What Drives Regional Unemployment Disparities in European Regions? A Space-Time Econometric Modeling Approach

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Abstract

This paper investigates the evolution of the geographical distribution of unemployment rates in a sample of 241 NUTS-2 regions belonging to 23 European countries between 2000 and 2011. To that end, a spatially augmented labor market model with interdependence among regional economies is presented. In this framework, labor market performance of a particular region is affected not only by its own labor market characteristics but also by the the unemployment rates experienced by the remaining regions. Starting from the theoretical model, a dynamic spatial lag specification is derived and employed to analyze the role played by market equilibrium, disequilibrium and institutional factors shaping regional unemployment disparities. The empirical analysis uses spatial panel econometric techniques that integrate both spatial and temporal dynamics. In conjunction with spatio-temporal panel data regression model estimates, stochastic kernels are used to explore the effect of the various factors in the shape of the whole distribution of unemployment rate. The empirical results suggest that regional unemployment rate differences have decreased and that such regional convergence process has been driven by regional market equilibrium factors.

Keywords: Unemployment, Space-Time Econometrics, Regions, Europe.

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 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 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 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 Comission, 2010a). Moreover, attaining acceptable levels of unemployment is nowadays a top priority on the European Union s policy agenda (European Comission, 2010b) [1].

From an academic perspective, there are 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). Not only the magnitude of unemployment disparities among regions is as large as it is between countries (OECD, 2009[2]; Zeilstra and Elhorst, 2012) but also regions within a country may have different sources and structures of unemployment. A second reason pointed out by Elhorst (2003) is that macroeconomic studies performed at the country level (Bean, 1994; Scarpetta, 1996), give no explanation for the existence of regional unemployment dis-

[1] Europeś 2020 strategy, building on the previous economic 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.

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

parities. 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. Third, according to neoclassical theory, unemployment differentials among regions reflect an inefficient regional economic system. Therefore, reducing such disparities could not only counteract the downward depressive spiral effect in depressed regions but also lead to higher output and lower inflationary pressures (Taylor, 1996; Elhorst, 2003).

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 or institutional 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 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. On the other hand, the second view 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 adjustment processes to asymmetric shocks (i.e, a shortage of labor demand). The adjustment process may be fast or slow, and depending on its speed, unemployment disparities 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 where 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.

At this regard, 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, Herwartz and Niebuhr, 2011; Longhi et al, 2005; Zeilstra and Elhorst, 2012). Up to now, the empirical observation of the economic landscape in Europe has revealed the existence of persistent disparities in unemployment rates in countries such as Spain (Lopez-Bazo et al, 2005), Italy (Cracolici et al, 2007) or Germany (Patuelli et al, 2013). These findings suggest that the nature of regional unemployment disparities in some European economies could be the result of a long-run equilibrium rather than a short-term disequilibrium caused by temporary shocks. However, given that these studies are restricted to one country, they overlook the effect of institutions and cannot be generalized to the whole European setting.

An additional feature of unemployment rates in European regions that has been overlooked by most of the studies in the literature is that they exhibit both positive spatial and temporal correlations. As Elhorst (2003, 2005) point out, studies explaining the evolution of unemployment rates that did not take into account spatial and serial dynamic effects may have been miss-pecified. Regarding this issue, there are few applications integrating space-time dynamics. Pattachini and Zenou (2007) estimated a time-space recursive model for UK regions, Basile et al. (2012) estimated a dynamic durbin for 103NUTS-3 Italian regions and Vega and Elhorst (2013) estimated a dynamic spatial durbin for 112 European NUTS2 regions. The shortcomming of these space-time regional-based studies is that they ommit national labor market institutions and its influence on unemployment. Indeed, to the best of my knowledge only Zeilstra and Elhorst (2012) have analyzed the joint impact of regional and national level labor market institutional factors on regional disparities[3]. However, their focus is on the behavior of a representative region instead of the whole geographical distribution and the econometric specification employed does not include space-time dynamic effects. 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.

[3] In their study, they use a sample of 135 NUTS2 level regions and 11 UK NUTS-1 level regions (of 9 EU countries) for the period ranging from 1983-1997.

The lack of a space-time econometric analysis of unemployment disparities including both institutional and regional variables with a greater size 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*'. This paper is an attempt to overcome the shortcomings of previous studies by employing space-time modeling analysis tools. In order to analyze the regional unemployment phenomenon, a spatially augmented labor market model with interdependence among regional economies is presented. In this framework, externalities are used to model regional labor markets spatio-temporal interdependence, 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 by the remaining regions. Starting from the theoretical model, a dynamic spatial lag specification is derived and employed to explore the role played by market equilibrium, disequilibrium and institutional factors shaping regional unemployment disparities for a sample of 241 NUTS2 regions belonging to 23 EU countries ranging from 2000 to 2011. In a first step, the dynamic spatial panel estimation techniques developed by Lee and Yu (2010a, 2010b) and Elhorst (2012b) are used to quantify dynamic responses over tiem and space as well as space-time difussion impacts. Important methodological issues such as the inclusion of region-specific and time-specific fixed effects, spatial estimation methods, specification, reverse-causality, coefficient interpretation and the selection of the spatial matrix are addressed.

However, the focus of the present 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. Therefore, the study is not restricted to the dynamic spatial panel 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 different determinants have been removed. To that end, non-parametric methods are applied in line with the distribution dynamics approach of Quah (1993, 1996) and Magrini (2007). The stochastic kernel-based counterfactual results are complemented by the relative importance measure propsoed by Lindeman et al. (1980) and (Johnson and Lebreton, 2004). I find that regional unemployment rate differences have decreased and that such regional convergence process has been driven by regional market equilibrium factors dominating social and institutional amenities.

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 theoretical model and the derived dynamic spatial lag model employed to capture the effect of different factors as well as the estimation procedure and interpretation. The fourth section presents both, 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. The sample covers a total of 241 NUTS-2 regions belonging of 23 EU states[4]. 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. The study period goes from 2000 to 2011 and 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 2007 and hiked from 2008 to 2011. However, the linear fit shows that the overall pattern is that unemployment differentials between regions have decreased.

INSERT FIGURE 1 ABOUT HERE

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

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

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 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 Europes regional unemployment rates.

INSERT FIGURE 2 ABOUT HERE

In order to explore whether Figure 2 indicates a structural process of convergence I track the evolution of each regionś relative unemployment rate over time with a continuous transition matrix, that is, a stochastic kernel. As defined by Magrini (2004, 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 distribution[5]. Figure 3 presents the 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, the estimates show the presence of a peak centered near the value of 0.5 times the average. Therefore, the highest peak is formed by regions with unemployment rates below the European average. A remarkable feature of Figure 3 is that the probability mass flows along the main diagonal, which implies the

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

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. As it is clear, there is an important degree of mobility in the upper tail of the distribution. Specifically, amongst the regions with the highest unemployment rates, that is to say, (1.5 times above the European average in 2000), 35.2% of them moved to the range between 1 to 1.5 times the European average while the 27.8% of them 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.

INSERT FIGURE 3 ABOUT HERE

The slow convergence pattern observed in previous Figures 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 northern Europe regional economies who started with relatively low levels of unemployment and 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 geo-dynamics of relative unemployment in Figure 4, where the quartiles of the time differences in the relative positions are plotted. The first quartile of the geographical distribution covers the most successful relative improvements. Specifically, covers regions that improved more than a 18% their relative position. Particularly noteworthy in this regard is the case of regions of Poland that starting with a relative rate of 1.9 times above average, converged to a level 1.2 times higher. A markedly good performance is also found in many Italian regions and in the sout of France.Moreover, the second quartile comprises regions which are located within the range of -6% worsening to 18% improvement as it is the case of German landers or the east of France, that improved their position. The third quartile captures negative performance with respect the average European evolution, in the range between 6% and 26% changes. This is the case in zones of northern regions such as those belonging to Sweden, Denmark, Ireland, United Kingdom or Hungary. However, the worst results are obtained in the periphery of Europe. Starting from relatively high unemployment levels (i.e, 1.5 times above the EU average), during the study period spanish regions have increased its distance with respect the EU average (i.e, 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 worsened its unemployment figures to a level 1.6 times above it.

INSERT FIGURE 4 ABOUT HERE

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 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 WUR_t where W is a spatial weight matrix describing the spatial interdependences among the sample regions and UR_t is the European's relative unemployment level. The spatial weight matrix used in the analysis is defined as:

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

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[6]. W is row standardized so that is the relative and not the absolute distance which matters. Having

[6]The results of the kernel analysis are similar for different distance based matrices and available upone request

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 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 5. 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, which goes in line with the resolts presented in Overman and Puga (2002). Accordingly, spatial effects are a relevant factor explaining observed variations in unemployment rates. Further evidence on this issue 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, the regional distribution 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 unemploment rates below that average are more likely to be surrounded by other low-unemployment regions.

INSERT FIGURE 5 ABOUT HERE

3 Methodology

3.1 A Space-Time Unemployment Model.

In line with the findings obtained in Section 2, recent papers have shown that regional unemployment rates are also affected by neighboring regions outcomes (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 builts on the Blanchard and Katz (1992) regional labor market framework including both, neighboring effects and institutional variables. 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 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. Given this interdependence, the induced changes of unemployment in neighbouring areas may spill over again to adjacent labor markets, including the location where the shock originated. The model reads as:

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

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

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

$$u_{it} = n_{it} - l_{it} \tag{5}$$

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 $i = j$. Both wages and price levels are expressed in logarithms. The α_i and δ_i parameters are positive, β and γ are 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 ($X_{w,it}$) 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 a Dynamic Spatial Lag Model (DSLM):

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

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 $\Theta = (\alpha_1 + \alpha_6)$.

Space-time dynamic models such as that of Equation (6) produce a situation where a change in the ith observation of the rth explanatory variable at time t will produce contemporaneous and future responses in all regions' dependent variables u_{it+T}. This is due to the presence of a time lag, a spatial lag and a cross-product term reflecting space-time diffusion (Derbasy et al., 2012). The fact that feedback effects and spillovers effect can exist requires to think about equation (6) as reflecting the outcome of a long-run equilibrium or steady state. Changes in the explanatory variables stacked in X, are then interpreted as setting in motion forces that lead to a new long-run equilibrium. Additionally, one can rewrite Equation (6) in the short form of a two-way fixed effects DSLM, as follows:

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

where u_t denotes a Nx1 vector consisting of observations for the unemployment rate measured in percentages for every region $i = 1, 2, ..N$ at a particular point in time $t = 1, 2, ..T$, X_{it}, is an NxK matrix of exogenous aggregate socioeconomic and economic covariates with associated response parameters β contained in a Kx1 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 $\epsilon_t = (\epsilon_{1t}, ..., \epsilon_{Nt})^T$ is a vector of i.i.d disturbances whose elements have 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 autoregressive coefficient. W is a NxN 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. $\mu_i = (\mu_1, ..., \mu_N)^T$ is a vector with region fixed effects, and $\lambda_t = (\lambda_1, ..., \lambda_T)$ 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 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 (2010a, 2010b) 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 (2010a,b) 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)[7]. 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, 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:

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

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 $\Sigma = (I - W)\,(I - W)'$. 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

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

matrix to the model in order to get:

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

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 rewriten as:

$$U_t^* = \tau U_{t-1}^* + \rho W U_t^* + \eta W U_{t-1}^* + X_t^* \beta + \mu^* + \epsilon_t^* \tag{10}$$

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 $+\omega_{max-1}$ denotes the second largest eigenvalue of the spatial weights matrix W. Importantly the latter restriction is less exigent that 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 the *r-th* explanatory variable of X_t in region 1 up to region N (say x_{ir} for $i = 1, ..., N$, respectively), at a particular point in time t is:

$$\frac{\partial U_t}{\partial X_t^r} = \left[(I - \rho W)^{-1}\right]\beta \tag{11}$$

while the long run effect is given by:

$$\frac{\partial U_t}{\partial X_t^r} = \left[(1-\tau)I - (\rho+\eta)W\right]^{-1}\beta^{(r)} \tag{12}$$

According to Elhorst (2012), 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 $\rho \neq 0$. Finally, the *total* effect, which is object of main interest, is the sum of the direct and indirect impacts. Interestingly, in the previous model it is possible to compute -own $\partial u_{it+T}/\partial x_{it}^{r}$ and cross-partial derivatives $\partial u_{it+T}/\partial x_{jt}^{r}$ 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 the data generating process can be expresed as:

$$U_{it} = \sum_{r=1}^{K} Q^{-1} \left(I\beta^{r} \right) X_{it}^{(r)} + Q^{-1} \left(\mu_i + \lambda_t + e_{it} \right) \tag{13}$$

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

$$Q = \begin{bmatrix} B & 0 & \dots & & 0 \\ C & B & & & 0 \\ 0 & C & \ddots & & \vdots \\ \vdots & & \ddots & & \\ 0 & \dots & & C & B \end{bmatrix} \tag{14}$$

where $C = -\left(\tau + \eta W\right)$ and $B = \left(I_N - \rho W\right)$. 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 arising from a permanent change at time t in rth variable takes the form in Equation (x):

$$\frac{\partial U_{t+T}}{\partial X_t^r} = \sum_{s=1}^{T} \left[(-1)^s \left(B^{-1} C \right)^s B^{-1} \right] \beta \tag{15}$$

Notice that matrix of the right hand side of previous equation collapses to equation as s goes to infinity. Representation of direct and indirect effects at the different time horizons is difficult because they are different from one region to another because of the diagonal and off-diagonal elements of the so-called simultaneous spatial multiplier matrix $(I - \rho W)^{-1}$ and long-run multiplier matrix $\left[(I - \rho W) - (\tau + \eta W)^{-1} \right]$ 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 elements.

3.3 The Empirical Specification.

Equations (2) to (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 pionering 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 previous model and findings of existing studies on the determinants of unemployment disparities (Elhorst, 2003). However, the choice of these variables 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 employment growth (EMP) and cyclical output fluctuations (YGAP) are included. If a region creates employment at a faster rate the European average, unemployment in that region should decrease relatively (Diaz, 2011). A 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 level[8]. According to Isserman (1986) this variable is 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.

C) Equilibrium Labor Market Variables.

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. Specialization is measured by means of Herfhindal index (HF).and participation rates are are also included (PAR). 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 manufacturing (MANU) and non-market services (NM). Regions specialized in declining industries such as manufacturing may exhibit higher unemployment rates than regions specialized in growing industries such as public services. However, the reverse may also be true given the large multipliers associated to these sectors (Elhorst, 2003). 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 expected[9]

D) Equilibrium Demographic Factors.

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 unem-

[8]Real 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: $min \sum_{t=1}^{T} \left\{ (y_t - \mu_t)^2 - \lambda \left[(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1}) \right]^2 \right\}$ 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 value of 100.

[9]Following 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.

ployment if its natural population growth rate exceeds its employment growth rate. Eventhough these variations have no inmmediate 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 between 54 and 64 years old (OLD). As the survey of Elhorst (2003) documents, results of empirical studies at usually find a positive effect on unemployment outcomes. 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 attainment[10]. 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.

Amenities may be 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 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 cathegory of amenities.

F) Institutions.

Following macroeconomic research I consider the role of labour market institutions,

[10] I 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 $25 - 64$ 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.

provided that they may be crucial determinants behind the evolution of unemployment (HeRwartz and Niebuhr, 2013). In order to approximate institutional effects I introduce the employment protection legislation (EPL), a bargaining coverage index (COV), a coordination index (COORD) and both the tax wedge (TWED) and the unemployment benefitis (UB)[11].

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. However, according to Boeri and Van Ours (2008) a stronger EPL reduces job creation, because employers are more reluctant to open a vacancy. Thus, the effects of the EPL on unemployment ambiguous.

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 indicator. The 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. Nevertheless, under collective bargaining schemes, a higher union density should lead to higher wages and lower employment which in turn should rise unemployment (Nickell, 1997, 1998).

Additionally, the characteristis of the 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

[11]Given that these covariates are usually measured by the different organizations responsible of the data collection and construction in different numeric scales they all have been normalized between 0 and 100 by applying a max-min transformation in order to favour the comparability and the interpretation of the results.

between the bargaining partners in order to reach consensus. However, the differences between the degree of centralization and coordination indexes provided by the Institutional Characteristics of Trade Unions Database (ICTWSS) 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). According to Calmfors and Drifill (1998) and Zeilstra and Elhorst (2012), the effect of centralized and coordinated bargaining outcomes on unemployment is conditional to the bargaining coverage. Thus, I follow Zeilstra and Elhorst (2012) and I combine these variables into three new variables: bargaining coverage index in regions with low coordination index, bargaining coverage index in regions with intermediate coordination index and bargaining coverage index in regions with high coordination index. At this regard, both Longhi et al (2005) and Zeilstra and Elhorst (2012) find evidence of a hump shaped relationship between bargaining coverage level and the level of unemployment.

In order to approximate the generosity of the unemployment benefit system which depends on the duration, replacement ratio and the conditions for recieving a benefit I use the index of the OECD. Unemployment benefits may also affect unemployment through different chanels. 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, unemployment benefits increase the expected profit of participating in the labor market with respect the one associated to inactivity. As Elhorst and Zeilstra (2007) this higher participation generally has a negative effect on unemployment. However, 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).

Finally, I control for the gap between the cost of labor to the firm and the net wage of the worker, the so called tax wedge. The extent to which the tax wedge may affect 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. However, this relation also depends on the unemployment benefits. If increasing tax wedge is balanced with decreasing unemployment benefits both wages and unemployment should increase less (Daveri et al, 2000). However, most of the empirical studies find a positive relationship between the tax wedge and unemployment (Nickell 1997, 1998; Elmeskov, 1998; Daveri et al., 2000) while Scarpetta (1996) and Di Tella and Macculoch (2005) find an insignificant effect.

Table 1 shows the mean, the standard deviation and expected signs of all the covariates used in the empirical analysis.

INSERT TABLE 1 ABOUT HERE

4 Results

This section reports and discusses the empirical findings. It is divided into two main subsections. Initially, I report the results of the DSLM estimation. In a second step, I use the DSLM estimated effects to feed a stochastic kernel conditioning simulation exercise in order to assess the effect caused by the different set of factors on the whole distribution of unemployment rates.

4.1 Dynamic Spatial Lag Model Results.

The first issue that needs to be addressed is the possibility of a reverse-causality nexus between unemployment and the various controls given that our theoretical model suggests some variables such as wages or other institutional controls may be endogenous. In order to assess the direction of causality between regional unemployment and the set of covariates I run Granger Causality tests in a panel framework using LSDV estimator. Specifically, I consider a dynamic panel model with fixed time and region specific effects. The number of lags (m) is specified to be identical for all variables. Since Granger causality test results may depend on the choice of lag specification, I report the results for a maximum lag order of three years and then determine the optimal lag specification based on the Bayesian Information Criterion (BIC). The results are reported in Table 2 below. Columns (2) and (5) report the F-statistic while Columns (3) and (6) report the p-values associated to the null of the causality direction going from unemployment to any control. Columns (4) and (6) report the BIC. As implied by the BIC, the optimal number of lags for all the controls is 3 and for most of the variables it is possible to reject the hypothesis of endogeneity [12]. However, both the real wage and the education variables appear to be endogenous. This result suggests that the unemployment rate affects wage-setting and the educational decision of agents. Because of the scarcity of available instruments for regional level data, I lag these variables the required periods for the predictive power of unemployment on real wages and educational achievement to die out. Importantly,

[12] This result is robust for panel granger tests based on pooled and fixed spatial effects as alternative specifications for a number of lags m=1,2,3.

when entering these variables lagged one period, granger causality tests reject the hypothesis of endogeneity.

INSERT TABLE 2 ABOUT HERE

Table 2 reports the statistics associated to the key aspects guiding the optimal model selection within a dynamic spatial panel data framework: *i)* the choice of the W matrix, *ii)* the specification of the model including either fixed spatial effects or both, spatial fixed and time-period fixed effects, and *iii)* the existence or not of space-time co-integrating relationships.

The results of space-time panel data analysis and the model performance depend strongly on the spatial connectivity matrix W used by the researcher. Indeed, one of the most critized 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. 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. Columns 1 to 3, report the performance of DSLM model with spatial fixed and time effects for a broad range of alternative specifications of W and puts together the three previous selection procedures.

I begin by considering several matrices based on the k-nearest neighbours ($k = 5, 10, 15, 20$) computed from the great circle distance between the centroids of the various regions. Additionally, I construct various inverse distance matrices with different cut-off values above which spatial interactions are assumed negligible. As an alternative, I also consider inverse power distance and exponential distance decay matrices whose off-diagonal elements are defined by $w_{ij} = \frac{1}{d_{ij}^{\alpha}}$ for $\alpha = 1.25, \ldots, 3$ and $w_{ij} = -exp(\theta d_{ij})$ for $\theta = 0.005, \ldots, 0.03$, 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 us to avoid the identification problems raised by Manski (1993). Table **??** show that, according to these criteria, the most appropriate matrix in our context is $W_{ij} = -exp(0.015d_{ij})$ which imposes an speed of decay in the intensity of spatial interactions of 1.5% as distance among regional units increases.

A second issue is whether or not include time period fixed effects for each spatial scheme. Using Monte Carlo simulation experiments, Lee and Yu (2010) show that ignoring time-period fixed effects may lead to large upward biases in the coefficient of the spatial lag. This is due to the fact that most variables tend to increase and decrease together in different spatial units along the business cycle. In the baseline scenario I include both spatial and time period fixed effects and I check whether time effects could be restricted. At this regard, columns 4 to 5 report F-statistics and p-values associated to the restriction of the time effects parameters. As can be observed the corresponding F-tests reject the inclusion of time-period fixed effects in when using is $W_{ij} = -exp(0.015d_{ij})$. On the other hand, each W and each parameter specification may yield different behaviors in terms of space-time stability. To find out whether the two-way effects models are stable for each model configuration I calculate $\tau + \rho + \eta$ and carried out a two-sided Wald-test to investigate the null hypothesis $\tau + \rho + \eta = 1$. Columns 6 to 9 report the parameter sum, the f-statistic and the p-value. Importantly, when using this matrix the model is stable and does not suffer from spatial cointegration (i.e, $\tau + \rho + \eta = 0.91$). At this regard, the Wald test display a statistic of 35.57 with p-value 0.00. Therefore, I use this model to perform inference on the effect of the different covariates.

INSERT TABLE 3 ABOUT HERE

Using the selected DSLM, both the simultaneous (Columns 2 to 4) and the long run (Columns 5 to 7) direct, indirect and total effects are simulated[13]. The simultaneous direct effects shown in column (2) are different from the estimates of the response parameters shown in column (1) of Table 4. 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 7-9% depending on the specific control. As shown by McMillen (2003, 2010) the DSLM model structure imposes a unique ratio between the spillover and direct effects for every explanatory variable, which in this case is 1.2. However in the long run, the accumulation of spillover effects and diffusion effects raises this ratio to 3.5. This amplification, apart from the first period where effects are mainly pure feedbacks effects, is due to the time dependence of the shocks. Consistent with macroeconomic theory, most of the variables present a considerable higher impact in the long run than in the short run. Given that 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 direct or indirect effects but I directly analyze the dynamics of the total effects.

INSERT TABLE 4 ABOUT HERE

As for the disequilibrium variables, I find that in the short run the growth rate of employment (EMPG), exerts a negative effect on unemployment of about -0.33%.

[13] Overall, both the quantitative and the qualitative results obtained with this W matrix are very similar to those obtained with other spatial matrixes

This result goes in line with that obtained in Zeilstra and Elhorst (2012) or Vega and Elhorst (2013) who find also find a total positive effect of -0.12% and 0.07% respectively. Nevertheless, a permanent change of 1% in the employment growth rate in the long run generates a strong negative effect on unemployment of -1.57%. Aggregate demand shocks captured by the real GDP gap also exert a negative influence on unemployment of -0.09% in the short run and -0.42% in the long run which. This result supports previous findings of Taylor and Bradley (1997).

With respect to market equilibrium variables, I find that high levels of wages tend to increase the level of unemployment which goes in line with the theoretical model outlined above and supports the findings of Partridge and Rickman (1997a,b). Moreover, the total effects associated to the productive structure show that regions with a high share of employment in manufacturing and industry tend to have lower levels of unemployment. As explained by Elhorst (2003) this specific result might be associated to larger employment multipliers in industry that in the service sector activities, which are largely dependent on the demand created by the other two sectors of the economy. Indeed, the effect of employment in non-market services and services is positive. 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. Noting the negative simultaneous effect of sectoral specialization in unemployment of 0.08% and the negative long run impact of 0.39%, I find that diversified production structures may help to reduce unemployment rates which is Longhi et al (2005). The positive sign of participation rates in the short run (0.28%) and in the long run (1.34%) 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. This result goes in line with those of Blanchard and Katz (1992) and Decressin and Fats (1995).

All of the demographic variables are significant and have the expected signs. The negative effect of the share of old with respect the young population in the short run (-0.32%) and in the long run (-1.5%) supports previous findings of Molho (1995): younger populations tend to suffer more unemployment problems that beset those with a proportion of older people. Additionally, a permanent increase in the skills and education in a region appear to be inversely related to the unemployment rate (-0.13%)

and (-0.64%) in the short and long run respectively, which suggests there is a positive influence on regional labor demand of skills and that more educated populations tend to suffer less problems of unemployment as in Partridge and Rickman (1995). As regards to the effect of migration I find a negative effect as in Lopez-Bazo et al (2005) suggesting that rate at which new jobs are created with the arrival of immigrants is above the destruction of jobs in the reception region.

Finally, amenities, approximated by employment density, are positively related to unemployment suggesting that the effect of amenities is negatively related with the reduction of regional unemployment disparities. 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 in densely populated regions. Regarding the effect of national institutional variables included in the model, results show that unemployment benefits rise unemployment while the tax wedge reduces regional unemployment levels. Regarding the effect of bargaining coverage conditional to thelevel of centralization and coordination, the expected inverted U pattern is obtained: as expected, decentralized or highly centralized systems outperform medium centralized models. Finally I find that the effect of EPL on unemployment is negative suggesting the worker protection effect outweights the negative effect in the hiring associated to an expectation of higher costs.

One of the aims of this study is to explore the importance of the various factors explaining regional unemployment disparities. As explained by Ulrike Gromping (2007), assigning shares of relative importance to a set of regressors that are uncorrelated is simple. However, the regressors of the space-time unemployment model used in this analysis are correlated which makes the assignment of relative importance a more difficult task (Johnson and Lebreton, 2004). The relative contribution of the various factors is explored by the LMG method (Lindemand, et al, 1980) who proposed to decompose the R^2 by using sequential sums of squares from the linear model, the size of which depends on the order of the regressors in the model in order to obtain an overall assessment by averaging over all orderings of regressors. This proposal has not found its way in econometric analysis for two main reasons. First, it is computationally challenging given that it requires the researcher to estimate 2^{p-1} models where

p is the number of regressors[14] and its properties are not yet well understood. For p regressors, the LMG method assigns to each regressor X_i the following share:

$$LMG(i) = \frac{1}{p}\sum_{j=0}^{p-1}\left(\sum_{S\subseteq 2,\ldots,p,n(S)=j}\frac{svar\left(\{i\}\left|S\right.\right)}{\binom{p-1}{j}}\right) \tag{16}$$

where $evar\left(S\right) = var\left(Y\right) - var\left(Y\left|X_j, j\right.\right)$ and $svar\left(M\left|S\right.\right) = evar\left(M\cup S\right) - evar\left(S\right)$ denote the explained variance based on regressors with indeces from S and the sequantially added explained variance when adding the regressors with indices in M to a model that already contains the regressors with indices in S. Note that the true coefficient of determination $R^2\left(S\right)$ is the ratio $evar(S)/var(Y)$.

The results of the different factors are reported in Table 5 below. As it can be observed disequilibrium variables account for 14.7% of unemployment rate space-time variability. On the other hand I find that market equilibrium variables are the most relevant group of variables accounting for a 45.67.% of the total variance. Specially remarkable are the cases of the real wage, which accounts by itself for a 22.% of the unemployment variability and the total participation rate which accounts for a 14.02.%. Demographic factors account for a 21.05.% of the variance, which is a considerable share. The most important factor of this group is the share of old people. Amenities do no seem to be a relevant factor while on the other hand, the joint of effect of the various labor market institutions accounts for a 14.76.% of the unemployment disparities.

INSERT TABLE 5 ABOUT HERE

4.2 Stochastic Kernel Simulation.

[14]Given that all orthers 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 $p = 22$, 2.097.152,00 models are estimated.

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. However, note that in Lopez-Bazo et al. (2005) the counterfactual distribution is computed by assuming the coefficients in the model are common to all regions regardless its precise value in each region which imposes a high degree of homogeneity. From Equation (x) we know that the total effect of the K variables included in the unemployment rate model is given by $left((I-\rho W_{ij})^{-1}\sum_{k=1}^{K}\beta_i^k$. In order to better capture regional heterogenous transmission patterns I do not average The effect of a factor X^k on the unemployment rate differential of region i in period t U_{Xi} is computed as:

$$U_{Xi}^k = \left(X_{i,t} - \overline{X}_t\right)\hat{\beta}_x\left(I - \rho W_{ij}\right)^{-1} \tag{17}$$

where $X_{i,t}$ is a vector with observations for the variables included in factor X^k for that province and that time period, $\overline{X}_t$ is the vector of averages across provinces for those variables in period t and $\hat{\beta}_x\left(I - \rho W_{ij}\right)^{-1}$ is the vector of total effects associated to the covariate K. Secondly, conditional unemployment rate differentials are computed by substracting the effect of the factor from the unemployment rate differentials:

$$UCOND_i^k = (U_{i,t} - U\bar{t}) - U_{Xi}^k \tag{18}$$

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 pronounced 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.

INSERT FIGURE 6 ABOUT HERE

INSERT FIGURE 7 ABOUT HERE

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.

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 begining f 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 istead 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).

Model selection criteria such as bayesian posteriors 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 1.5% 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 particular, LMG methodology shows that market equilibrium factors are the key driver of unemployment outcomes accounting for a 45% of its variability.

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.

6 References

Alogoskoufis G, Manning A (1988): Wage setting and Unemployment persistence in Europe, Japan and the USA. *European Economic Review* , 32, 698-706. North-Holland.

Anselin L (2010): Thirty Years of Spatial Econometrics. *Papers in Regional Science*, 89, 3-25.

Anselin L, Bera A (1998): *Spatial Dependence in Linear Regression Models with an Introduction to Spatial Econometrics.* In: A. Ullah and D.E.A. Giles (eds.), *Handbook of Applied Economic Statistics*, 237-289. Marcel Dekker, New York.

Anselin L, Le Gallo J., Jayet H (2008): Spatial panel econometrics, in: L. Matyas P. Sevestre (eds) *The Econometrics of Panel Data, Fundamentals and Recent Developments in Theory and Practice*, 3rd edn, pp. 627662, Dordrecht, Kluwer

Baltagi B H (2001): *Econometric Analysis of Panel Data.* Second Edition. John Wiley & Sons, New York.

Baddeley M, Martin R, Tyler P (1998): Transitory Shock or Structural Shift? The Impact of the Early 1980s Recession on British Regional Unemployment. *Applied Economics.* 30, pp. 19-30.

Basile R, Girardi A, Mantuano M (2009): Regional unemployment traps in Italy: assessing the evidence. *ISAE Working Papers.*

Basile R, Girardi A, Mantuano M (2012): Migration and Regional Unemployment in Italy. *The Open Urban Studies Journal*, 2012, 5, 1-13

Bean CR (1994) European Unemployment: A Survey. *Journal of Economic Literature.* 32, pp. 573-619.

Belot M, Van Ours J (2001): Unemployment and labor market institutions: an empirical analysis. *Journal of the Japanese and International Economies.* 15, 403-418.

Belot M, Van Ours J (2004): Des the recent succes of some OECD countries in lowering unemployment rates lie in the clever design of their labor market reforms?. *Oxford Economic Papers*, 56, 621-642.

Boeri T, Van Ours (2008): The Economics of Imperfect Labor Markets. *Princeton University Press*, Princeton, NJ

Blanchard OJ (2006): European unemployment: the evolution of facts and ideas. *Economic Policy.* 21, 45, pp 559.

Blanchard OJ, Katz LF (1992): Regional Evolutions. *Brookings Papers on Economic Activity*, 1, pp.1-75.

Blanchard OJ, Wolfers J (2000): The role of shocks and institutions in the rise of European unemployment: the aggregate evidence. *The Economic Journal*,110, No 462.

Bubbico R L, Dijkstra L (2011): The European Regional Human Development and Human Poverty Indices. *Regional Focus*, No 2.

Calmfors, L. (1993) Centralisation of wage bargaining and macroeconomic performance: A survey, *OECD Economic Studies*, 21:161-191.

Calmfors, L. and J. Driffill (1988) Bargaining structure, corporatism and macroeconomic performance, *Economic Policy*, 6:13-61.

Cracolici M F, Cuffaro M, Nijkamp P, Scienza V (2007): Geographical distribution of unemployment: An analysis of provincial differences in Italy. *Growth and Change*, 38(4), 649-670.

Corrado L, Fingleton B (2012): Where is the econmics in spatial econometrics?. *Journal of Regional Science* 52, 210-239.

Daveri F, Tabellini G, Bentolila S, Huizinga H (2000): Unemployment, growth and taxation in industrial countries, *Economic Policy*, 30, 47-104.

Debarsy N., Ertur C, LeSage JP (2012): Interpreting Dynamic Space-time Panel Data Models, *Statistical Methodology*, 9, 158-171

Decression J., Fats A. (1995) Regional Labor Marker Dynamics in Europe. *European Economic Review*, 39, pp. 1627-1655.

Diaz A (2011): Spatial Unemployment Differentials in Colombia. Universite Catholique de Louvain Working Paper.

Dijkstra L (2010): The Regional Lisbon Index. *Regional Focus*, No 3.

Di Tella and Macculoch (2005): The consequences of labor market flexibility: panel data evidence based on surey data, *European Economic Review*, 49, 1225-1259.

Elhorst J P (2003): The mystery of regional unemployment differentials. Theoretical and empirical explanations. *Journal of Economic Surveys*. 17, 709-748.

Elhorst JP (2005): Models for dynamic panels in space and time. An application to regional unemployment in the EU. Paper prepared for 45th meetings of the European Regional Science Association in Amsterdam, 23-27 August 2005.

Elhorst J P (2010): Applied Spatial Econometrics: Raising the Bar. *Spatial Economic Analysis*, 5, 9-28.

Elhorst J P (2012a): Spatial Panels. *Spatial Economic Analysis*, 5, 9-28.

Elhorst J P (2012b): Dynamic spatial panels: models, methods, and inferences. *Journal of Geographical Systems*, 14:528 DOI 10.1007/s10109-011-0158-4

Elmeskov J, MacFarlan M (1993): Unemployment Persistence. *OECD Economic Studies*, 21.

European Comission (2010a): Fifth Report on Economic, Social and Territorial

Cohesion. *Communication*, COM(2010) 642, Brussels.

European Commission (2010b): Europe 2020. A strategy for smart, sustainable and inclusive growth. *Communication*, COM (2010), 2020. Brussels.

Groenewold N. (1997) Does Migration Equalise Regional Unemployment Rates? Evidence from Australia. *Papers in Regional Science* 76, 1-20.

Gromping, U. (2006): Relative Importance for Linear Regression in R: The Package relaimpo. *Journal of Statistical Software*, 17, Issue 1.

Gromping, U. (2007): Estimators of Relative Importance in Linear Regression Based on Variance Decomposition. *The American Statistician*, Vol. 61, No. 2 14

Harris R, Moffat J, Kravtsova V (2011): In search of W. *Spatial Economic Analysis* 6, 249270.

Herwartz H, Niebuhr A (2011): Growth, unemployment and labour market institutions: evidence from a cross-section of EU regions. *Applied Economics*, 43, 30, 4663-4676.

Isserman A, Taylor C, Gerking S, Schubert U (1986): Regional Labor Market Analysis. In: Nijkamp P. (ed.) *Handbook of Regional and Urban Economics*, 1, 543-580. Elsevier, Amsterdam.

Jackman, R (1998): European unemployment: Why is it so high and what should be done about it?. In: Debelle, Guy and Borland, Jeff, (eds.) Unemployment and the Australian Labour Market. Reserve Bank of Australia, Australia.

Johnson, J.W., and Lebreton, J. M. (2004), History and Use of Relative Importance Indices in Organizational Research, *Organizational Research Methods*, 7, 238257.

Keller W, Shiue, C H (2007): The origin of spatial interaction, *Journal of Econometrics*, 140, 304332.

LeSage J , Pace R K (2009): *An Introduction to Spatial Econometrics.* Chapman and Hall, Boca Raton, FL.

Lee L F (2004) Asymptotic distribution of quasi-maximum likelihood estimators for spatial autoregressive models, *Econometrica*, 72, 18991925.

Lee L F, Yu J (2010a): Estimation of Spatial Autoregressive Panel Data Models with Fixed Effects. *Journal of Econometrics*, 154, 165-185.

Lee L F, Yu J (2010b): A spatial dynamic panel data model with both time and individual effects. *Econometric Theory*, 26, 564-594.

Lee, L F, Yu J (2013): Identification of Spatial Durbin panel models. Working paper presented in the Conference on Cross-sectional Dependence in Panel Data Models

Lindeman, R. H., Merenda, P. F., and Gold, R. Z. (1980), Introduction to Bivariate and Multivariate Analysis, Glenview, IL: Scott, Foresman.

Longhi S, Nijkamp P, Traistaru I (2005): Is Sectoral Diversification a Solution to Unemployment? Evidence from EU Regions.*Kyklos*, 58, 4, 591610.

López-Bazo, Tomás del Barrio and Manuel Arts (2005): The geographical distribution of unemployment in Spain. *Regional Studies*, 39,3, 305-318.

Magrini S (2004): Regional (Di)Convergence. *Handbook of Regional and Urban Economics.* In: J. V. Henderson and J. F. Thisse (eds.), *Handbook of Regional and Urban Economics*, 2741-2796. Elsevier, Amsterdam.

Magrini S (2007): Analysing Convergence Through the Distribution Dynamics Approach: Why and how?. *Working Paper No. 13,* Department of Economics, University of Venice CaFoscari.

Manski C F (1993): Identification of Endogenous Social Effects: The Reflection Problem. *Review of Economic Studies*, 60, 531-542.

Marston S T (1985): Two Views of the Geographic Distribution of Unemployment. *The Quarterly Journal of Economics* 100, 57-79.

McMillen D P (2003): Spatial Autocorrelation or Model Misspecification? *International Regional Science Review,* 26, (2), 208-217.

McMillen D P (2010): Isssues in Spatial Data Analysis. *Journal of Regional Science*, 50, 119-141.

Molho I. (1995a) Migrant Inertia, Accessibility and Local Unemployment. *Economica* 62, 123-132.

Molho I. (1995b) Spatial Autocorrelation in British Unemployment. *Journal of Regional Science* 35, 641-658.

Nickell S, Nunziata L, Ochel W (2005): Unemployment in the OECD since 1960s. What do we know?. *The Economic Journal*, No 115.

Niebuhr A (2003): Spatial interaction and regional unemployment in Europe. *European Journal of Spatial Development*, 5, 2-24

OECD (2009): Regions at a glance. *OECD, Paris.*

OECD (2013): Protecting jobs, enhancing flexibility: A new look at employment protection legislation. *OECD Employment Outlook 2013.* 65-126.

Overman H G, Puga D (2002): Unemployment clusters across Europes regions and countries. *Economic Policy.* 34, pp 115-147.

Partridge M D, Rickman D S (1997a) State Unemployment Differentials: Equilibrium Factors vs. Differential Employment Growth. *Growth and Change.* 28, pp. 360-379.

Partridge M D, Rickman D S (1997b) The Dispersion in US State Unemployment Rates: The Role of Market and Non-market Equilibrium Factors. *Regional Studies.*

31, pp. 593-606.

Patacchini E, Zenou Y (2007): Spatial Dependence in Local Unemployment Rates. *Journal of Economic Geography*, Vol. 7, Issue 2, pp. 169-191, 2007

Patuelli R, Quah D (1996): Regional Convergence Clusters across Europe. *European Economic Review* 40, 951-958.

Scarpetta S (1996): Assessing the Role of Labour Market Policies and Institutional Settings on Unemployment: A Cross-Country Study. *OECD Economic Studies*,26, pp. 43-98

Simon C J (1988) Frictional Unemployment and the role of Industrial Diversity. *Quartely Journal of Economics* 103, pp. 715-728

Taylor J (1996) Regional Problems and Policies: A European Perspective. *Australasian Journal of Regional Studies* 2, pp. 103-131.

Taylor J, Bradley S. (1997) Unemployment in Europe: A Comparative Analysis of Regional Disparities in Germany, Italy and the UK. *Kyklos* 50, pp. 221-245

Vega S H, Elhorst J P (2014): Modelling Regional Labor Market Dynamics in Space and Time. *Papers in Regional Science*, DOI: 10.1111/pirs.12018

Zeilstra and Elhorst (2012):Integrated Analysis of Regional and National Unemployment Differentials in the European Union. *Regional Studies*, DOI: 10.1080/00343404.2012.708404.

Vega S H, Elhorst J P (2013): On spatial econometrics models, spillovers and W. Paper presented in the ERSA 53th Congress, Palermo, Italy.

Yu J, Jong R, Lee F (2008): Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large, *Journal of Econometrics*, 146: 118-134.

Yu J, Jong R, Lee F (2012): Estimation for spatial dynamic panel data with fixed effects: the case of spatial cointegration. *Journal of Econometrics*, 167: 16-37.

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:

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

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.

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: $HF_{i,t} = 100 \left(\frac{x_{irt}}{\sum_r x_{irt}} \right)^2$ where r denotes the sector and it is computed over all sectors in the Cambridge Econometrics Database: agriculture, manufacture, construction, distribution, non-market services and financial services.

INDUSTRY MIX. Industry mix data is taken from the Cambridge Econometrics database. The shares of employment in the various sectors are computed as:
$MANU_{i,t}$= Manufacture Share $= 100 \left(\frac{MANU_{i,t}}{EMP_{i,t}} \right)$
$NMS_{i,t}$= Non Market Services Share $=100 \left(\frac{NMS_{i,t}}{EMP_{i,t}} \right)$
where $MANU_{i,t}$ and $NMS_{i,t}$ denote the number of employed in the manufacture and non-market 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.

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

$FEM_{i,t} = 100 \left(\frac{LF_F EM)_{i,t}}{LF_{i,t}} \right)$, where $LF_F EM_{i,t}$ 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 nmumber 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.

7 Figures

Figure 1: Unemployment Dynamics 2000-2011

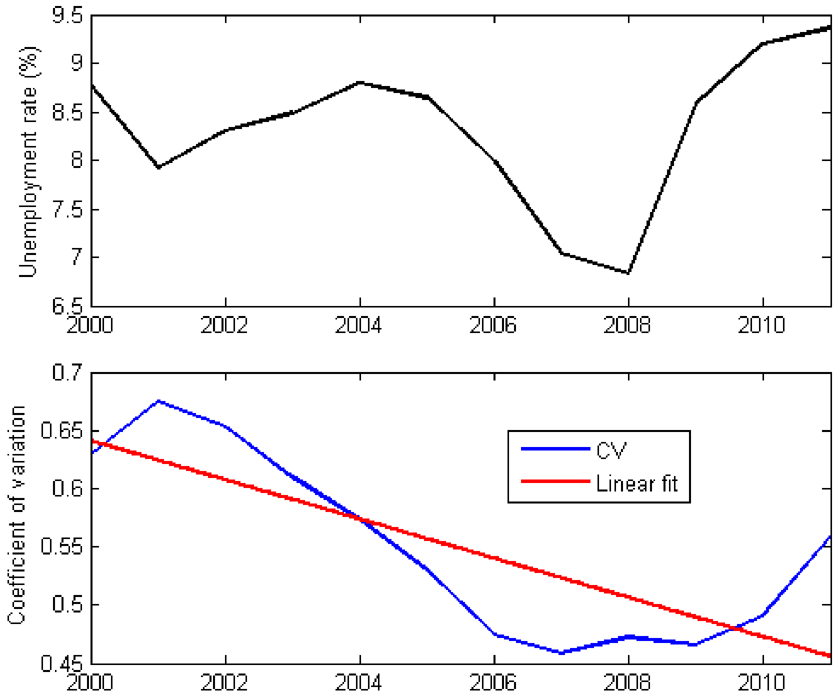


Figure 2: Unemployment Relative Distribution

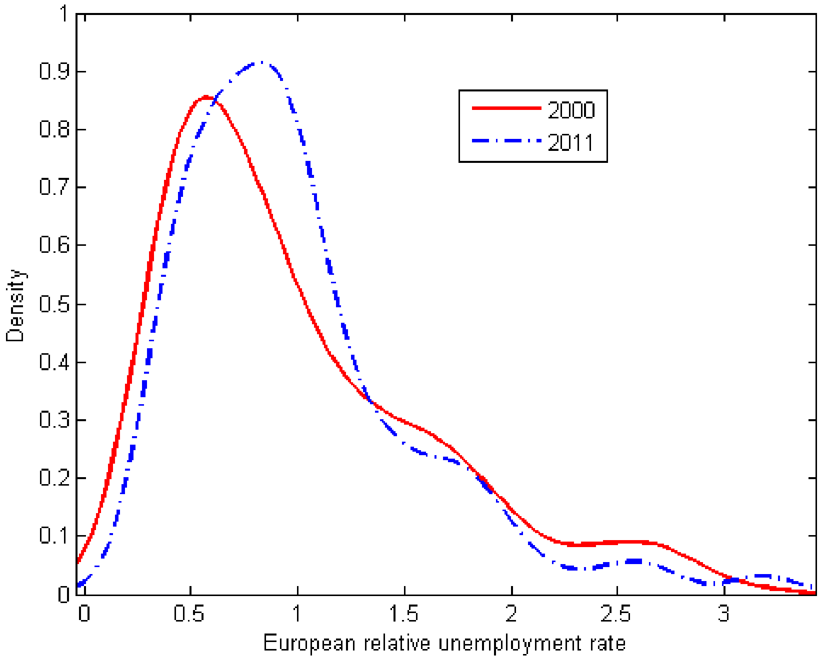


Figure 3: Relative Unemployment Rate Distribution Dynamics

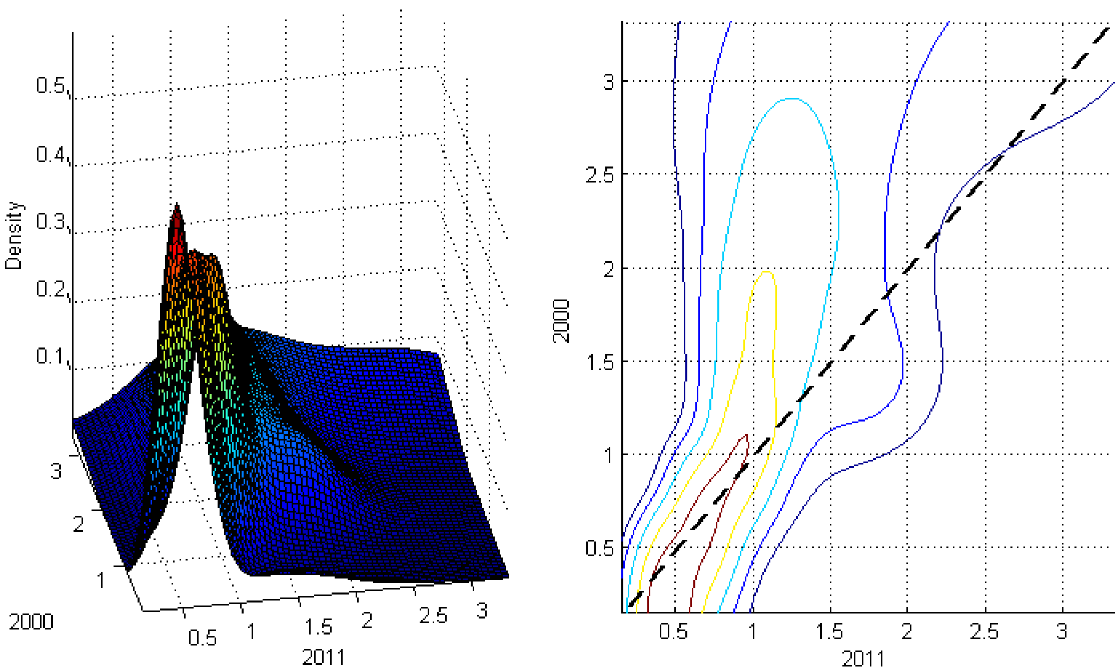


Figure 4: Relative Unemployment Geo-Dyanmics

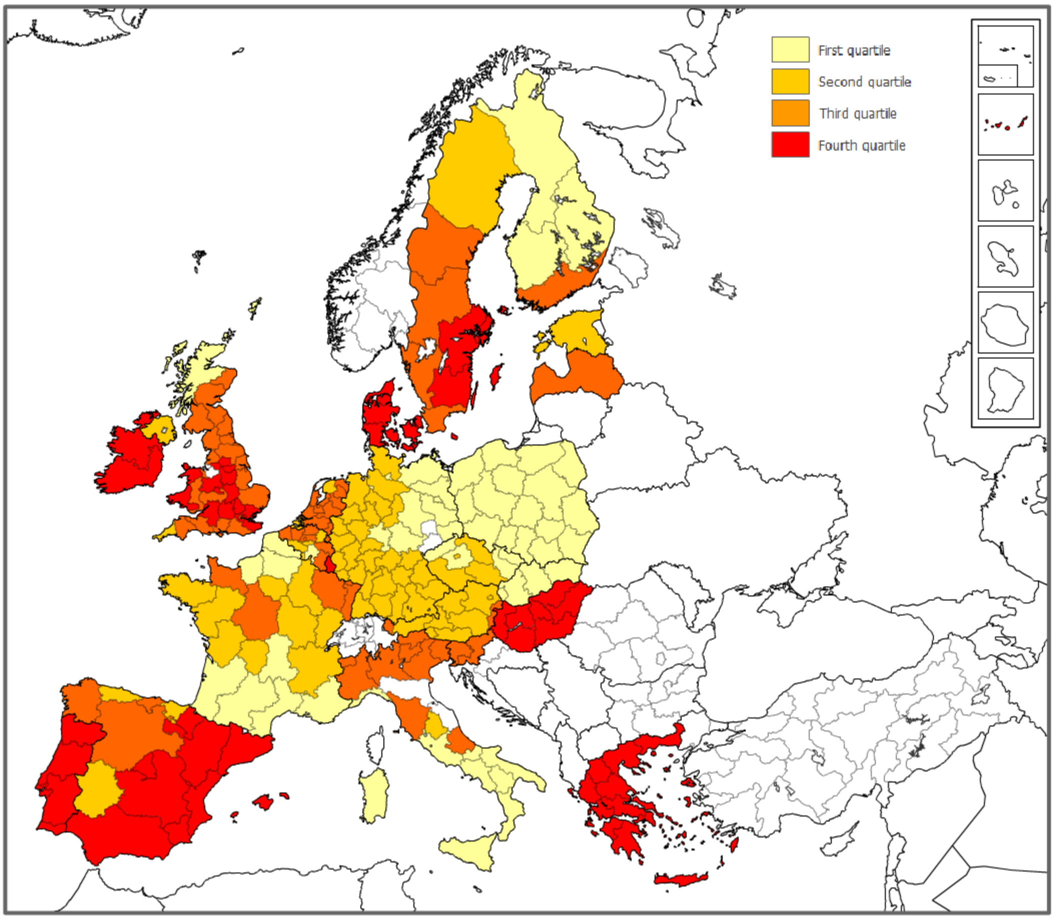


Figure 5: Neighboring Effects

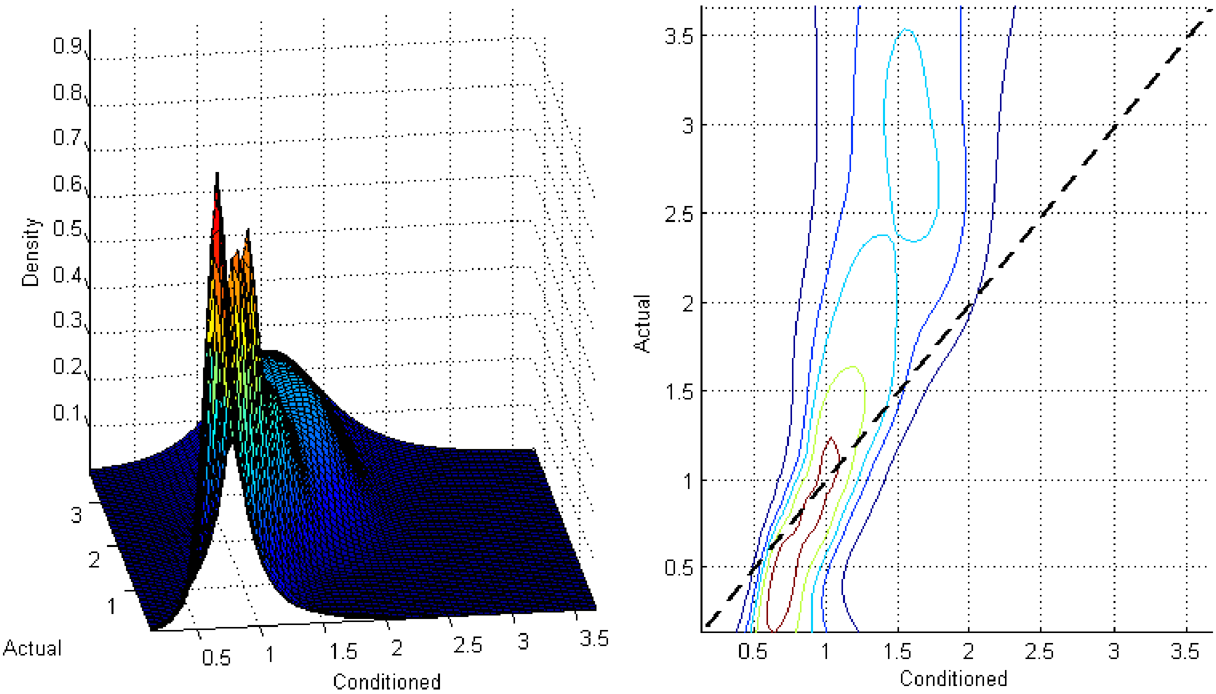


Figure 6: Disequilibrium Variables

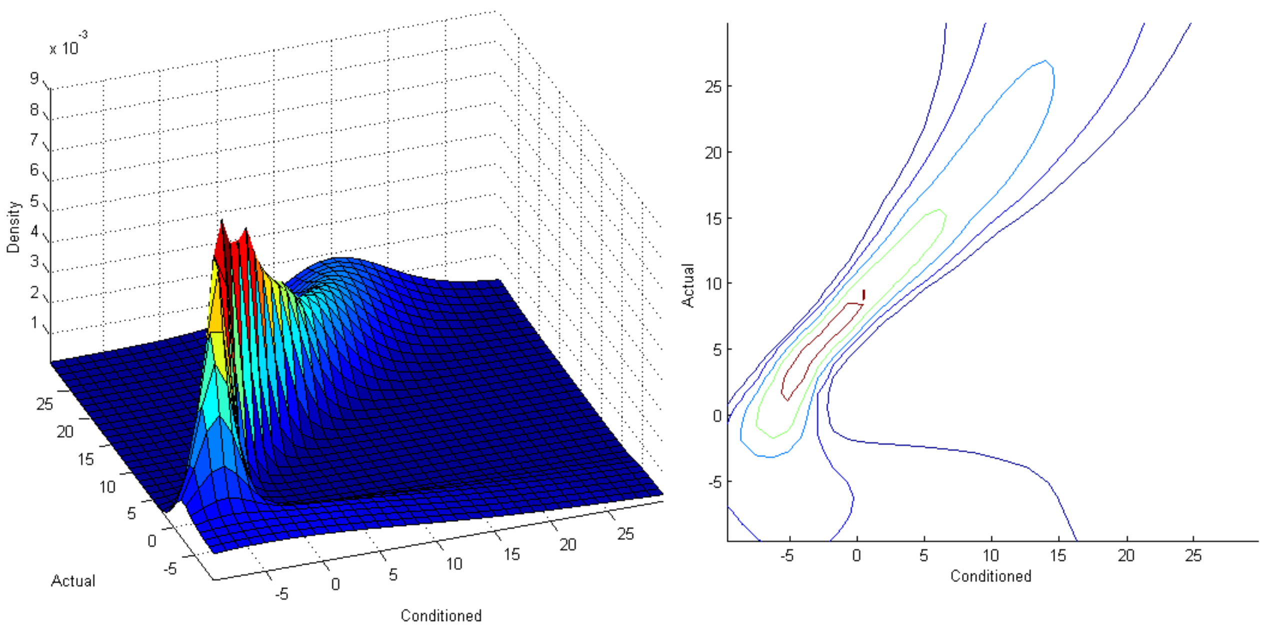
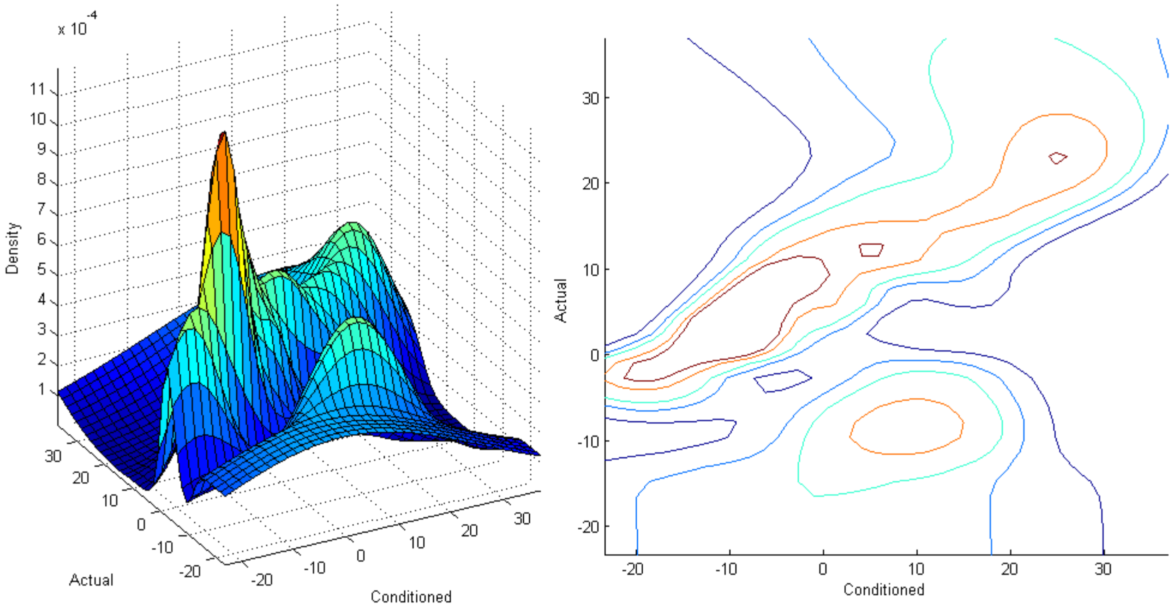


Figure 7: Market Equilibrium Variables



8 Tables

Table 1: Unemployment drivers: Theoretical Summary

Variable	Mean	Standard deviation	Expected Effect
Disequilibrium Factors			
Employment Growth	0.59	3.26	-
Real GDPper worker Cycle	0.12	3.20	-
*Market Equilibrium Factor*s			
Herfhindal Index	76.81	2.75	+
Real Wage	234.74	112.26	+
Manufacture	18.27	6.91	?
Non Market Services	29.07	6.74	?
Demographic Factors			
Net Migration	2.98	6.26	-
Old	11.22	3.29	-
Participation	44.51	3.09	?
Human Capital	37.77	8.51	-
Amenities	190.8	625.4	?
Institutions			
Unemployment Benefits	51.66	12.8	+
Tax Wedge	39.7	6.69	+
Bargaining Coverage—Low Coordination	6.45	10.48	-
Bargaining Coverage—Medium Coordination	60.8	21.57	+
Bargaining Coverage—High Coordination	7.62	22.53	-
Employment Protection Lesgilation	34.51	18.91	?

Table 2: Reverse Causality Statistics

Factors	Number of Lags = 2			Number of Lags =3		
	F-statistic	P-value	BIC	F-statistic	P-value	BIC
Disequilibrium Factors						
Employment Growth	79.33	0.00	11096.55	66.75	0.00	9907.85
Real GDP Gap	55.85	0.00	10728.09	38.58	0.00	9646.62
Market Equilibrium Factors						
Real Wage Level	0.49	0.62	19409.28	0.20	0.89	17714.54
Industry	9.93	0.00	4925.77	4.19	0.01	4357.69
Non Market Services	76.84	0.00	5731.11	53.95	0.00	5191.97
Herfhindal Index	4.19	0.02	-12657.96	4.85	0.00	-11063.91
Total Participation	9.75	0.00	7135.62	14.93	0.00	6290.59
Demographic Factors						
Migration	34.98	0.00	3001.25	24.02	0.00	2910.19
Pop Share Old	39.58	0.00	7119.54	29.83	0.00	6447.86
Human Capital	0.43	0.65	8904.81	0.44	0.72	8204.22
Amenities	1.23	0.29	15909.89	4.35	0.00	14156.74
Institutional Factors						
Unemployment Benefits	21.17	0.00	10198.52	20.18	0.00	8929.66
Tax Wedge	53.54	0.00	8539.06	27.88	0.00	7891.13
BC—LC	48.58	0.00	11582.91	23.54	0.00	9372.85
BC—MC	4.98	0.01	9621.90	9.06	0.00	8856.23
BC—HC	2.99	0.05	19281.36	11.14	0.00	17219.47
Employment Protection Legislation	19.88	0.00	-4772.35	21.97	0.00	-4129.97

Notes: The independent variable generating F-statistics and p-values reported is in all cases the unemployment rate. BIC is computed as $B = -2ln(L) + kln(NT)$.

Table 3: Model Selection Statistics

	Log Likelihood	$\widehat{\sigma}_u^2$	Bayesian Posterior	$\eta + \tau + \rho$	F-statistic	p-value	Time-Effects	p-value
Cut-off 500 km	4579.29	1.22	1.00	0.92	18.42	0.00	2.08	0.02
Cut-off 1000 km	4577.55	1.31	0.00	0.93	7.84	0.01	2.41	0.01
Cut-off 1500 km	4516.61	1.33	0.00	1.00	0.03	0.87	3.67	0.00
Cut-off 2000 km	4473.72	1.36	0.00	1.04	2.06	0.15	4.44	0.00
Cut-off 3000 km	4457.70	1.37	0.00	1.11	10.08	0.00	4.79	0.00
$1/d^{\alpha}$, $\alpha = 1.25$	4472.75	1.32	0.00	1.09	9.13	0.00	4.44	0.00
$1/d^{\alpha}$, $\alpha = 1.50$	4499.08	1.28	0.03	1.06	5.23	0.02	4.51	0.00
$1/d^{\alpha}$, $\alpha = 1.75$	4518.83	1.25	0.93	1.02	1.00	0.32	2.16	0.01
$1/d^{\alpha}$, $\alpha = 2$	4524.87	1.23	0.00	0.99	0.36	0.55	1.75	0.06
$1/d^{\alpha}$, $\alpha = 2.25$	4522.73	1.22	0.04	0.95	5.07	0.02	1.13	0.33
$1/d^{\alpha}$, $\alpha = 2.5$	4519.61	1.22	0.00	0.93	14.28	0.00	1.31	0.21
$1/d^{\alpha}$, $\alpha = 2.75$	4516.22	1.22	0.00	0.91	26.51	0.00	1.72	0.06
$1/d^{\alpha}$, $\alpha = 3$	4510.69	1.22	0.00	0.89	40.98	0.00	1.94	0.03
$exp - (\theta d)$, $\theta = 0.005$	4600.54	1.21	0.00	0.96	3.22	0.07	0.68	0.75
$exp - (\theta d)$, $\theta = 0.01$	4586.89	1.14	0.00	0.94	12.08	0.00	0.63	0.80
$exp - (\theta d)$, $\theta = 0.015$	4566.22	1.13	1.00	0.91	35.57	0.00	1.46	0.14
$exp - (\theta d)$, $\theta = 0.02$	4544.64	1.16	0.00	0.88	64.88	0.00	1.56	0.10
$exp - (\theta d)$, $\theta = 0.03$	4500.25	1.20	0.00	0.84	122.29	0.00	3.95	0.00
Nearest Neighbor ($K = 5$)	4557.23	1.20	0.01	0.87	67.85	0.00	1.61	0.09
Nearest Neighbor ($K = 10$)	4577.85	1.22	0.13	0.89	46.03	0.00	0.92	0.52
Nearest Neighbor ($K = 15$)	4572.75	1.25	0.00	0.90	30.70	0.00	0.34	0.98
Nearest Neighbor ($K = 20$)	4560.23	1.29	0.00	0.89	32.28	0.00	0.41	0.95
Nearest Neighbor ($K = 25$)	4562.15	1.31	0.00	0.88	35.58	0.00	0.44	0.94

Notes: The optimized log-likelihood values reported correspond to the dynamic spatial lag with fixed spatial effects.

Table 4: Dynamic Spatial Lag Model Results

	Model Estimates	Short Run Effects Direct	Short Run Effects Indirect	Short Run Effects Total	Long Run Effects Direct	Long Run Effects Indirect	Long Run Effects Total
Employment Growth	-0.14***	-0.15***	-0.18***	-0.33***	-0.35***	-1.22***	-1.57**
	(-12.42)	(-12.57)	(-10.36)	(-12.05)	(-10.12)	(-3.44)	(-4.14)
Real GDP Gap	-0.04***	-0.04***	-0.05***	-0.09***	-0.09***	-0.32***	-0.42***
	(-3.86)	(-3.81)	(-3.84)	(-3.89)	(-3.20)	(-2.61)	(-2.82)
Real Wage Level	0.00***	0.00***	0.01***	0.01***	0.01***	0.04**	0.05**
	(3.39)	(3.41)	(3.35)	(3.37)	(3.25)	(2.34)	(2.56)
Industry	-0.21***	-0.22***	-0.27***	-0.49***	-0.52***	-1.80***	-2.32***
	(-7.07)	(-7.20)	(-6.61)	(-7.00)	(-6.54)	(-3.32)	(-3.89)
Non Market Services	0.10***	0.11***	0.13***	0.24***	0.26***	0.88***	1.13***
	(3.47)	(3.47)	(3.40)	(3.49)	(3.47)	(2.72)	(2.95)
Herfhindal	0.03***	0.04***	0.04***	0.08***	0.09***	0.31**	0.39**
	(2.68)	(2.65)	(2.58)	(2.63)	(2.66)	(2.11)	(2.26)
Net Migration	-0.14**	-0.15**	-0.19**	-0.34**	-0.36**	-1.22*	-1.57*
	(-2.20)	(-2.20)	(-2.17)	(-2.21)	(-2.04)	(-1.82)	(-1.90)
Pop. Share Old	-0.13***	-0.14***	-0.17***	-0.32***	-0.34***	-1.16***	-1.50***
	(-6.38)	(-6.43)	(-5.93)	(-6.25)	(-5.48)	(-3.09)	(-3.56)
Participation	0.12***	0.13***	0.16***	0.28***	0.30***	1.04***	1.34***
	(6.71)	(6.73)	(6.34)	(6.68)	(6.43)	(3.32)	(3.88)
Human Capital	-0.05***	-0.06***	-0.07***	-0.13***	-0.14***	-0.49**	-0.63***
	(-3.94)	(6.73)	(-3.78)	(-3.92)	(-3.30)	(-2.35)	(-2.58)
Amenities	0.00**	0.00	0.00**	0.01**	0.01**	0.01*	0.02*
	(1.99)	(2.00)	(1.99)	(1.97)	(1.90)	(1.82)	(1.84)
Unemployment Benefits	0.03***	0.03***	0.04***	0.07***	0.07***	0.25**	0.32***
	(3.16)	(3.16)	(3.13)	(3.16)	(3.07)	(2.50)	(2.68)
Tax Wedge	-0.04***	-0.04***	-0.05**	-0.09***	-0.09**	-0.32**	-0.41**
	(-2.62)	(-2.62)	(-2.55)	(-2.61)	(-2.35)	(-1.95)	(-2.07)
UDCOV—LC	-0.02*	-0.02**	-0.03*	-0.05*	-0.05*	-0.18	-0.23*
	(-1.94)	(-1.96)	(-1.93)	(-1.93)	(-1.87)	(-1.62)	(-1.69)
UDCOV—MC	0.01	0.01	0.01	0.03	0.03	0.10	0.13
	(0.76)	(0.77)	(0.77)	(0.76)	(0.76)	(0.72)	(0.73)
UDCOV—HC	-0.01***	-0.01***	-0.02***	-0.03***	-0.03***	-0.12**	-0.15**
	(-2.92)	(-2.93)	(-2.87)	(-2.89)	(-2.74)	(-2.26)	(-2.41)
EPL	-0.04	-0.05	-0.06	-0.10	-0.11	-0.37	-0.48
	(-4.55)	(-4.60)	(-4.46)	(-4.55)	(-4.37)	(-2.96)	(-3.32)
Unemployment Time Lag	0.51***						
	(33.07)						
Space-Time Lag	-0.18***						
	(-7.55)						
Spatial Lag	0.58***						
	(32.82)						

Notes: The dependent variable is the unemployment rate. The simulation of effects in both the short and the long run follows the algorithm proposed by Elhorst (2013) pp.19x

Table 5: Relative Importance Summary

Variable	Relative Contribution	Final Effect	Expected Effect
Disequilibrium Factors	14.7		
Employment Growth	9.78	-	-
Real GDPper worker Cycle	4.92	-	-
Market Equilibrium Factors	45.67		
Herfhindal Index	1.32	+	+
Real Wage	22.58	+	+
Manufacture	2.11	-	?
Non Market Services	5.64	+	?
Participation	14.02	+	?
Demographic Factors	21.05		
Net Migration	6.31	-	-
Old	10.06	-	-
Human Capital	4.68	-	-
Amenities	3.81	+	?
Institutions	14.76		
Unemployment Benefits	3.3	-	+
Tax Wedge	0.74	+	+
Bargaining Coverage—Low Coordination	2.05	-	-
Bargaining Coverage—Medium Coordination	3.48	+	+
Bargaining Coverage—High Coordination	3.56	-	-
Employment Protection Lesgilation	1.63	-	?