Modeling regional labor market dynamics in space and time

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Modeling regional labor market dynamics in space and time

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Abstract
This paper extends the seminal Blanchard and Katz (1992) regional labor market model to include interaction effects using a dynamic spatial panel data approach. Three key contributions of this extended model are: (i) the unrealistic assumption that regions are independent of one another no longer has to be made, (ii) the magnitude and significance of so-called spillover effects can be empirically assessed, and (iii) both the temporal and spatial propagation of labor demand shocks can be investigated. Using annual data from 1986-2010 for 112 regions across 8 EU countries, both the non-spatial and spatial models are estimated. It is found that the majority of the spillover effects are highly significant. Consistent with economic theory, the impact of a region-specific demand shock is largest in the region where the shock instigates. The shock also propagates to other regions, especially impacting the first and second-order neighbors.

Key words: Regional labor markets, dynamic spatial panel models, spillover effects

JEL classification: R23, C31, C33

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1. Introduction

Attaining acceptable levels of employment, unemployment, and participation is a top priority on the European Union's policy agenda, as they are important indicators of economic and social welfare.[1] Focusing on these labor market variables at a national level can hide striking differences between regions within countries (see e.g., Elhorst, 2003; OECD, 2009; Eurostat, 2010). For example, the variation in unemployment rates between regions within countries is even larger than that between countries.[2] Recent figures from Eurostat on regional labor market disparities across the EU show stark contrasts between regions and due to the recent economic crisis, it is predicted that these disparities will only increase (Eurostat, 2010). This makes it extremely pertinent to understand the impact of shocks on regional labor markets.

The response of regional labor markets to region-specific shocks has gained a vast amount of attention in the literature, especially following the seminal paper of Blanchard and Katz (1992) on demand shocks to regional labor markets in the United States. In contrast to a single equation approach, they develop a three-equation vector autoregressive (VAR) model which can decompose the response of a regional labor market to a demand shock into changes in regional unemployment, participation, and employment growth over time. To the extent that a demand shock is not reflected in a change of the unemployment or participation rate, it is absorbed by migration (i.e. migration acts as a "residual"). An attractive feature of the model is that it allows for the mutual interaction between these variables. Individuals may not decide to join the labor force because of poor employment prospects. For example, students may decide to stay longer at the university which shows up not as higher unemployment, but rather as lower participation (Blanchard, 2006). Since all these variables are interrelated, the model represents the complexity of labor market interactions well.

Another attractive feature of the model, which will be described in more detail in Section 2, is that it is regional in nature. Therefore, Blanchard and Katz (1992) and subsequent studies use regional data for their estimations. Most studies find that migration plays a more limited role as an adjustment mechanism to a labor demand shock for European regions than Blanchard and Katz originally found for US states (see e.g. Decressin and Fatás, 1995; Broersma and Van Dijk,

[1]See for example, the recent *Europe 2020* growth strategy.

[2]The differences in unemployment rates within OECD countries were almost twice as high as those between countries in 2006; e.g., it was found that in Canada, Germany, the Slovak Republic and Spain, unemployment rates ranged from as low as 5% in some regions to above 20% in others (OECD, 2009).

2002; Mäki-Arvela, 2003; Gács and Huber, 2005), although there are exceptions (Fredriksson, 1999; Tani, 2003). A positive aspect of these studies is that regional heterogeneity is taken into account since regional data is used for the estimations. What has largely been lacking, however, is the incorporation of a spatial dimension.[3] This is a significant shortcoming because regions are treated as independent entities, whereas it is more likely that neighboring regions interact with one another. Recently, the OECD (2009, p. 101) concluded that the performance of neighboring regions influences the performance of any other region.

This paper extends the Blanchard and Katz (1992) model to include interaction effects using a dynamic spatial panel data approach. This approach has recently gained more attention in the spatial econometrics literature (Yu et al., 2008; Lee and Yu, 2010a; Elhorst, 2012) as well as in applications to other fields such as consumption (Korniotis, 2010), commuting (Parent and LeSage, 2010), and housing prices (Brady, 2011). Important methodological issues such as region-specific and time-specific fixed effects, estimation methods, and specification, selection, and different normalization procedures of the spatial weights matrix will be addressed. Using annual data from 1986-2010 for 112 regions across 8 EU countries, both the non-spatial and spatial models are estimated. A valuable aspect of the spatial model developed in this paper is that the magnitude and significance of so-called spillover effects can be empirically assessed using a methodology recently introduced by LeSage and Pace (2009). Another key contribution of the extended model is that both the temporal and spatial propagation of labor demand shocks can be investigated.

The remainder of the paper is structured as follows. Section 2 starts with an overview of the Blanchard and Katz model and theoretical background. Then, our methodology to extend the model with interaction effects using a dynamic spatial panel data approach is outlined. Section 3 describes the data that is used for estimating the model. Section 4 presents and analyzes the empirical results and Section 5 concludes.

2. Methodology

2.1 Blanchard and Katz model

[3]To some extent linkages between regions are taken into account by the migration "residual," but the models do not explicitly incorporate a spatial dimension.

To investigate the response of regional labor markets to demand shocks in the United States, Blanchard and Katz (1992) develop a three-equation vector autoregressive (VAR) model that describes the interaction between unemployment, participation, and employment growth at the regional level over time. This model, from now on referred to as the Blanchard-Katz model, is particularly useful for analyzing adjustment processes after a demand shock. In its basic form, the Blanchard-Katz model reads as

$$u = \beta_{11}u[-1] + \beta_{12}p[-1] + \beta_{13}e[-1] + \beta_{14}e + \varepsilon_1, \quad (1a)$$
$$p = \beta_{21}u[-1] + \beta_{22}p[-1] + \beta_{23}e[-1] + \beta_{24}e + \varepsilon_2, \quad (1b)$$
$$e = \beta_{31}u[-1] + \beta_{32}p[-1] + \beta_{33}e[-1] + \varepsilon_3, \quad (1c)$$

where the endogenous variables *u*, *p*, and *e* are the unemployment rate, the logarithm of the labor force participation rate, and the employment growth rate, respectively.[4] The model is recursive in nature because both unemployment and participation in period *t* are explained by employment growth in period *t* and employment growth in period *t*-1, whereas employment growth is only explained by participation in period *t*-1 and unemployment in period *t*-1. Whereas Blanchard and Katz (1992) use variables normalized to the national level, this is controlled for in this study by time dummies.[5] The model is estimated equation by equation as in Blanchard and Katz (1992). Unlike their study, however, the equations are not estimated for each region. The entire sample is pooled together in order to estimate interaction effects. Baltagi et al. (2000) find that pooled models outperform their heterogeneous counterparts, which tend to produce implausible estimates even with relatively long time series. Pooling all regions together also allows us to control for region-specific fixed effects, which is also the motivation of Blanchard and Katz (1992) for pooling the entire sample in addition to estimating the equations for each US state.

Unemployment and participation are defined in levels, while employment is defined as a growth variable. This is because unemployment and participation are stationary series (integrated of order 0), whereas employment is non-stationary (integrated of order 1). If non-stationary time series are used in regression analysis, this leads to spurious results (Greene, 2003). The problem

[4]Blanchard and Katz (1992) and subsequent studies define all variables in logs. The reason why the unemployment rate is not expressed in logs is because the original model consists of the employment growth rate, participation rate, and employment rate. We follow previous studies, including Blanchard and Katz (1992), by using the unemployment rate instead of the logarithm of the employment rate since log(E/LF) ≈ −(U/LF) where E, U, and LF denote the levels of employment, unemployment, and the labor force.
[5]Details follow when the extension of the model is described.

is solved by using employment growth instead of the employment level. To test whether these variables in our sample are stationary, we performed the individual cross-sectionally augmented Dickey-Fuller (CADF) test developed by Pesaran (2007).[6] The null hypothesis of a unit root has been rejected for 93 of the 112 time series of the unemployment rate variable and for all time series of the participation rate and the employment growth rate variables at five-percent significance.

However, given the short time-span of our time series—each time series consists of only 25 observations—the results may suffer as a result of low power. Therefore, we also performed the CADF panel data unit root test of Pesaran (2007). This test statistic is based on the average of the individual CADF tests. We found -15.03 for the unemployment rate, -18.69 for the participation rate and -29.83 for employment growth, which represents a rejection of a unit root in all three variables at one-percent significance (the critical value according to Pesaran's Table II(b) is approximately -2.07). The conclusion must be that the variables are stationary and that the system of equations extended to include spatial interaction effects may be estimated when using the data in panel.

To analyze the repercussions of a region-specific labor demand shock, the estimated system of equations (1) is used to conduct impulse-response analysis. By extrapolating the model over several time periods, it is possible to observe how the model evolves and to what equilibrium values the endogenous variables converge to. We follow Blanchard and Katz (1992) and previous studies in associating unexpected changes in regional labor demand as an innovation to the error term in equation (1c). By calculating the differences in the endogenous variables before and after the shock over time, it is possible to observe the impact of a change in regional labor demand.

Before describing our extension of the model it is intuitive to outline the theoretical background in which the empirical model is embedded, which is provided in more detail in Blanchard and Katz (1992). Our presentation also draws from the comprehensive description of the model in Elhorst (2003). The model assumes that regions produce different bundles of goods and that there exists both labor and firm mobility across regions. The simple framework consists

[6]The test statistic is the t-value of the lagged dependent variable in a standard augmented Dickey-Fuller regression augmented with the cross-section averages of lagged levels and first-differences of the individual series. These additional variables are important since we will extend the model with spatial (which are cross-sectional) interaction effects in the next section.

of four equations, for short-run labor demand, wage setting, labor supply, and the long-run effects of labor demand in a region, specified as

$$w_{it} = -a(s_{it} - u_{it}) + z_{it}, \qquad a > 0, \tag{2a}$$
$$w_{it} = -bu_{it} + x_i^w, \qquad b > 0, \tag{2b}$$
$$s_{i,t+1} - s_{it} = cw_{it} - gu_{it} + x_i^s + \varepsilon_{it}^s, \qquad c, g > 0, \tag{2c}$$
$$z_{i,t+1} - z_{it} = -dw_{it} - ku_{it} + x_i^d + \varepsilon_{it}^d, \qquad d, k > 0, \tag{2d}$$

where subscript *i* stands for regions, *t* denotes time, w_{it} is log wage, s_{it} is log labor supply, u_{it} is the unemployment rate, z_{it} measures the long-term effects of labor demand, and ε_{it}^s and ε_{it}^d are white noise that capture shocks in labor demand and supply. As can be seen from the first equation, labor demand and wages are negatively related. The logarithm of the employment level is approximately given by s_{it} - u_{it}, with the positive parameter *a* reflecting the downward-sloping demand curve. Thus, ceteris paribus, lower wages make a region more attractive to firms.

However, other variables may also affect labor demand, which is captured in the shift term x_i^d in equation (2d). The decision of firms to create or locate their business in a particular place also depends on factors such as local taxes and the labor relations environment. The effect of unemployment on labor demand is not as clear. Although higher unemployment provides firms with a larger labor pool and thus induces firm in-migration, it could also indicate that the region is coping with economic problems such as fiscal crises, etc. that could result in the opposite effect. In addition, if a region is relatively underperforming it is most likely that the higher skilled labor force can more readily migrate to another region, resulting in a less skilled labor pool from which firms can choose from.

The wage setting equation (2b) shows that higher unemployment leads to lower wages. Including the shift term x_i^w also allows for factors other than the unemployment rate that affect the regional wage rate. Although some studies have found that higher wages may compensate for higher unemployment, most studies find that there is a wage curve, i.e. the wages of workers in labor markets with higher unemployment are lower compared to individuals working in a region with lower unemployment (Blanchflower and Oswald, 1994). Equation (2c) allows labor supply to depend on both relative wages and relative unemployment. Higher wages and lower unemployment increases labor supply through more labor force participation and inward migration of workers. Although the role of commuting is not mentioned in Blanchard and Katz

(1992), like net inward migration, net inward commuting also causes both regional labor supply and demand to increase. However, it is more likely that the supply-side effects dominate since commuters tend to spend more of their income where they reside rather than the region they work in (Elhorst, 2003). Although in their framework Blanchard and Katz (1992) specify that the unemployment rate has a negative effect on labor force participation, it could theoretically also have a positive effect known as the additional worker effect. Yet, more empirical studies have found that fewer jobs induce less people to enter the labor (i.e. a net discouragement effect). We come back to this issue when the empirical results are analyzed.

Focusing on the adjustment mechanisms to a positive labor demand shock, it follows from the theoretical framework that initially unemployment is expected to fall and labor force participation to increase, leading to an increase in wages depending on how flexible wages are on a regional level. This will, in turn, induce a net inward migration of labor which will bring the variables back to their equilibrium levels. The initial positive shock in labor demand can potentially be reversed because of a rising wage level and other factors deterring firms from entering a region or causing a net out-migration of firms. Whether lower regional unemployment encourages or deters firm entry is not as clear, but will be investigated with the empirical estimation results. The theoretical framework, like the empirical model, does not take into account how a shock affects neighboring regions.[7] For example, an adverse labor demand shock in region *i* could also cause unemployment rates in neighboring regions' to increase, which could lessen the net outward migration of labor from region *i*. In the following section, the extension of the model to include these interaction effects is outlined.

2.2 Extension of Blanchard-Katz model: A dynamic spatial panel data approach

Each equation in model (1) is extended to the following dynamic spatial panel data model

$$Y_t = \tau Y_{t-1} + \delta W Y_t + \eta W Y_{t-1} + X_t \beta + W X_t \theta + \mu + \alpha_t \iota_N + \varepsilon_t, \qquad (3)$$

where Y_t denotes an Nx1 vector consisting of one observation of the dependent variable for every

[7]This paper focuses on extending the model to incorporate these interaction effects. Further steps forward could be to extend the model from its recursive form into a simultaneous equations model to simulate labor supply shocks, and to include other factors into the model such as wages and labor market institutions.

region ($i = 1,\ldots,N$) in the sample at a particular point in time ($t = 1,\ldots,T$) and X_t is an NxK matrix of explanatory variables. W is a non-negative NxN matrix of known constants describing the spatial arrangement of the regions in the sample. For example, elements W_{ij} can reflect the geographical distance between regions or take a positive value if regions i and j share a common border and zero otherwise. Main diagonal elements W_{ii} are set to zero since no region can be viewed as its own neighbor.

A vector or matrix with subscript t-1 denotes its serially lagged value, while a vector or a matrix pre-multiplied by W denotes its spatially lagged value. τ, δ, and η are the response parameters of respectively, the lagged dependent variable Y_{t-1}, the lagged dependent variable in space WY_t, and the dependent variable lagged both in space and time WY_{t-1}. δ is referred to as the spatial autoregressive coefficient, η the lagged spatial autoregressive coefficient, while β and θ represent Kx1 vectors of response parameters of the explanatory variables. $\varepsilon_t = (\varepsilon_{1t}, \ldots, \varepsilon_{Nt})^{\mathrm{T}}$ is a vector of independently and identically distributed (i.i.d.) disturbance terms, whose elements have zero mean and finite variance σ^2. $\mu = (\mu_1, \ldots, \mu_N)^{\mathrm{T}}$ is a vector with regional fixed effects, one for every unit in the sample, α_t is the coefficient of a time period fixed effect, one for every time point in the sample (except one to avoid perfect multicollinearity), while ι_N is an Nx1 vector of ones.

The model in (3) is formally known as the dynamic spatial Durbin model in the literature. An empirical application of this model can be found in Debarsy et al. (2012). It should be stressed that some X variables are observed at time t-1, even though we use the subscript t in (3). This detail is omitted for the moment to avoid confusion with previous descriptions of the dynamic spatial Durbin model. We apply a bias corrected estimator developed by Lee and Yu (2010b) for a dynamic spatial panel data model with spatial and time period fixed effects. First, the model is estimated by the ML estimator for a non-dynamic spatial lag model with spatial and time period fixed effects. By providing rigorous asymptotic theory, they show that this ML estimator is biased when both the number of spatial units (N) and the number of time points (T) in the sample go to infinity such that the limit of the ratio of N and T exists and is bounded between 0 and ∞ ($0<\lim(N/T)<\infty$). Thereupon, they introduce a bias corrected ML estimator, which produces consistent parameter estimates provided that the model equation is stable, i.e., $\tau + \delta + \eta < 1$. In our case, however, it is more important to check whether the entire system of equations is stationary. Adding subscripts for equation number and type of variable to the

notation in equation (3), the system of equations converges to an equilibrium (using $Y_t = Y_{t-1} = Y^*$) after a shock if the largest eigenvalue of the 3*N*x3*N* matrix on the right-hand side of (4) is less than one. In this equation *I* represents the identity matrix and the subscripts *e* and *e*[-1] the coefficients of the employment growth rate in the same and the previous time period, respectively.

$$\begin{bmatrix} u^* \\ p^* \\ e^* \end{bmatrix} = \begin{bmatrix} \delta_{1u}W + \tau_{1u}I + \eta_{1u}W & \beta_{1p}I + \theta_{1p}W & \beta_{1e}I + \theta_{1e}W + \beta_{1e[-1]}I + \theta_{1e[-1]}W \\ \beta_{2u}I + \theta_{2u}W & \delta_{2p}W + \tau_{2p}I + \eta_{2p}W & \beta_{2e}I + \theta_{2e}W + \beta_{1e[-1]}I + \theta_{1e[-1]}W \\ \beta_{3u}I + \theta_{3u}W & \beta_{3p}I + \theta_{3p}W & \delta_{3e}W + \tau_{3e}I + \eta_{3e}W \end{bmatrix} \begin{bmatrix} u^* \\ p^* \\ e^* \end{bmatrix} + \begin{bmatrix} \mu_1 + \alpha_{1t}\iota_N + \varepsilon_{1t} \\ \mu_2 + \alpha_{2t}\iota_N + \varepsilon_{2t} \\ \mu_3 + \alpha_{3t}\iota_N + \varepsilon_{3t} \end{bmatrix} \quad (4)$$

This important stationarity condition is checked when the estimations are carried out.

2.3 Direct effects and spatial spillover effects

Many empirical studies use point estimates of a spatial econometric model to test the hypothesis as to whether or not spatial spillover effects exist. However, LeSage and Pace (2009, p. 74) have 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. By rewriting equation (2) as

$$Y_t = (I - \delta W)^{-1}(\tau I + \eta W)Y_{t-1} + (I - \delta W)^{-1}(X_t\beta + WX_t\theta) + (I - \delta W)^{-1}(\mu + \alpha_t\iota_N + \varepsilon_t), \quad (5)$$

the matrix of partial derivatives of *Y* with respect to the k^{th} explanatory variable of *X* in unit 1 up to unit *N* at a particular point in time can be seen to be

$$\left[\frac{\partial Y}{\partial x_{1k}} \dots \frac{\partial Y}{\partial x_{Nk}}\right]_t = (I - \delta W)^{-1}[\beta_k I_N + \theta_k W] \quad (6)$$

These partial derivatives denote the effect of a change of a particular explanatory variable in a particular spatial unit on the dependent variable of all other units in the short term. The expression in (6) will be used to determine direct effects and indirect (spatial spillover) effects. Since both the direct and indirect effects are different for different regions in the sample, the presentation of both effects is difficult. With N regions and K explanatory variables, it is possible to obtain K different NxN matrices of direct and indirect effects. Even for small values of N and K, it may be challenging to compactly report these results. Therefore, LeSage and Pace (2009) propose to report one direct effect measured by the average of the diagonal elements on the right-hand side (6), and one spatial spillover effect measured by the average row sums of the off-diagonal elements of this matrix. The total effect is the sum of the direct and indirect effects.

It should be noted that Debarsy et al. (2012) have derived the mathematical formulas of the direct and indirect effects estimates of the dynamic panel data model given by equation (3), both in the short term and the long term. The short-term effects are given in (6). Similarly, we could use their formulas for the long-term effects. However, since we have a system of equations in this study, where a change in one dependent variable affects another dependent variable in the same or in the next time period, the long-term direct and indirect effects of this system will be different from those of the single equations. These long-term effects of the entire system can be simulated by conducting an impulse-response analysis over time. Equation (4) is less useful in this respect, since it does not give information about the propagation of a shock over time.

2.4 Specification and selection of spatial weights matrix

One of the most criticized aspects of spatial econometric models is that the spatial weights matrix W cannot be estimated, but needs to be specified in advance. Recently, Corrado and Fingleton (2012) pay particular attention to this issue. Despite their criticism, they point out that alternatives to W that have been proposed by e.g., Folmer and Oud (2008) and Harris et al. (2011), such as entering variables in the regression model that proxy spillovers, also requires identifying assumptions. In other words, this approach also involves an *a priori* specification of the spatial relation between units in the sample.

Considering that this is a critical issue in spatial econometric modeling, it is not surprising that there have been many studies that attempt to investigate how robust results are to

different specifications of W and which one is to be preferred. For example, in a recent Monte-Carlo study, Stakhovych and Bijmolt (2009) demonstrate that a weights matrix selection procedure based on goodness-of-fit criteria increases the probability of finding the true specification. The most widely used criterion is the log-likelihood function value, but this approach has received criticism because it only finds a local maximum among competing models and it might be the case that the correctly specified W is not included (Harris et al., 2011).

LeSage and Pace (2009) propose the Bayesian posterior model probability as an alternative criterion to select models. The basic idea is as follows. Suppose that we are considering S alternative models based on different spatial weights matrices. The other model specification aspects (e.g., the explanatory variables) are held constant. The Bayesian model comparison approach requires setting prior probabilities to each model s *(*s = 1,…,S*)*. 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 Bayesian methods and then posterior probabilities are computed based on the data and the estimation results of the set of S models. An attractive feature of this approach is that it does not require nested models for the comparisons, *w*hereas tests for significant differences between log-likelihood function values (e.g likelihood ratio test) cannot formally be used if models are non-nested, i.e. for alternative spatial weights. LeSage and Pace (2009) set out this selection procedure for a cross-sectional data set, while we use it in this paper in a panel data setting.[8]

Since the specification of the spatial weights matrix is integral to the structure of the endogenous and exogenous spatial lags, several alternative matrices are considered when estimating the model. The first W matrix is based on the binary contiguity principle (denoted as W1 in Table 1): $w_{ij} = 1$ if regions i and j share a common border and $w_{ij} = 0$ otherwise. It should be noted that we include neighboring regions across national borders as well. This is because it may be the case that regions that are close-by will interact more not only if they are located in the same country, but also if they are located in different countries. This could especially be the case with increased integration among EU member states.

[8]We come back to this issue before presenting our spatial weights model comparison results. Some studies also use Bayesian methods to compare models that differ in the set of explanatory variables (LeSage and Parent, 2007), or the set of explanatory variables in combination with alternative spatial weight matrices (LeSage and Fischer, 2008). In this paper, we compare ten alternative models that differ in the spatial weight matrix specification.

The second W we use is a binary contiguity matrix whose elements are post-multiplied by population size (P), $w_{ij} = P_j$ if regions i and j share a common border, where we take the average population for each region over 25 years ($W2$ in Table 1).[9] This construction has the advantage that W is kept constant over time and is allowed since population size does not change much over this period. We consider this second specification because it can be expected that regions with larger populations have a greater influence than those with fewer inhabitants, so that W is no longer symmetric. For example, whereas $W1$ takes into account that the Community of Madrid borders Castile-La Mancha, $W2$ also reflects the fact that the Community of Madrid has a much larger population and thus, a shock in this region of Spain will have more of an effect on its neighbors than vice versa. A potential problem of this second matrix, in contrast to the first, is that the elements of W are not truly exogenous, one of the conditions made to the ML estimator developed by Lee and Yu (2010b). This is because people may migrate to other regions depending on the labor market conditions in these regions relative to those in their home region. Some of the other matrices specified below may also suffer from this problem. We come back to this issue when discussing the results.

In order to take into account distance between regions we use a third weights matrix ($W3$ in Table 1) based on inverse travel times (t): $w_{ij} = 1/t_{ij}$.[10] Travel times are a better reflection of the true distance between regions since impediments other than just the geographical distance are included. For example, travel time over land takes into account different road types, national car speed limits, and speed constraints in urban and mountainous areas; overseas travel time depends on embarkation waiting time and the travel time by ferry (for more details, refer to Schürmann and Talaat, 2000). If regions are more accessible to each other (e.g., in terms of the effort, time, or cost that is required to reach them), this provides a greater opportunity for interaction between households and firms in different regions. Lower travel times can be beneficial for workers commuting daily from one region to another, or for the unemployed to find a job in another region when the job prospects in their own region are less promising.

The construction of the fourth spatial weights matrix ($W4$ in Table 1) is based on population sizes and inverse travel times: $w_{ij} = P_j/t_{ij}$. It is therefore a hybrid matrix combining both the size of the regions and also the distance between them. We did not restrict the weights

[9]The data for regional population is taken from Eurostat (see Section 3 for details).
[10]The data comes from Schürmann and Talaat (2000), which was part of a report compiled for the General Directorate Regional Policy of the European Commission.

to only contiguous regions since it can be the case that the travel time already takes this into account. However, just in case, we also specified a related spatial weights matrix (*W*5 in Table 1) that restricts the weights to contiguous neighbors because the population size could overestimate the strength of the connections between regions: $w_{ij} = P_j/t_{ij}$ if regions *i* and *j* share a common border.

In the sixth spatial weights matrix not only are first-order neighbors considered (e.g., that Madrid is a neighbor of Castile-La Mancha), but also second-order neighbors (e.g., Madrid and Aragón). In our specification of this matrix (denoted *W*6 in Table 1), no distinction is made between first and second-order neighbors, i.e. they are treated with equal weights: $w_{ij} = 1$ if regions *i* and *j* share a common border or if they share the same first-order neighbor. This concept can be thought of in terms of the number of direct and indirect connections a person has in a social network where the first-order identifies friends and the second-order friends of friends (LeSage and Pace, 2009). In our case, it might be commuting (e.g., you can live in one place and commute to another for work and this could take place through various regions). To further explore the inclusion of higher-order neighbors, we also incorporate third-order neighbors to the previous specification (*W*7 in Table 1).[11]

Even though increased integration among EU member states might make national boundaries less relevant, it is still realistic to assume that there are barriers (social, political, cultural, etc.) between neighboring countries. It could also be the case that people are simply not willing to move and work in a neighboring region of a different country, even if the region is close-by. We therefore consider a *W* matrix based on the binary contiguity principle of sharing a common border, but limit contiguity to within country linkages only (*W*8 in Table 1): $w_{ij} = 1$ if regions *i* and *j* share a common border and are located in the same country.

Since spatial interaction can also be determined by economic variables rather than physical features of how units are spaced, we also consider 'economic distance.'[12] For example, Fingleton and Le Gallo (2008) take into account the size of each area's economy (measured in terms of the total employment level) and argue that it is more realistic to base spatial spillovers relative to economic distance. Therefore, we estimate the model using a binary contiguity matrix whose elements are postmultiplied by regional GDP (*W*9 in Table 1), where we take the average

[11]We could continue to consider powers of the spatial weight matrices W^4, W^5, etc., but even including third-order neighbors does not result in a better fit of the data.
[12]For a concise overview of this concept, see Corrado and Fingleton (2011).

GDP for each region over 24 years: w_{ij} = GDP_j if regions i and j share a common border.[13] It is expected that the impact of regions with greater 'economic mass' will be greater than the other way around, so that the spatial weights matrix is asymmetric.

The final spatial weights matrix that we construct is based on a gravity-type of model specification ($W10$ in Table 1), with typical element $w_{ij} = [(\mathrm{GDP}_i * \mathrm{GDP}_j)/\mathrm{t}_{ij}]$. Thus, the interaction is expressed as a ratio of the multiplied economic mass of region i and region j over the travel time between regions i and j. This type of model has recently gained even more attention in the social sciences, such as the gravity model of trade in international economics (see e.g., Brakman and Bergeijk, 2010).[14] It is expected that the level of flows (trade, migration, commuting, etc.) between regions will depend on both scale and distance impacts.

The weights matrices are row-normalized so that the entries of each row sum to unity to facilitate interpretation and computation of the magnitude of spatial dependence. Even though this is common practice in applied research, row normalization is not free of criticism. For example, when an inverse travel time matrix is row normalized its economic interpretation in terms of distance decay is no longer valid. First of all, because of row-normalization the impact of unit i on unit j is not the same as that of unit j on unit i. Secondly, as a consequence of row normalization, information about the mutual proportions between the elements in the different rows of the spatial weights matrix gets lost. For example, remote and central regions will end up having the same impact, i.e. independent of their relative location. For these reasons, we re-estimate the model with all the different spatial weights, but instead of normalizing by row, we scale the elements of each matrix by the maximum eigenvalue. By using this approach there is a re-scaling factor that leads to an equivalent specification to the weights matrix before normalization (Kelejian and Prucha, 2010). The bias corrected estimator developed by Lee and Yu (2010b) only works if W is row-normalized. Therefore, we adopt their estimation procedure spelled out for the spatial fixed effects model (without time dummies) and add time dummies in the form of regular X variables to estimate the model using W normalized by the maximum eigenvalue.

[13]The data for regional GDP (expressed in PPPs) is taken from Eurostat. Since data for 2010 is not yet available we take the average over the period 1986-2009. There is also data unavailability for the Italian regions from 2002-2006.
[14]The name of the model is due to its similar formulation to Newton's law of universal gravitation. The difference is that we use t rather than t^2.

Another important issue to note is that the Bayesian Markov Chain Monte Carlo (MCMC) routine for spatial panels required to be able to compute Bayesian posterior model probabilities does not exist yet. James LeSage provides Matlab routines to determine the cross-sectional version of the Bayesian MCMC approach at his Web site www.spatial-econometrics.com. As an alternative, one may replace all cross-sectional arguments of this routine by their spatial panel counterparts, e.g., a block-diagonal $NT \times NT$ matrix, diag(W,…,W) as argument for W. Although less efficient from a computational viewpoint, this works well if $N \times T$ is not too large.

Table 1 shows the log-likelihood function values and posterior model probabilities associated with the extended Blanchard-Katz model based on the alternative weights matrices and normalization approaches. An illuminating result is that spatial weights matrices that account for factors such as population size, inverse travel times, and regional GDP—factors that may be said to be endogenous to the system—are outperformed by spatial weights matrices that measure whether two regions share a common border or whether they share a common first-order neighbor—factors that are truly exogenous. From a methodological viewpoint, this is an extremely important result since one of the conditions made to the ML estimator developed by Lee and Yu (2010b) is that the spatial weights matrix should be exogenous. If the matrix best describing the data would depend on one of the economic distance measures, it may be interpreted as a form of misspecification since this result would be inconsistent with the applied estimator.

Insert Table 1

The Bayesian posterior model probabilities point to the first-order binary contiguity matrix limited to within country neighbors ($W8$) for the unemployment rate equation. When $W8$ is scaled by the maximum eigenvalue, the posterior model probability is 1 and the log-likelihood value is also the highest. When row-normalization is applied, it is found that the posterior model probability is 0.655 and for $W6$ it is 0.345. Although there is only a slight difference between the log-likelihood function values of the $W6$ and $W8$ specifications, the posterior model probabilities are more reliable because this approach does not require nested models for the comparisons. For the employment growth equation, the second-order binary contiguity matrix extending across

national borders (*W*6) has the highest posterior model probability and log-likelihood function value. This result applies no matter which normalization procedure is used.

In contrast, for the participation rate equation it differs depending on how *W* is scaled. If row-normalization is applied, both the log-likelihood function value and Bayesian posterior model probabilities point to *W*6, whereas they point to *W*8 if the weights matrices are scaled by the maximum eigenvalue. Apparently, the normalization procedure makes a difference and deserves more attention in the literature. On the basis of these results, two important questions are whether to use the *W*6 or *W*8 specification for the participation rate equation and which normalization approach to apply. We first estimated the extended Blanchard-Katz model using *W*6 for the participation rate and employment growth equations and *W*8 for the unemployment rate equation, applying row-normalization which is common practice in the literature. However, the system of equations was not stationary; the maximum eigenvalue of the matrix on the right-hand side of equation (4) was larger than one. Applying maximum eigenvalue normalization to this latter *W* specification also resulted in an unstable system. We proceeded to estimate the model using *W*6 for the employment growth equation and *W*8 for the unemployment and participation rate equations, scaling the weights matrices by the maximum eigenvalue. The system of equations was again unstable. However, row-normalizing the weights matrices resulted in a stationary system with largest eigenvalue of 0.9826. In addition, the sum of the coefficients of the variables Y_{t-1}, WY_t and WY_{t-1} in the single equations are smaller than one, which is a requirement to apply the bias corrected estimator of Lee and Yu (2010b).

The stationarity of the entire system is an additional and also extremely important criterion to meaningfully investigate the effects of a shock in labor demand. Since *W*6 and *W*8 do not include factors such as inverse travel time, row-normalization does not result in information loss. Therefore, the empirical results reported in the paper are based on using *W*8 for the unemployment and participation rate equations and *W*6 for the employment growth equation.[15] The finding that spatial interaction effects in the employment growth equation extend across national borders is reasonable. Since employment growth reflects labor demand and firms are willing to purchase inputs from suppliers located in different countries (Overman and Puga, 2002), cross-national borders do not matter as much. In contrast, the demarcation of interaction

[15]As a robustness check, the results were compared using the alternative *W* specifications and normalization approaches and it is found that they result in similar inferences.

effects among regions within country borders for the unemployment and participation rate equations reflects the low labor mobility in the EU compared to the US, especially across national borders (Puga, 2002; European Commission, 2010).

3. Data

The regional level data on unemployment, participation, and employment is obtained from the Labor Force Survey provided in Eurostat's regional database.[16] The empirical analysis is based on a sample of 112 regions across 8 EU countries covering a period of 25 years, from 1986-2010. Although data is available from 1983 for most countries in our sample, regional unemployment data prior to 1986 is limited and not mutually consistent, creating problems for comparability across countries (Overman and Puga, 2002).[17] Eurostat uses a hierarchical classification of NUTS1, NUTS2, and NUTS3 level regions, NUTS being the French acronym for Nomenclature of Territorial Units for Statistics. Due to data availability, NUTS 2 regions are used in this study.[18] Even though there is data for Greece and Ireland, they are not included in the sample because starting with an unbroken study area was necessary to be able to test the different spatial weights matrices against each other. After taking these factors into consideration, the countries (number of regions within parentheses) included in our analysis are: Belgium (11), Denmark (1), France (21), West Germany (30), Italy (20), Luxembourg (1), the Netherlands (12), and Spain (16). These NUTS2 level regions are depicted in Figure 1.

Insert Figure 1

The regional unemployment rate is measured as the ratio of the number of unemployed people and the number of people in the labor force. The labor force (economically active population) consists of the sum of unemployed and employed individuals. Since unemployment data often suffer variations across countries and time in the definition or measurement of

[16]Data can be accessed at http://epp.eurostat.ec.europa.eu/portal/page/portal/region_cities/introduction.
[17]For Spain, data registration began in 1986 when it became a member of the EU.
[18]Eurostat (2008) provides a comprehensive overview of the levels of disaggregation and data descriptions.

unemployment rates, we use Eurostat's harmonized unemployment rates.[19] To obtain the participation rate, we take the logarithm of the ratio of the labor force and the working age (15-64) population. The employment growth rate is calculated as the logarithm of the ratio of the number of people employed in period *t* and the number of people employed in period *t*-1. Instead of providing summary statistics for each individual region and time period, we facilitate the visualization of our sample by depicting the variables for the most recent year data is available using ArcGIS (see Figure 1). It can be observed that when a particular region has a low value, the chances are high that surrounding regions also have low values and vice versa, especially if these regions are located in the same country. This finding provides an indication that spillovers between regions may exist. To formally test whether this is the case, we proceed to the estimation results presented in the following section.

4. Results

The estimation results are reported in Table 2. We find that using either form of spatial weights normalization results in similar estimates and inferences.[20] Since normalizing the spatial weights matrix to have row-sums of unity resulted in a stationary system and is most frequently used in the empirical literature, the reported results are based on this approach.[21] We also include the estimation results without any interaction effects in the first column of Table 2. In this way, the results from the non-spatial Blanchard-Katz model can be compared to those of the spatially extended model.

Insert Table 2

The coefficient estimates of the traditional Blanchard and Katz variables in both the non-spatial and spatial models are significantly different from zero, mainly at the 1% level. The coefficients of the serially lagged endogenous variables, especially for the unemployment and participation rates, are large and significant, which is in line with the observation in previous

[19]A person is unemployed if s(he) is without work, currently available for work, and seeking work, which requires the person to take specific steps in a specified period to seek paid employment or self-employment. For more details, refer to Eurostat (2010).
[20]This also holds for the direct, indirect, and total effects presented in Table 3.
[21]The results based on maximum eigenvalue normalization are available upon request.

studies that labor market variables tend to be strongly correlated over time. The coefficients of the variables measuring interaction effects in column (2) are also highly significant. This result corroborates that these variables should not be excluded from the model. Omission of relevant explanatory variables results in a misspecified model, whose coefficients will be biased and inconsistent (Greene, 2003).

4.1 Direct and indirect effects vs. coefficient estimates of spatial model

As models containing spatial lags of dependent and explanatory variables become more complicated with a greater wealth of information (LeSage and Pace, 2009), due care should be taken when interpreting the coefficient estimates. Whereas these coefficient estimates represent the marginal effect of a change in an explanatory variable on the dependent variable in the non-spatial model, this is not the case in the spatial model. For this purpose, we report the short-term direct and indirect effect estimates derived from equation (6) in Table 3. The description "short-term" requires careful interpretation since some explanatory variables are observed in the previous time period. For example, the short-term effect of participation on unemployment (see equation 1a) represents the effect after one year, whereas the short-term effect of employment growth on unemployment represents the effect in the same year. The direct effect estimates include feedback effects that arise as a result of impacts passing through neighboring units (e.g., from region *i* to *j* to *k)* and back to the unit that the change originated from (region *i*). This is precisely the reason that there are differences between the *direct* effects and coefficient estimates of the X variables. In general, these feedback effects appear to be relatively small.[22]

Insert Table 3

In contrast, the discrepancies between the spatial lag coefficients and the *indirect* effect estimates are quite substantial. A striking pattern that emerges from Tables 2 and 3 is that the coefficients of the *WX* variables all have the opposite sign compared to the corresponding coefficients of the *X* variables, whereas this is not the case for all the indirect effect estimates.

[22]For example, the direct effect and the coefficient estimate of *e* in the *u* equation are -0.127 and -0.120, respectively. The feedback effect therefore amounts to around 5.51%.

The coefficient of the spatially lagged value of employment growth in the unemployment rate equation is positive (0.043), whereas its indirect (spatial spillover) effect is negative (-0.066). If we were to take the former coefficient of 0.043 as reflecting the indirect effect, this would lead us to conclude that the employment growth rate exerts a positive and significant indirect impact on the unemployment rate. Many empirical studies use the point estimates to test for the existence of spatial spillover effects. However, the results from this study illustrate that this may lead to erroneous conclusions.

The fact that the indirect effect of *e* on *u*, just as the direct effect, is negative rather than positive indicates that job growth in region *i* not only decreases the unemployment rate in region *i*, but also in other regions *j*. Specifically, we find that if the employment growth rate in region *i* increases by one percentage point, the unemployment rate in neighboring regions decreases by 0.066 percentage points. Therefore, an increase in the economic opportunities available to individuals in a particular region does not appear to worsen the job prospects of individuals living in neighboring regions. In general, we also find substantial differences between the other spatial lag coefficients and indirect effects, indicating that a partial derivative interpretation (as outlined in Section 2.3) provides a more valid basis to test for the existence of spatial spillovers.

4.2 Statistical significance and interpretation of direct, indirect, and total effects

In addition to quantifying the magnitude of the direct, indirect (spillover), and total effects, we also indicate whether they are statistically significant in Table 3. Due to the fact that the direct and indirect effects are composed of different coefficient estimates according to complex mathematical formulas and the dispersion of these effects depends on the dispersion of all coefficient estimates involved, it cannot be seen from the coefficient estimates and the corresponding t-values whether they are significant. To overcome this limitation, LeSage and Pace (2009, p. 39) suggest simulating the distribution of the direct and indirect effects using the variance-covariance matrix implied by the maximum likelihood estimates.

Therefore, we use the variation of 1,000 simulated parameter combinations drawn from the multivariate normal distribution implied by the ML estimates in order to draw inferences regarding the statistical significance of the effects. Based on the calculated t-statistics, we find that the two indirect effect estimates in the unemployment rate equation differ significantly from

zero, providing evidence of the existence of spatial spillovers in regional labor markets. In the other two equations (*p* and *e*), the indirect effects are also highly significant, with the exception of the employment growth rate in the participation rate equation.

The direct effect of employment growth (*e*) on the unemployment rate (*u*) is highly significant and has the expected sign. If a regional economy creates new jobs, this increases the opportunities available for the currently unemployed population. Specifically, we find that an increase of one percentage point in the employment growth rate in a particular region decreases the unemployment rate in its own region by 0.127 percentage points. The spatial spillover effect is also negative and significant with a magnitude of -0.066. As was mentioned previously in Section 4.1, this indicates that job growth in a particular region is also favorable to surrounding regions.

The direct effect of *p* in the *u* equation is negative and significant. If the participation rate increases by one percentage point in region *i*, the unemployment rate in region *i* decreases by 0.034 percentage points. This result corroborates the majority of previous empirical studies. Whereas the accounting identity states that the effect of the participation rate on the unemployment rate should be positive (i.e. if the participation rate increases, *ceteris paribus*, the number of unemployed must also increase), Layard (1997) points out that increased participation encourages the growth of more local jobs. Elhorst (2003) identifies 11 empirical studies with negative and significant effects of (male, female, or total) participation rates, while 3 studies report a positive but insignificant effect and only one study a positive and also significant effect. Therefore, overall, the negative effect dominates. The positive spatial spillover effect is significant and suggests a discouragement effect on neighboring regions (0.039, t-value = 2.426). The total effect is also positive, but turns out to be insignificant.

It is found that a one percentage increase in the regional employment growth rate increases the participation rate by 0.35 percentage points in the region itself. Although the spatial spillover effect has a negative sign suggesting adverse effects on the participation rate in neighboring regions, the magnitude is small and statistically insignificant. The total effect is quite substantial and significant (0.344, t-value = 25.314). A change in the regional unemployment rate also has a significant impact on the participation rate. A one percentage point increase in the unemployment rate in region *i* reduces the participation rate in that region by 0.122 percentage points. Therefore, fewer jobs induce less people to enter the labor force. In

other words, there is a net discouragement effect over the additional worker effect in the own region. By contrast, the spatial spillover effect is positive and significant (0.101, t-value = 4.518). This result implies that people may change their participation decision and move to neighboring regions for work if the labor market conditions in their own region are relatively less promising. The total economy-wide effect, although smaller in magnitude, is negative and significant like the direct effect estimate.

Turning to the last equation of the three-equation model, employment growth, we find that the direct and spatial spillover effect estimates are substantial and highly significant. A rise of one percentage point in the unemployment rate increases the employment growth rate by 0.199 percentage points in the region itself, but decreases the employment growth in neighboring regions by 0.367 percentage points. These results are in line with the neoclassical convergence hypothesis that lagging regions are catching up with leading regions. If the unemployment rate is relatively high, firms are more willing to move to these regions since they have the benefit of hiring employees from a larger labor pool and because people who work in labor markets with higher unemployment rates earn a substantially lower wage, known as the wage curve effect (Blanchflower and Oswald, 1994). Finally, if the participation rate increases by one percentage point, employment growth decreases significantly by 0.482 percentage points. Conversely, this latter impact significantly increases employment growth in other regions by 0.339 percentage points. The total economy-wide effect is therefore negative, although insignificant.

4.3 Impulse-response analysis

To investigate the repercussions of a labor demand shock on other regions in the long term, the extended Blanchard-Katz model is used to conduct impulse-response analysis. In contrast to the non-spatial model, exogenous shocks also propagate across space. In other words, the impulse response functions include temporal dynamic effects as in a standard VAR model, as well as spatial dynamic effects. Figure 2 depicts the labor market adjustment process in the region itself following an employment growth shock of one percent over a ten year period. The unemployment rate drops by around 0.13 percentage points at time $t = 1$. In the first few years, the impact persists, but dies down quite rapidly in the following years. In the fourth year, the decline in the unemployment rate is much less with a magnitude of around -0.06. The

participation rate rises to around 0.35 percentage points in the first year, but the effect diminishes with magnitudes of around 0.22 and 0.18 in the second and third years, respectively. After around five to seven years, the effect of the shock on all variables weakens entirely.

Insert Figure 2

In order to facilitate the visualization of the impact of a region-specific shock on neighboring regions, we present maps using ArcGIS (Figure 3) as well as impulse-response functions that take into account both the time and spatial dimensions of the demand shock (Figure 4). Figure 3 illustrates the initial response of the labor market in all regions in our sample to a positive demand shock in Île-de-France (Paris) region. In contrast to a standard VAR, the shock in a particular region is not entirely idiosyncratic; an employment shock is simultaneously accompanied by employment shocks in other regions through the model's spatial autoregressive structure. This is illustrated by the third panel of Figure 3. The initial employment shock in the region itself is larger than in neighboring regions (the darker the shading, the stronger the responses). The shock also propagates to other regions, especially impacting first and second-order neighbors.

Insert Figure 3

The strongest responses to the shock are in Basse-Normandie, Champagne-Ardenne, Haute-Normandie, Pays-de-la-Loire, and Picardie. In Haute-Normandie and Picardie, the unemployment rate initially decreases by around 0.027 and 0.026 percentage points, respectively. Basse-Normandie, Haute-Normandie, and Pays-de-la-Loire experience the largest additional employment growth of respectively, 0.105, 0.091, and 0.102 percentage points. The largest increase in the labor force participation rate following the positive shock in labor demand in Île-de-France occurs in Champagne-Ardenne of around 0.0372 percentage points, followed by Picardie with 0.0367 percentage points. These magnitudes actually increase in the first few years. For example, in Champagne-Ardenne the participation rate rises to around 0.047 percentage points in the second year. Regions outside of France, such as the Belgian provinces also have higher impacts in the second year. For example, in Hainaut the unemployment rate declines by

0.0089 percentage points in the first year, while in the second year the magnitude is -0.0112. This indicates that it takes more time for the full effects of the shock to be felt due to the propagation across space. In contrast, in the Paris region all values are highest in the first year.

An interesting observation from these results is that in some cases the second-order neighbors are more affected by the shock than the first-order neighbors, as is the case for Basse-Normandie and Pays-de-la-Loire. Another interesting outcome is that while the changes in the unemployment rates, participation rates, and employment growth rates follow a similar pattern, differences exist both within regions and also in terms of the amount of regions affected by the shock. For example, for some regions the one percent employment growth shock in the Paris region affects the unemployment rate more than the other labor market variables, and vice versa.

Insert Figure 4

The additional employment growth observed in all other regions is due to the highly significant coefficient estimate of the spatially lagged employment growth variable (0.631, t-value = 19.065) in Table 2. However, this effect decreases markedly after the second year. This can be observed in Figure 4 which shows the evolution of unemployment, participation and employment growth over both space and time. For presentation purposes, the impact of the shock on the labor market variables are ordered so that in the middle we observe regions that are most affected, which in our empirical application consist of regions located in France. In addition, the region that instigated the shock, Île-de-France, is eliminated from Figure 4. This is because the impact of this shock is already shown in Figure 2 and since it is much larger than the spillover impact in neighboring regions, it would dominate the figure. Just as in the region itself (Figure 2), the effect of the shock on all variables in neighboring regions weakens considerably after around five to seven years. A notable difference is that the impact on the participation and unemployment rates following a demand shock seems to be more persistent in neighboring regions than in the region where the shock instigates.

5. Conclusions

This paper extends the seminal Blanchard and Katz (1992) regional labor market model to include interaction effects using a dynamic spatial panel data approach. A valuable aspect of the

extended model is that the assumption that regions are independent of one another no longer has to be made. Unlike the original model, the spatial Blanchard-Katz model developed in this paper allows for the quantification of spatial spillover effects. Another key contribution of this model is that both the temporal and spatial propagation of labor demand shocks can be investigated. Before estimating both the non-spatial and spatial models using a panel of 112 EU regions from 1986-2010, important methodological issues are addressed including the estimation method, stationarity of the model, and the specification, selection, and different normalization procedures of the spatial weights matrix. Although row-normalizing the weights matrix is common practice in the literature, the justification and consequences of using this procedure instead of alternative normalization approaches is largely ignored and deserves more attention in future research.

From the estimation results of the extended Blanchard-Katz model, it is found that the coefficients of the variables measuring interaction effects are highly significant. The coefficient estimates, however, do not represent the marginal effect of a change in an explanatory variable on the dependent variable. Therefore, a methodology recently introduced by LeSage and Pace (2009) is applied to calculate direct, spillover, and total effects. We find discrepancies between the spatial lag coefficient values and the spillover effects. For example, the coefficient of the spatially lagged value of employment growth in the unemployment rate equation is positive, whereas its spatial spillover effect is negative. The majority of the spillover effects and all the direct effects are highly significant.

To investigate the impact of a region-specific labor demand shock on other regions, the extended model is used to conduct impulse-response analysis. Consistent with economic theory, the impact of a demand shock is largest in the region where the shock instigates. Yet, the shock also spreads to other regions, especially impacting the first and second-order neighbors, which is a reasonable result. As in the region itself, the effect of the shock on the unemployment, participation, and employment growth rates weakens after around five to seven years. A notable difference is that the impact in other regions becomes larger after the first year indicating that it takes more time for the full effects of the shock to be felt due to the propagation across space. In contrast, in the region where the shock takes place the impacts are highest in the first year. Extending the model from a recursive to a simultaneous equations model so that the labor market effects of a supply shock can be meaningfully simulated is a path that deserves more attention

(cf. De Groot and Elhorst, 2010). Including additional variables such as wages and labor market institutions in the model could also provide further insights into regional labor market dynamics.

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Table 1. Spatial weights model comparison

		Row normalization		Maximum eigenvalue normalization	
Spatial weights	Equation	Log-likelihood function value	Bayesian posterior model probability	Log-likelihood function value	Bayesian posterior model probability
$W1$ Binary contiguity across national borders	u	9183.27	0	8956.21	0
	p	7470.85	0	7278.37	0
	e	5616.46	0	5554.09	0
$W2$ Population sizes	u	9142.75	0	8896.72	0
	p	7444.25	0	7216.90	0
	e	5580.83	0	5510.47	0
$W3$ Inverse travel times	u	8826.71	0	8614.08	0
	p	7380.90	0	6820.50	0
	e	5596.22	0	5466.77	0
$W4$ Hybrid matrix of $W2$ and $W3$	u	8764.51	0	8664.42	0
	p	7234.30	0	6893.40	0
	e	5429.65	0	5480.39	0
$W5$ $W4$ restricting weights to contiguous neighbors	u	9110.13	0	8791.37	0
	p	7430.75	0	7176.83	0
	e	5561.38	0	5504.85	0
$W6$ First-order and second-order neighbors	u	9191.72	0.345	8935.84	0
	p	7480.60	1	7114.17	0
	e	5668.46	1	5620.64	1
$W7$ W6 including third-order neighbors	u	9111.07	0	8844.96	0
	p	7455.80	0	6955.29	0
	e	5617.61	0	5557.54	0
$W8$ Binary contiguity within national borders	u	9191.14	0.655	8977.53	1
	p	7466.45	0	7285.26	1
	e	5609.08	0	5580.25	0
$W9$ Economic distance	u	9137.05	0	8826.61	0
	p	7441.22	0	7136.43	0
	e	5579.06	0	5494.89	0
$W10$ Gravity-type model	u	8760.91	0	8629.79	0
	p	7354.90	0	7049.11	0
	e	5571.58	0	5413.00	0

Table 2. Non-spatial and spatial Blanchard-Katz model estimation results

Dependent variable	Explanatory variables	(1) Non-spatial model		(2) Spatial model	
u	u_{t-1}	0.868	(92.269)	0.810	(55.465)
	Wu	—	—	0.603	(28.099)
	Wu_{t-1}	—	—	-0.426	(-15.823)
	p_{t-1}	-0.012	(-2.043)	-0.025	(-3.253)
	Wp_{t-1}	—	—	0.027	(2.427)
	e	-0.152	(-24.275)	-0.120	(-21.467)
	We	—	—	0.043	(5.039)
R^2		0.964		0.978	
p	p_{t-1}	0.884	(92.201)	0.839	(58.187)
	Wp	—	—	0.342	(13.264)
	Wp_{t-1}	—	—	-0.183	(-5.428)
	u_{t-1}	-0.115	(-7.245)	-0.193	(-6.608)
	Wu_{t-1}	—	—	0.174	(4.409)
	e	0.515	(48.832)	0.524	(47.043)
	We	—	—	-0.186	(-9.489)
R^2		0.976		0.980	
e	e_{t-1}	-0.110	(-5.641)	-0.116	(-7.908)
	We	—	—	0.631	(19.065)
	We_{t-1}	—	—	0.185	(5.336)
	u_{t-1}	-0.051	(-1.729)	0.212	(4.716)
	Wu_{t-1}	—	—	-0.274	(-4.637)
	p_{t-1}	-0.233	(-13.517)	-0.331	(-14.823)
	Wp_{t-1}	—	—	0.296	(8.501)
R^2		0.252		0.414	

Notes: Results reported under column (2) are based on using weights matrix W8 for the u and p equations and W6 for the e equation. t-values in parentheses.

Table 3. Spatial Blanchard-Katz model: Direct, indirect (spillover), and total effects

Equation	Explanatory variable	Direct effect	Indirect effect	Total effect
u	e	-0.127	-0.066	-0.193
		(-21.497)	(-4.909)	(-11.685)
	p	-0.034	0.039	0.004
		(-3.520)	(2.426)	(0.384)
p	e	0.350	-0.007	0.344
		(48.630)	(-0.549)	(25.314)
	u	-0.122	0.101	-0.022
		(-6.997)	(4.518)	(-1.285)
e	u	0.199	-0.367	-0.168
		(4.645)	(-3.309)	(-1.631)
	p	-0.482	0.339	-0.143
		(-13.649)	(3.352)	(-1.462)

Notes: See note under Table 2. Because p is measured in logs, while u and e are both measured in percentage points, we make the following adjustment. For the u equation, $u = \ln(p)\beta$, where β is the coefficient estimate. Since $\partial u/\partial p = \partial u/p\partial lnp = \beta/p$ and $\bar{p} = 0.67$ in our sample, we report $\beta/\bar{p}$ for ease of interpretation. The e equation has a similar expression to that of u. In contrast, for the p equation, $\ln p = u\beta$ and thus, $\partial p/\partial u = p\partial lnp/\partial u = p\beta$, which is approached by $\bar{p}\beta$.

Figure 1. Regional unemployment, participation and employment growth rates in 2010

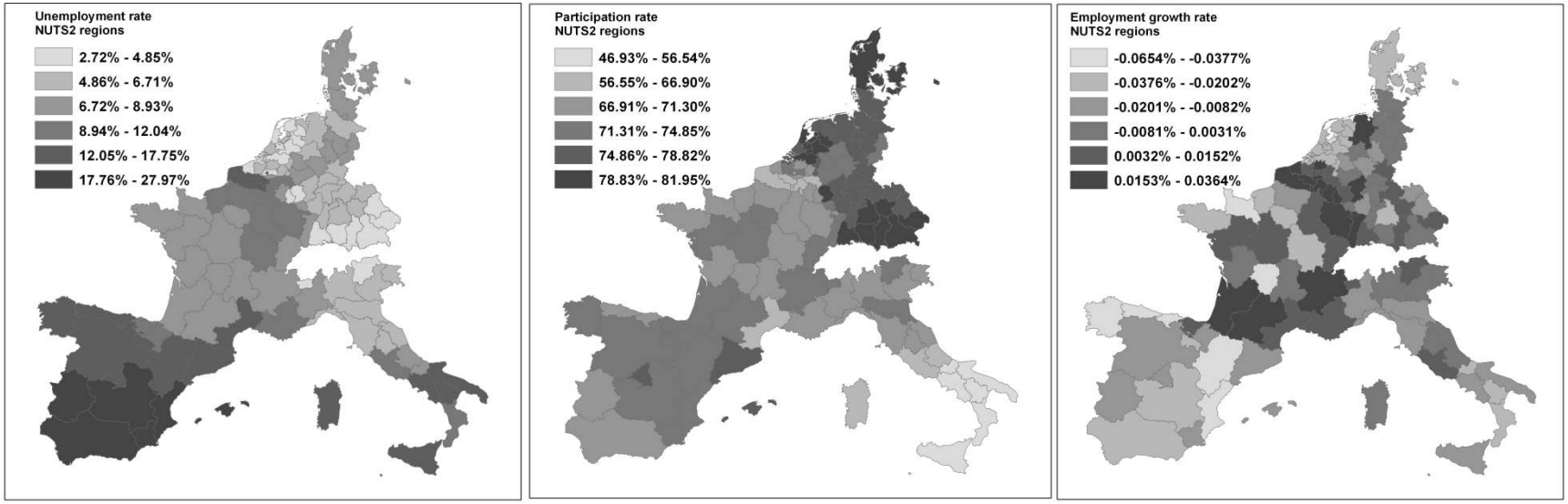


Figure 2. Regional labor market response to a demand shock on *region itself*

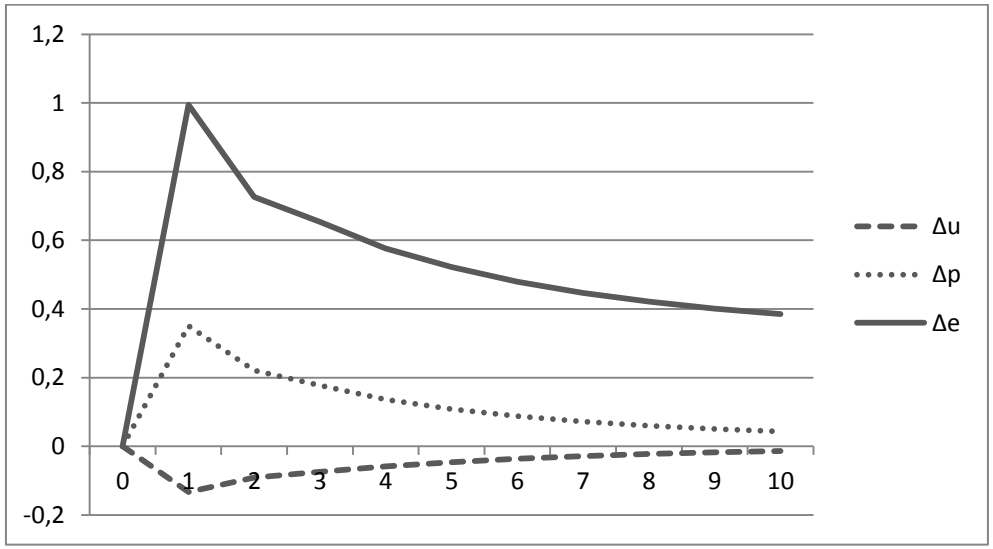


Figure 3. Regional labor market response *across space* to a demand shock in the Île-de-France region

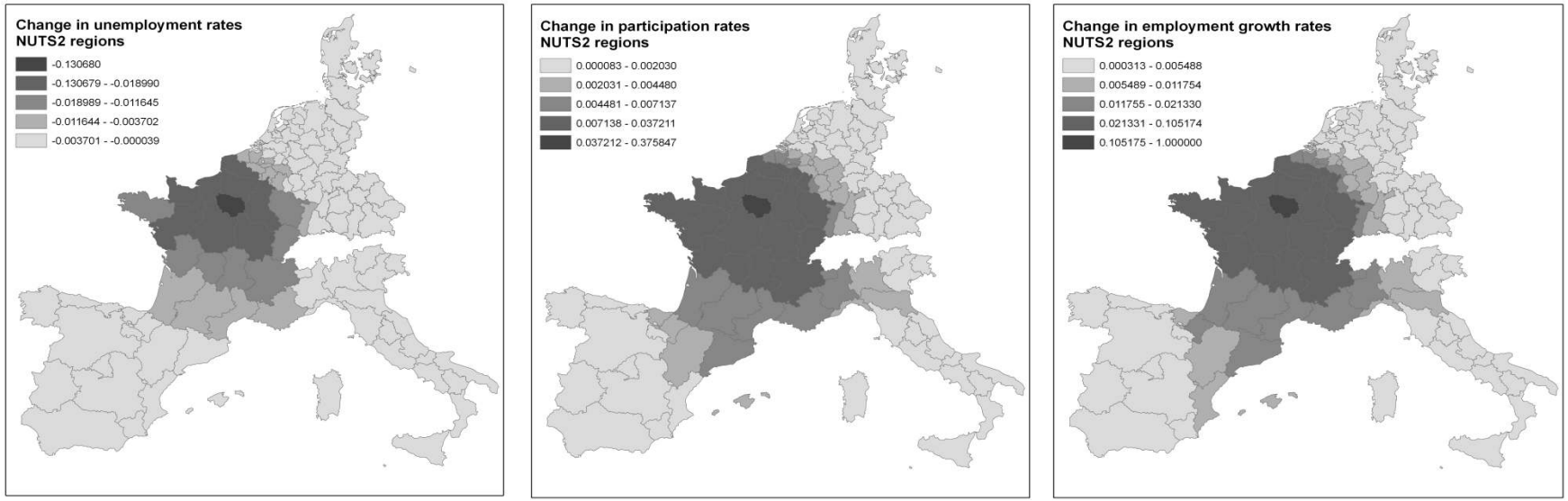
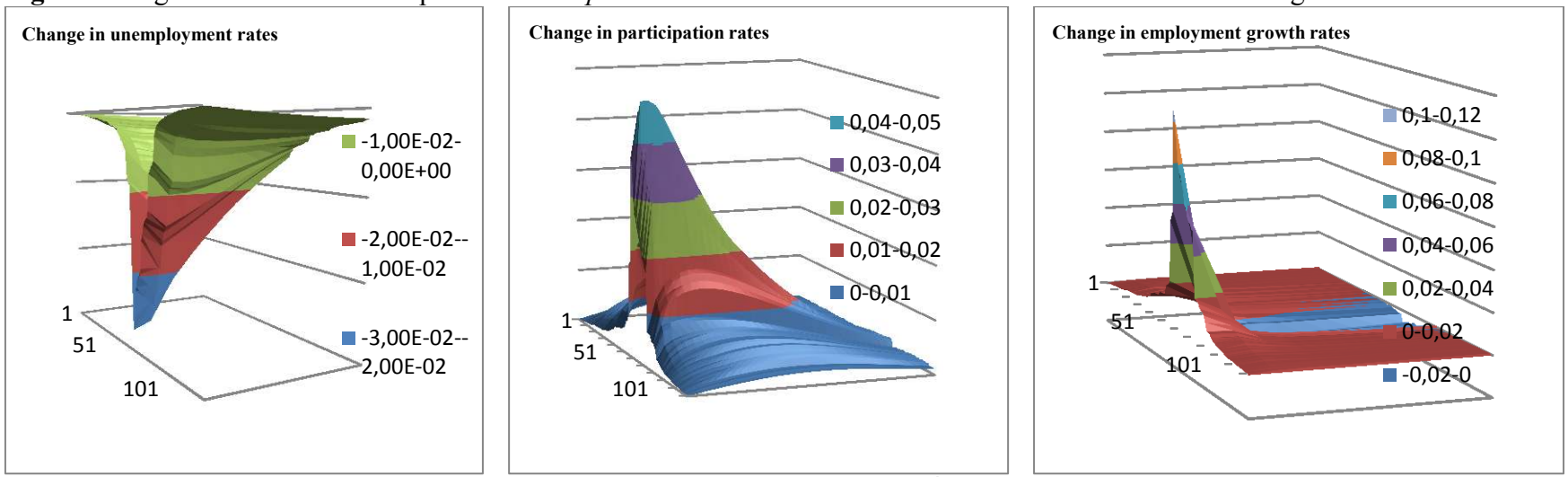


Figure 4. Regional labor market response *across space* and *over time* to a demand shock in the Île-de-France region



Notes: The bottom left axis plots the regions, where we include all regions with the exception of Île-de-France. The bottom right axis indicates the time horizon of 10 years and the legend at the right shows the magnitude of the changes.