} - Z_{nt} \delta$ and $J_n = I_n - (1/n) \iota_n \iota_n'$ is the deviation from the group mean transformation, which is a projector. The optimization of previous log-likelihood with respect θ yields a parameter bias that can be corrected applying a bias corrected estimator:

$$\hat{\theta}_{nT}^{d1} = \hat{\theta}_{nT}^d + \frac{1}{T} \left(-\frac{1}{nT} E \frac{\partial^2 \ln L_{n,T}^d(\hat{\theta}_{nT}^d)}{\partial \theta \partial \theta'} \right)^{-1} a_{1,n}(\hat{\theta}_{nT}^d) + \frac{1}{n} \left(-\frac{1}{nT} E \frac{\partial^2 \ln L_{n,T}^d(\hat{\theta}_{nT}^d)}{\partial \theta \partial \theta'} \right)^{-1} a_{2,n}(\hat{\theta}_{nT}^d)$$

where the term $\frac{\partial^2 \ln L_{n,T}^d(\hat{\theta}_{nT}^d)}{\partial \theta \partial \theta'}$ denotes the second-order derivative of the log-likelihood function:

$$\frac{1}{nT} \frac{\partial^2 \ln L_{n,T}^d(\hat{\theta}_{nT}^d)}{\partial \theta' \partial \theta} = -\frac{1}{nT} \times \quad (20)$$

$$\left(\begin{array}{ccc} \frac{1}{\sigma^2} \sum_{t=1}^T \tilde{Z}'_{nt} J_n \tilde{Z}_{nt} & \frac{1}{\sigma^2} \sum_{t=1}^T \tilde{Z}'_{nt} J_n W_n \tilde{Y}_{nt} & \frac{1}{\sigma^4} \sum_{t=1}^T \tilde{Z}'_{nt} J_n \tilde{V}_{nt}(\theta) \\ \frac{1}{\sigma^2} \sum_{t=1}^T \left((W_n \tilde{Y}_{nt})' J_n W_n Y_{nt} + \text{tr} G_n^2(\rho) \right) & \frac{1}{\sigma^4} \sum_{t=1}^T (W_n \tilde{Y}_{nt})' J_n \tilde{V}_{nt}(\theta) & \\ * & & -\frac{nT}{2\sigma^4} + \frac{1}{\sigma^6} \sum_{t=1}^T \tilde{V}'_{nt}(\theta) J_n \tilde{V}_{nt}(\theta) \end{array} \right) \quad (21)$$

and the parameters $a_{1,n}(\theta) = a_{1,n}$ and $a_{2,n}(\theta) = a_{2,n}$ are calculated as:

$$a_{1,n} = \left(\begin{array}{c} \frac{1}{n} \text{tr} \left((J_n \sum_{h=0}^{\infty} A_n^h) S_n^{-1} \right) \\ \frac{1}{n} \text{tr} \left(W_n (J_n \sum_{h=0}^{\infty} A_n^h) S_n^{-1} \right) \\ 0_{k_x \times 1} \\ \frac{1}{n} \tau \text{tr} \left(G_n (J_n \sum_{h=0}^{\infty} A_n^h) S_n^{-1} \right) + \frac{1}{n} \eta \text{tr} \left(G_n (J_n \sum_{h=0}^{\infty} A_n^h) S_n^{-1} \right) + \frac{1}{n} \text{tr} (J_n G_n) \\ \frac{n-1}{n} \frac{1}{2\sigma^2} \end{array} \right) \quad (22)$$

and

$$a_{2,n} = \left(\begin{array}{c} 0_{1 \times (k_x + 2)} \\ \frac{1}{n} \ell'_n G_n \ell_n \\ \frac{1}{2\sigma^2} \end{array} \right) \quad (23)$$

2. Stochastic Kernel Estimation

Stochastic kernel estimation measures the likelihood of a region shifting one place in the ranking of European regional development rates. As explained by Quah (1996) and Magrini (2007), it provides evidence about the shape of the dynamic distribution and the mobility within it. Specifically, I use unconditional stochastic kernels to analyze convergence dynamics and conditional kernels to explore the role played by the spatial location of the various regions in explaining regional unemployment disparities. Consider a group of n regions, indexed by i , and suppose time is continuous with $t \in (0, \infty]$. Then let $y_i(t)$ be the unemployment rate of region i at time t and $\bar{y}(t)$ the average regional development level for the whole group of economies at the same point in time. Next, normalize RLI scores with respect to the period average:

$$\phi(t) = y_i(t) - \bar{y}(t) \tag{24}$$

This transformation separates the effects of aggregate forces from the effects of economy-specific forces on the cross-sectional distribution, after conditioning out their aggregate effects. Next, consider a stochastic process $\phi(t), t \geq 0$ and denote by $F_{\phi(t)}$ the distribution of $\phi(t)$ and by $f_{\phi(t)}$ the density function associated with $F_{\phi(t)}$. The aim is to describe the law of motion of the stochastic process $\phi(t)$. The simplest way of modeling the distribution dynamics is with a first order autoregressive process specification:

$$f_{(\phi(t+s))} = \int_{-\infty}^{\infty} M_{t,s}(\phi) f_{\phi(t)} d\phi \tag{25}$$

where $M_{t,s}$ is a stochastic kernel, mapping the Cartesian product of regional development values and measurable sets to the interval $[0,1]$. More explicitly, the stochastic kernel maps the density at time t into the density at time $t+s$ and tracks where points in $f_{\phi(t)}$ end up in $f_{(\phi(t+s))}$. Hence, this is the operator upon which attention must be focused in order to analyze the dynamics of the entire distribution of regional development

between t and $t + s$. An estimate of the stochastic kernel can be obtained by dividing the estimate of the joint probability density function: $\hat{f}_{\phi(t),\phi(t+s)}$ by the estimate of the marginal probability density function $\hat{f}_{\phi(t)}$:

$$\hat{p}_{t,s} = \hat{f}_{\phi(t+s)|\phi(t)} = \frac{\hat{f}_{\phi(t),\phi(t+s)}}{\hat{f}_{\phi(t)}} \quad (26)$$

The general form of the kernel estimator of $f_{\phi(t),\phi(t+s)}$ is:

$$\hat{f}_{\phi(t),\phi(t+s)} = \frac{1}{n |\mathbf{H}|} \sum_{i=1}^n K(\mathbf{H}^{-1}(\mathbf{x} - \mathbf{x}_i)) \quad (27)$$

where $K(\phi) = \frac{1}{2\pi} e^{-\frac{1}{2}(\phi(t)'\phi(t+s))}$ is a bivariate Gaussian kernel function and \mathbf{H} is the bandwidth matrix. It is well established in the literature (Silverman, 1986) that, while the kernel estimator is not very sensitive to the choice of K , the choice of the bandwidth is quite crucial. I follow Wand and Jones (1993), who demonstrate the adequacy of a diagonal bandwidth matrix $\mathbf{H} = \text{diag}(h_{\phi(t)}, h_{\phi(t+s)})$. As a result, the kernel estimator reduces to:

$$\hat{f}_{\phi(t),\phi(t+s)} = \frac{1}{n} \sum_{i=1}^n \left[\frac{1}{\sqrt{2\pi}h_{\phi(t)}} e^{-\frac{1}{2}\left(\frac{\phi(t)-\phi_i(t)}{h_{\phi(t)}}\right)^2} \frac{1}{\sqrt{2\pi}h_{\phi(t+s)}} e^{-\frac{1}{2}\left(\frac{\phi(t+s)-\phi_i(t+s)}{h_{\phi(t+s)}}\right)^2} \right] \quad (28)$$

The above bivariate product kernel is the product of two one-dimensional kernels, each estimated using a fixed specific bandwidth. The results might suffer, however, if a fixed bandwidth is used to estimate multimodal or long-tailed density functions. The solution is to use a bandwidth that varies at different points of the sample data. The specific option applied here is to follow Abramson (1982) by using at each data point a bandwidth obtained by rescaling the fixed bandwidth $h_{\phi(t)}$ by a factor α inversely related to the density at that point. Abramson (1982) proposed the use of $\alpha = 1/2$, showing that this produces less bias than the fixed bandwidth estimate.

$$h_{\phi(t)} \propto f_{\phi(t)}^{-\alpha} \quad (29)$$

Using these local bandwidths, the bivariate kernel estimator used in the analysis to estimate the joint probability $\hat{f}_{\phi(t),\phi(t+s)}$ becomes:

$$\hat{f}_{\phi(t),\phi(t+s)} = \frac{1}{n} \sum_{i=1}^n \left[\frac{1}{h_{\phi_i(t)}} K \left(\frac{\phi(t) - \phi_i(t)}{h_{\phi_i(t)}} \right) \frac{1}{h_{\phi_i(t+s)}} K \left(\frac{\phi(t+s) - \phi_i(t+s)}{h_{\phi_i(t+s)}} \right) \right] \quad (30)$$