A Regional Perspective on the Economic Resiliency of Central and East European Economies

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Abstract

In this paper we examine resiliency, the ability to absorb and recover from economic shocks, in 199 Nuts-3 regions in Central and Eastern Europe following the 2008 global financial crisis. We find that regional productivity has a clear influence on the ability to resist and recover from shocks. More productive regions fare better than do regions with low output per worker. Moreover, regions that resist shocks well also recover to a greater extent. Finally, we find strong positive regional spillovers, which means that regions tend to form clusters of high-performing and low-performing areas, a process that exacerbates regional income disparities.

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I. Introduction

In part due to the slow recovery from the global financial crisis of 2008, there has been a renewed interest in the concepts of economic resiliency, the ability of economies to absorb economic shocks and to recover from them. The traditional approach in macroeconomics was that downturns are temporary and that the economy would return more or less quickly to the long-term growth path of GDP as idle workers and capital were put back to use. In the literature on resiliency, this is called the single-equilibrium approach, where a system is seen as returning to the status *ex ante*. The aftermath of the 2008 crisis put this traditional view into question. Figure 1 shows that the world's major economies reacted differently to the initial shock, at least quantitatively if not qualitatively, and none of them were able to recover to the pre-crisis trend of real GDP. Thus, macroeconomic resiliency came to be seen not as a return to the pre-crisis state or growth path, but rather as the adaptation to the new circumstances in which the economy finds itself as a result of the crisis. Ball (2014), Haltmeier (2012), Martin *et al.* (2014) and Reinhart and Rogoff (2014), using somewhat different methodologies and data sets, all demonstrate intercountry differences in both the resistance to shocks and in the recovery from them. Central and Eastern Europe (CEE) appears to have been particularly hard hit by the crisis, and recovery was less dynamic than it was in the older EU countries (Figure 2).

At the national level, resiliency to shocks depends on the openness of the economy, to the country's exchange rate regime, to the structure of production, and to national policies to deal with the effects of the shock. Return to the *status quo ex ante* is difficult because shocks create shortfalls in labor, capital and technology related to the decline in output. Reduced investment during the downturn lowers the capital to labor ratio, workers leave the labor force thus reducing the labor force participation ratio and, if unemployed, they cease to acquire human capital from learning by doing and their existing skills atrophy. Research and development also decline, and, together with lower levels of investment in capital that embodies new technology, combine to reduce the level or growth of total factor productivity. National-level recovery from the effects of the crisis also depends on these same national characteristics, on counter-cyclical policies and on measures reversing the decline in productivity and the supply of factors of production. To the extent that the shock changes relative prices and wages, structural changes are also an important component of resiliency and recovery.

In this paper, we examine resistance, to and the recovery from, the global financial crisis in CEE countries at the regional level, using NUTS-3 statistical regions of nine countries, Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania and Slovakia. There are three motives for examining CEE resistance and recovery at the regional level. The first motive is that, by focusing on regions of a single country rather than on cross-country comparisons, we are able to hold constant a number of variables that influence resistance and recovery. These include national counter-cyclical policies, the exchange rate regime, openness to international trade, social policies and demographics. This makes it easier to identify the effects of other factors that play a role in resistance and recovery. The second motive is that, in the regional economics literature, there is a lack of empirical research on regional economic resiliency and even on the nature of regional spatial effects or spillovers in CEE economies. Available studies cover only individual transition economies. The third motive is that our study is related to the growing emphasis on the link between economic systems and regional inequality (Stiglitz, 2012; Piketty, 2014, etc.), as well as to the debate on the importance of institutions and geography in economic development (Acemoglu, Johnson, and Robinson, 2002). The spatial models we estimate in this paper include both institutional and geographic factors and capture their interactions in a social learning framework, so they naturally emphasize the importance of both factors in understanding regional resistance and development. The spatial regressions models are also useful for understanding regional inequality issues. For instance, Martin et al., (2016, p. 583) state that “the study of regional cyclical resistance and recoverability is … integral to understanding long-run patterns of uneven regional development”. Our study should be seen in the context of growing post-transition income disparities between regions in the CEE economies. Capital cities and the regions close to them have gained significantly in population and, more important, in per capita income, while peripheral regions in these countries have experienced declines in per capita income, thus contributing to growing income inequality in the CEE economies. Hence, our study further sheds some light on inequality issues from a long-run perspective and beyond a national level, and also complements Stiglitz (2012), Piketty (2014) and other related studies.

The remainder of the paper is organized as follows: Section II reviews the literature on regional resiliency, on spatial regression models and on the literature of regional responsiveness in CEE. Section III explains the data sources and main variables of interest. Stylized facts on regional resistance and recovery in CEE are presented in Section IV, which also explains how we capture regional spillovers. Section V explains the construction of indexes used in our regression models. Sections VI and VII provide the specification of the regression model and present and discuss the parameter estimates, respectively. Section VIII concludes.

II. Literature Survey

Studies on regional resiliency in economics have examined regional resiliency in the face of ecological disasters, demographic and technological change, shifts in demand and globalization. The *Cambridge Journal of Regions, Economy and Society* (2010), and the *Journal of Regional Science* (2012) have published special issue on regional resiliency that cover many of the key conceptual issues. This literature survey consists of three parts. In the first part, we summarize the literature regarding different concepts of resiliency. In the second part, different spatial models employed in the literature are briefly introduced. The last part provides an overview of empirical studies using spatial models of regional resiliency.

II.1 Defining regional resiliency

Early studies of regional resiliency focused on understanding the process and patterns of resistance to change in the face of shocks. As the concept is used in different fields, including engineering, ecology, geography, sociology, etc., what signifies regional resiliency is shaped by their corresponding fields (Christopherson, Michie, and Tyler, 2010; Hassink, 2010; Hudson, 2010; Pike, Dawley, and Tomaney, 2010; Simmie and Martin, 2010; Wolfe, 2010). The literature provides three concepts of resiliency: single-equilibrium (engineering resiliency), multiple-equilibrium (path dependent or ecological resiliency), and adaptive resiliency.

According to the single-equilibrium approach, a regional economy facing a shock should return to its pre-shock equilibrium level. This approach assumes a stable, long-run relationship among the key economic variables driving economic performance and the free and flexible operation of factor markets. Resiliency is then measured in terms of how quickly a regional variable such as output, employment, etc. returns to the pre-shock equilibrium (Pendall, Foster and Cowell, 2010; Pike et al., 2010; Fingleton, Garretsen and Martin, 2012).

According to the path-dependency approach, the performance of a regional economy is assumed to be determined by economic forces (investment, migration, relative price changes, etc.) that also change as the result of the shock. Consequently, in the face of shocks, a region is unlikely to return to its previous pre-shock equilibrium path or state. Resiliency is then measured by the success of affected regions in moving from the suboptimal immediate post-shock state to a new equilibrium. In this view, resiliency is associated with flexibility and the ability to make adjustments to new circumstances. Such adjustments depend on the capacity of local firms, workers, market institutions and governments to undertake changes in the structure of economic activities. Such shifts generate multiple possible equilibrium states, depending on how regional parameters change (Hassink, 2010; Pike et al, 2010, Wolfe, 2010; Doran and Fingleton, 2018).

The third definition, adaptive resiliency, extends the path-dependency approach and views regional resiliency as a complex and evolving process, involving social learning by workers, firms, and institutions as they try to overcome uncertainty in the face of a shock (Hansink, 2010; Hudson, 2010; Pike at al., 2010). According to this view, resiliency to shocks is determined by, and determines, factors such as industrial structure (specialization vs diversity), institutions, agglomeration economies and others (Doran and Fingleton, 2014; Martin, Sunley, Gardiner and Tyler, 2016; and Doran and Fingleton, 2018). In other words, adaptive resiliency assumes an endogenous, two-way causal relationship between economic outcomes and shocks and their underlying regional determinants. Martin and Sunley (2016) argue that regional resiliency includes four consecutive phases: risk, resistance, reorientation and recoverability, and they all depend on the size, nature and duration of shocks. In the risk phase, regions recognize that they are vulnerable to internal and external shocks. The resistance stage captures how firms, economic sectors, institutions and other key players resist shocks and adjust, and then adapt to the shocks (i.e., the reorientation step). The recoverability step captures fruits of making the required adjustments and the degree to which regions recover from the shock. Martin et al., (2016, p. 583) state that "the study of regional cyclical resistance and recoverability is … integral to understanding long-run patterns of uneven regional development".

II.2. A brief review of spatial regression models

Lesage and Fischer (2008) developed spatial regression models to test for resiliency in a regional growth setting. Their empirical framework is based on specifying a full spatial

Durbin Model (SDM) and discussing its variants. The starting point for the development of their model is the following simple pooled linear regression:

$$y_{it} = x_{it}\beta + \varepsilon_{it} \quad (1)$$

where the variable y represents a vector of observed values of the dependent variable, for example regional output or employment, and vector x is a vector of k independent variables. i is an index for the cross-sectional dimension (regions) while t is an index that captures the time dimension. β is a vector that captures the impact of the independent variables on the dependent variable. The error term, ε, has a zero mean and constant variance and is independently and identically distributed.

Equation (1) does not include any spatial effects. To capture the impact of potential spillovers from one region to another on the dependent variable, Lesage and Fischer (2008) specify the following SDM model:

$$y_{it} = \rho W y_{jt} + x_{it}\beta_1 + W x_{jt}\beta_2 + \varepsilon_{it} \quad (2)$$

Equation 2 indicates that the link between y and x in region i is not only a function of independent variables in region i but also of the explanatory variables for other regions, j.[1] Hence, the SDM model shows the way in which region i is influenced by developments in region j through spatial spillover effects. W is called the spatial weight matrix and its elements represent the spatial dependency among the observations. In some cases this spillover effect is limited to spillovers from adjacent regions so the effect is captured by a dummy variable thsat takes a value of 1 if two regions share a border and a value of zero otherwise (i.e. a contiguity matrix) or by other measures of distance between regions. In particular, the term Wy_{jt} captures the characteristics of neighboring or related regions and ρ, called the spatially lagged dependent variable, shows the economic significance of neighboring independent variables on the

[1] For example, other regions may mean all other regions in a country or contiguous regions only.

dependent variable. A positive and significant value of ρ indicates positive spatial dependency in that the dependent variable in region i is positively related to developments in related regions j. Note that ρ must be less than 1. On the other hand, the Wx matrix represents explanatory variables from related regions with β_2 capturing their economic significance for the dependent variable in region i. Finally, β_1 captures the impact of the independent variables in region i on the dependent variable in the same region (i.e., own effects).

Lesage and Fischer (2008) suggest two additional spatial models that are nested within the SDM model, namely, the spatial autoregressive (SAR) model (when β_2=0 and $\rho \neq 0$) and the spatial error (SEM) model (when $\beta_2 = -\beta_1\rho$). Thus, while the SDM yields unbiased parameter estimates because it is a generalization of the SAR and SEM models, testing for the above parameter restrictions can improve effciency of the estimates.[2] Consequently, it is of some value to select the correct type of spatial model. To do so, Lesage and Pace (2009) and Elshort (2009) suggest that the SDM model should be estimated first and then be tested against the alternative SAR and SEM models by checking the validity of the above coefficient restrictions. Once the correct model is chosen, Lesage and Pace (2009) recommend estimating the direct, indirect and total effects for each independent variable. The direct effect captures the impact of explanatory variables in region i on the dependent variable. The indirect effect represents the spillovers from related regions. How these effects are measured is discussed below.

II.3 Review of empirical spatial studies

There is little research on regional economic resiliency of CEE economies. Much of the study the regions of the CEE countries focus on regional income dispersion and on regional spatial effects or spillovers. Regarding the latter, Elshort, Blien and Wolf (2007) estimate a spatial wage curve for Eastern German districts during 1993-1999 and report that estimates of

[2] The SDM model also handles possible endogeneity bias resulting from both simultaneity and omitted variables.

unemployment elasticities are sensitive to the inclusion of spatially correlated error terms in their specifications. Baltagi and Rokicki (2014) also estimate the spatial wage curve for Poland using individual data from the Polish Labor Force Survey at the NUTS-2 level, and they report significant spatial unemployment spillovers across regions.

Kholodin et al. (2012) find significant convergence of income levels among high-income regions located near each other. This suggests the existence of the kind of spatial effects discussed in the previous section. In CEE counties, there seems to have been a lack of convergence in regional incomes. The capital cities and their neighboring regions have prospered in all CEE countries, also suggesting strong regional spillovers, but there are also regions in each country where performance is relatively poor.

III. Data and variables

The data used in this study refer to NUTS-3 statistical regions in nine Central and Eastern European Countries (CEECs: Bulgaria, Czechia, Estonia, Hungary, Latvia, Lithuania, Poland, Romania and Slovakia. The main source of data is Eurostat, but, in some cases, national sources (most notably the Polish Local Database, BDL from the Central Statistical Office, GUS) were also used to fill missing observations. Eurostat also provided the spatial data in the form of shapefiles with geographical coordinates, which are used in the article for the purpose of tracking spatial dependency and spillovers.

While we make use of the temporal information to capture the impact of pre-crisis regional features on regional resistance to the crisis, as well as the role of post-shock adjustments for the recovery, the models themselves are cross-sectional over the 199 NUTS-3 regions in our sample. Following Martin (2012) and Martin et al. (2016), we decompose resiliency into its two dimensions: resistance (the ability of a regional economy to resist or withstand an external shock) and recoverability (its ability to recover after the shock).

For measures of resistance we focus on a region's non-agricultural employment. We choose this variable for several reasons. First, non-agricultural employment is likely to be more sensitive to changes in economic conditions especially those due to external shocks. Agricultural employment, much of it self-employment, is less likely to respond to changes in economic conditions. Thus, regions with large agrarian populations would give the appearance of greater resistance merely due to the mix of agricultural and industrial employment. Second, changes in industrial production are easier to implement in the short run than are changes in the nature of agricultural production. Finally, policies to deal with shocks are largely directed toward the industrial sector.

Regional resistance is calculated in the following way. First, the non-agricultural employment change in region *i*, between the pre-crisis peak and the subsequent trough is

$$x_i = \frac{min\{e_{i2008}, e_{i2009}, \ldots e_{i2013}\} - max\{e_{i2006}, e_{i2007}, e_{i2008}\}}{max\{e_{i2006}, e_{i2007}, e_{i2008}\}} * 100\% \qquad (3)$$

where e_{i20xx} is the non-agricultural employment in region *i* in year 20xx. Thus, if region *i* loses employment as a result of the shock, $x_i < 0$. In this way we allow for differences in the years in which the crisis began to be felt in different regions and also for differences in the years in which the effects of the crisis on employment reached their maximum. An examination of the data on employment showed that the years of peak employment were sometime between 2006 and 2008 and the trough occurred sometime between 2008 and 2013.

In the second step, a raw index of regional resistance is calculated, using the country in which the region is located, *c,* as the baseline so that :

$$resraw_i = \frac{(x_i - x_c)}{|x_c|} \qquad (4)$$

where x_c is the decline in employment from peak to trough in country *c*.

Since $x_i \leq 0$:

$$resraw_i = \begin{cases} 1 & \text{when there was no decline in employment during the crisis} \\ \in (0,1) & \text{when the region is more resilient than its country of origin} \\ 0 & \text{when the region is as resilient as its country of origin} \\ < 0 & \text{when the region is less resilient than its country of origin} \end{cases}$$

Comparing $resraw_i$ indices for regions belonging to different countries makes little sense as country-specific variations of employment during and after the crisis influence the denominator. If, for example, a country's total employment declined only marginally during the crisis, the regional resistance index could be extremely large even for moderate declines of employment. Therefore, the resistance measures are standardized to zero mean and unit variance within each country by Equation 5:

$$res_i = \frac{resraw_i - \mu_c}{\delta_c} \qquad (5)$$

where μ_c is mean and δ_c is the standard deviation of regional resilience indicator values within the country. This standardization permits comparability of regional resistance across countries and abstracts from national resistance. Consequently,

$$res_i = \begin{cases} > 0 & \text{if the region was more resistant than an average region within the country} \\ < 0 & \text{if the region was less resistant than an average region within the country} \end{cases}$$

Our approach means that we weight all regions equally so they have an equal impact on the country average.[3]

We follow a similar procedure to calculate measures of regional recoverability (rec_i), which we define as the relative extent to which regional economies recovered, in terms of non-agricultural employment, between the trough of the crisis (anytime between 2008 and 2013) and the end of our sample, i.e. 2015.[4]

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[3] In practice the regions vary from 150,000 to 800,000 inhabitants.
[4] 2014 for Romanian regions, because data for 2015 were found to be unreliable.

$$y_i = \frac{e^*_{i2015} - min\{e_{i2008}, e_{i2009}, \dots e_{i2013}\}}{min\{e_{i2008}, e_{i2009}, \dots e_{i2013}\}} * 100\% \quad (6)$$

$$recraw_i = \frac{(y_i - y_c)}{y_c} \quad (7)$$

$$rec_i = \frac{recraw_i - \mu_c}{\delta_c} \quad (8)$$

Note that the values of $recraw_i$, unlike $resraw_i$, are not bounded, i.e.:

$recraw_i$ and rec_i

$$= \begin{cases} > 0 \text{ if the region had better recoverability than an average region in the country} \\ < 0 \text{ if the region had worse recoverability than an average region in the country} \end{cases}$$

IV. Stylized Facts About CEE Resistance and Recoverability

A broader picture of regional resistance and recoverability is obtained by using the Central and Eastern European (CEE) aggregate non-agricultural employment change as a counterfactual, thus substituted for x_c and y_c, respectively. By using the CEE average job loss or gain, the relative resiliency of countries is reflected in their regional resistance and recovery variables. Maps 1 and 2 in Figure 3 illustrate these indices, which are not stripped of country-wide factors. Note that the resilience indicator here has the same properties as $resraw_i$. Several regions in Poland, as well as the central and suburban parts of the capital city of Bucharest (in Romania) did not experience a decline of employment during the crisis whatsoever. Regions that proved resistant relative to the average CEE experience (those with dark shading) were generally clustered in Poland, Czechia and Slovakia, which reflected the relatively good performance of these economies at the onset of the crisis, as compared to other CEECs. This better performance may be due to the flexible exchange rate of the former two countries and to all three countries' close integration into the supply networks of multinational firms. On the other hand, most regions in the Baltic States, but also in Bulgaria and Romania (excluding Bucharest), showed little resistance to the crisis, the former likely due to their exchange rate arrangements. The most successful recovery was observed in a belt of Polish regions running from the north-central to eastern part of the country, in Estonia and Hungary, followed by Lithuania. In both of these maps, Poland stands out as the most heterogenous country, encompassing both well- and poorly-performing regions.

In Figure 4, Maps 3 and 4 illustrate regional resistance and recoverability in the regions under investigation, taking individual countries as a counterfactual. In this way, the country-wide layer is removed, and we can focus on region-specific factors only. Once the national effects are controlled for, there seems to be a rather limited degree of spatial clustering with regard to resistance and more of it with regard to recoverability. Moreover, regions that did not lose much employment during the crisis (or even gained employment), such as some capital cities, often did not recover as much as some other regions.

In order to formally check the existence of spatial dependence or clustering, we introduce spatial weighting matrices ($\boldsymbol{W}$) of two forms. The contiguity matrix contains ones, $\boldsymbol{W}(i,m)$, for contiguous regions i and m and zero otherwise. The inverse distance matrix takes the form:

$$\boldsymbol{W}(i,m) = 1/d(i,m) \tag{9}$$

where $d(i,m)$ is the distance between regions i and m. In both cases, we use matrices that allow for cross-national border regional spillovers as well as those that exclude such a possibility. Clearly, the possibility of spillovers between regions within a country is to be expected. Firms and workers can move from one region to a neighboring region with relative ease. Movements between regions in two different countries, even if they are contiguous, may be more difficult. The $\boldsymbol{W}$ matrices enable us to investigate spatial autocorrelation and they are also necessary for spatial regression effects, should the former be detected.

We test for the existence of spatial autocorrelation by using Moran's-I test, which employs the I statistic:

$$I = \frac{N}{W}\frac{\sum_i \sum_m w(i,m)[(x_i - \bar{x})(x_k - \bar{x})]}{\sum_i (x_i - \bar{x})^2} \tag{10}$$

where N is the number of regions (indexed by i and m) and x is the variable of interest. The null hypothesis is that the data are randomly distributed across regions. We report the p-values for the Moran's I spatial autocorrelation statistic in Table 1. Only in one case, that of the resilience measure when the inverse distance matrix is assumed, is the null hypothesis of no spatial autocorrelation not rejected. Residuals are therefore considered to be correlated with nearby residuals, as defined by $\boldsymbol{W}$, meaning that the dependent and explanatory variables exhibit regional clustering.

V. Explanatory variables

In line with previous studies, we consider explanatory variables that capture regional productivity differences and differences among regional social and economic structures. Productivity is measured by gross value added (GVA) per worker. Regional economic structures are proxied by shares of employment in agriculture and in industry, as well as by the Krugman specialization index (*ksi*):

$$ksi_i = \sum_{j=1}^{J} \left| \frac{z_{ij}}{Z_i} - \frac{v_j}{V} \right| \tag{11}$$

where

z_{ij}= j-sector output in region i
Z_i = total output in region i
v_j = j-sector output in the reference national economy
V: total output in the reference national economy

Low values of the Krugman index indicate that a region's economic structure closely resembles the national structure. This might be important, because a policy response to the crisis can be formulated to reflect the national structure of industry. Regions that exhibit pronounced differences from the national structure of industrial activity may thus find that national policies do not address their specific issues effectively.

As for recoverability, we want to check whether, in line with the hypothesis formulated by Martin and Sunley (2015), regional economies that adapt their structure in response to the shock so as to maintain core sectors are able to recover more effectively. We do this by means of the modified Lilien indices (*mli*) of structural change between two points in time (t_0 and t_1) as an explanatory variable in our recoverability equations (Lilien, 1982; Mussida and Pastore, 2012). The index is defined as:

$$mli_i = \sqrt{\Sigma(\bar{b}_{ijT}) \times \left\{\ln\left({b_{ijt_1}}/{b_{ijt_0}}\right) - \ln\left({B_{it_1}}/{B_{it_0}}\right)\right\}^2} \qquad (12)$$

where

b_{ijt_1} = variable of interest (employment or value added) in region i, sector j, time t_1

B_{it_1} = total employment or value added in region i, time t_1

$\bar{b}_{ijT}$ = average share of sector j in total regional employment or value added (in region i) in the period between t_0 and t_1.

The index is a measure of temporal dispersion. It takes the value of zero if no structural changes occurred between t_0 and t_1, while higher values are associated with larger structural shifts. The advantage of this index, as opposed to the original Lilien index, for example, is that it enables the structural change between two periods to be independent of the time sequence and it accounts for the weight (size) of the sectors.

Summary statistics for the dependent and explanatory variables are reported in Table 1. All variables exhibit appreciable variability over the 199 NUTS 3 regions. The resilience variable , which by construction has a mean of zero, is larger (in absolute value) for the minimum than for the maximum. That suggests that most severe falls in regional employment, relative to the national average, were quite large when compared to the margin by which better-performing regions experienced employment declines relative to the national average. In terms of recoverability, the opposite is the case; regions that performed better than the national average appeared to do so by a wider margin that did those regions that underperformed. This suggest that the resiliency of the CEE regions came at the expense of a widening gap between well-performing and poorly performing regions. Looking at the Lilien indices, the mean of the index of structural change in GVA is greater than that of employment. Thus, in the downturn, the structure of regional output changed more than did the structure of regional employment.

VI. Specification of the Model

Regional resistance and recoverability are modelled within the framework of the more general SDM model and two models with coefficient restrictions, the spatial autoregressive model (SAR) and the spatial lag of **X** (SLX) model. The SDM model is:

$$\boldsymbol{y} = \alpha\mathbf{i} + \rho\boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\beta + \boldsymbol{\varepsilon} \qquad (13)$$

$$\varepsilon \sim N(0, \sigma^2 I_n)$$

where $\boldsymbol{y}$ is the n × 1 vector of observations of the dependent variable, $\mathbf{i}$ denotes a n×1 vector of ones associated with the intercept term α, ρ is a scalar spatial autoregressive coefficient, $\boldsymbol{W}\boldsymbol{y}$ is the n × 1 vector of the spatially lagged dependent variable, where the proximities are specified according to a n × n non-stochastic spatial weight matrix $\boldsymbol{W}$ and $\boldsymbol{X}$ is the $n \times p$ matrix including p explanatory variables.

Equation (13) can be rewritten as:

$$\boldsymbol{y} = (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\alpha\mathbf{i} + (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\boldsymbol{X}\boldsymbol{\beta} + (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\boldsymbol{\varepsilon} \qquad (14)$$

This transformation makes it straightforward to calculate partial derivatives of expected values of $\boldsymbol{y}$ with respect to the explanatory variables as:

$$\left[\frac{\partial E(y)}{\partial x_{1k}}, \dots, \frac{\partial E(y)}{\partial x_{Nk}}\right] = (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\beta_k \qquad (15)$$

Diagonal elements of Equation 15 represent direct effects and off-diagonal effects represent spillover effects. SAR models enable the estimation of *global* spatial spillovers, which means that a change in $\boldsymbol{X}$ in any region is transmitted to all other regions, even when the two regions are not directly connected (Vega and Elhorst, 2013). Global spillovers include feedback effects that arise as a result of impacts passing through neighboring regions and returning to the region from which the change originated.

An alternative approach to modelling spillovers is embedded in the SLX model:

$$\boldsymbol{y} = \alpha\mathbf{i} + \boldsymbol{X}\beta + \boldsymbol{WX}\theta + \boldsymbol{\varepsilon} \quad (16)$$

This model produces *local* spillovers, i.e., those that occur between regions connected to each other (according to $\boldsymbol{W}$) and do not contain feedback effects (Golgher and Voss, 2016). In our study we examine both types of relationships to observe the nature of spatial spillovers.

In the presence of spatial autocorrelation among both dependent and independent variables, OLS, as well as 2SLS, is inconsistent and needs to be replaced by a better-suited estimation method (Kelejian and Prucha, 2002). Hence, the models are estimated using maximum-likelihood estimation corrected for heteroskedasticity, which is both consistent and relatively efficient compared to its popular alternatives such as spatial two-stage least squares.

We also follow LeSage and Pace (2009) and LeSage and Dominguez (2012), who show that the coefficients of some spatial models (e.g. the SAR model) cannot be interpreted as if they were simple partial derivatives, which is also evident in Equation 14. In line with their arguments, we calculate direct and indirect (spillover) effects, rather than reporting point estimates. Golgher and Voss (2016) show that the direct impacts in the SAR model can be computed as $\left(\frac{1}{n}\right) tr[S_k(\boldsymbol{W})]$, where $S_k(\boldsymbol{W})$ is a partial derivative matrix for variable *k*. Total impacts are equal to $\left(\frac{1}{n}\right) \boldsymbol{i}'[S_k(\boldsymbol{W})]\boldsymbol{i}$, and indirect impacts are the difference between total and direct impacts. Locality of spillovers in the SLX model implies that the interpretation of coefficients is straightforward: direct effects are represented by β, while indirect effects are represented by θ.

VII. Estimation results

VII.1 Estimates of the SDM model

Table 2 contains estimation results for the resistance equations. We find a very strong direct impact of pre-crisis labor productivity before the crisis on regional resilience once the crisis has struck. In the best-fitted models (judging by pseudo-R^2), we also find significant impact of productivity in neighboring regions on a region's resistance in those specifications where we use the inverse of the distance between regions as the distance measure. Thus, clustering, both positive and negative, is evident in the resistance case and spillover effects are important. The contiguity matrices do not give evidence of spillovers. This may be because NUTS-3 regions are sufficiently small so that spillovers from non-contiguous regions can easily take place. Introducing or restricting cross-border spillovers does not change the results.

The regions with economic structures that differ significantly from the national average relatively weathered the crisis relatively poorly. This might be because national policy responses were targeting aggregate national variables, so dissimilar regions could have faced "policy neglect" during the crisis.

Table 4 presents estimation results of the recoverability equations. Here, we want to check whether more resistant regions recover more efficiently and, whether structural changes undertaken during, and possibly in response to, the crisis matter for the recoverability. The results confirm this hypothesis in two ways. First, the direct effects of resistance and of structural change, whether in terms of value added or employment have significant effects on recoverability. Thus regions that fared relatively well in the downturn also tended to have better recoveries, again emphasizing the disparities between well-performing and poorly-performing regions. Recoverability also has strong positive spillover effects.[5] The direct effect of structural change is more difficult to interpret. This is because it is not clear whether these changes in structure were the result of better policies for adaptation to the crisis implemented by certain

[5] Thus, regions recover more efficiently when they are surrounded by other fast-recovering regions, but the neighborhood does not matter for resistance. Why this should be so requires further research.

regions, or whether high-productivity regions are by the nature of their higher-productivity sectors and (presumably) higher-skilled workers more adaptable in times of crisis.

VII.2 Robustness tests

In line with the discussion in Section II.2, we also estimated the SAR and SLX models. The parameter estimates (not reported here but available from the authors) for these two models are very similar to those of the more general SDM model, although the statistical properties of the two parameter-restricted models are somewhat better. We also experimented with additional explanatory variables, but the addition of too many variables exhausted the degrees of freedom quickly.

VIII. Conclusions

In this paper we have examined resiliency, the ability to absorb a and recover from economic shocks in 199 Nuts-3 regions in CEE following the 2009 global financial crisis. We find that regional productivity has a clear influence on the ability to resist and recover from shocks. More productive regions fare better than do regions with low output per worker. Moreover, regions that resist shocks well also recover to a greater extent. Finally, we find strong positive regional spillovers, which means that regions tend to form clusters of high-performing and low-performing areas, a process that exacerbates regional income disparities.

The paper also suggests areas of research on resiliency that deserve further study. The first is the need to add more covariates to the regressions explaining resistance and recovery. The second is to include "softer" covariates that reflect social mores and behaviors that may influence the extent to which the residents of regions are willing and able to respond to shocks in a flexible way.

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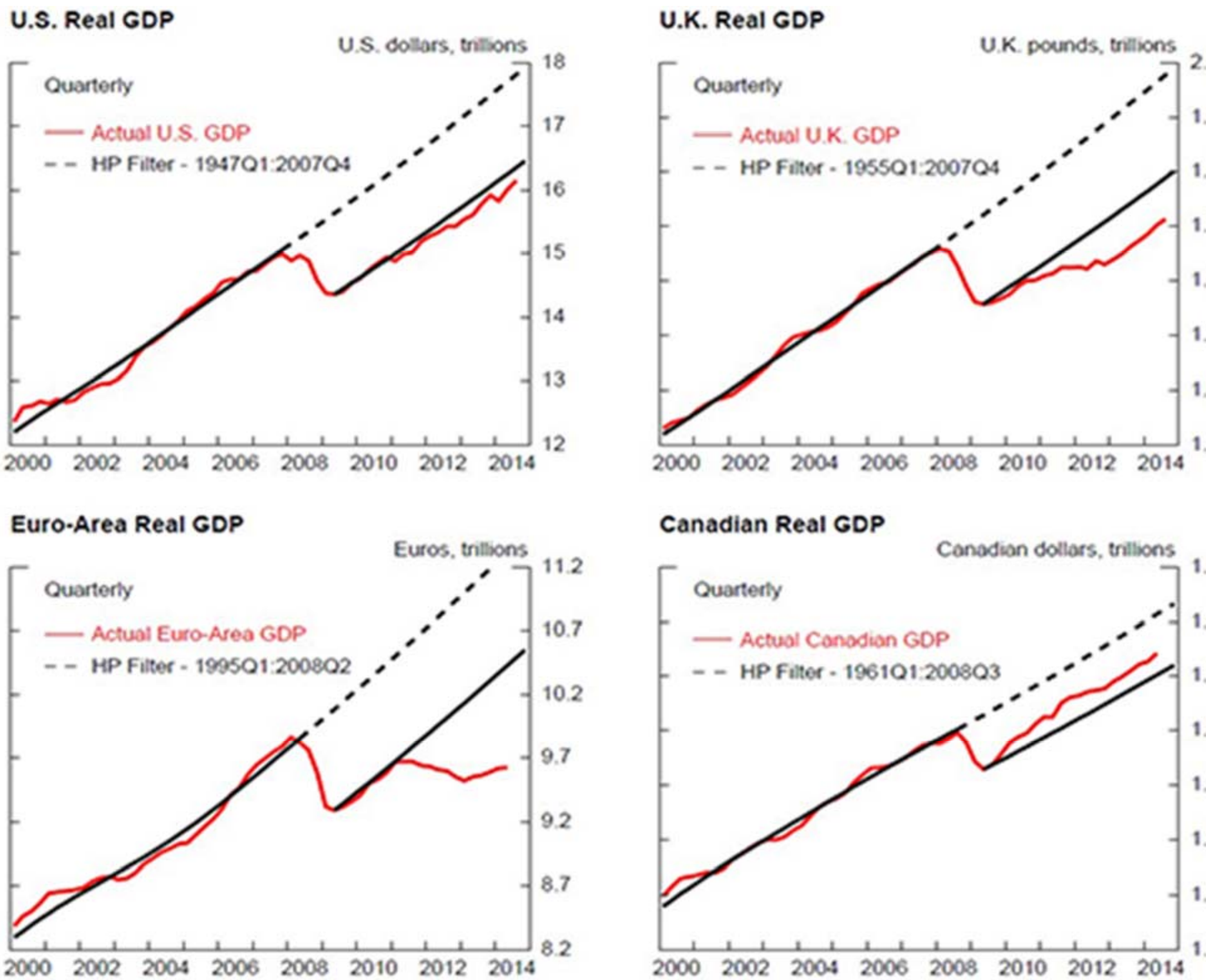
Figure 1: Resilience and Early Recovery of Major Economies



Source: Martin et al. 2014

Figure 2: Resistance and Recovery in the European Union

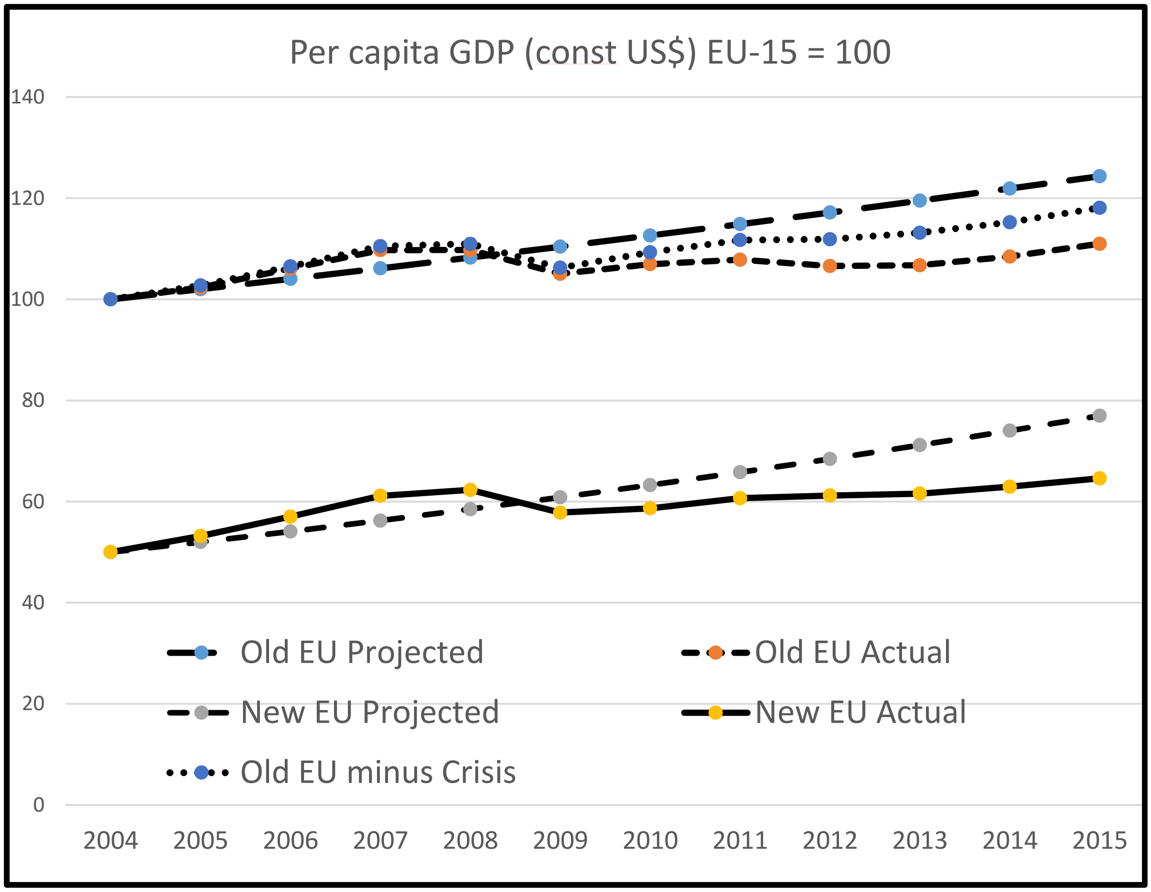


Figure 3: CEE Regional Resistance and Recovery vis a vis CEE Average

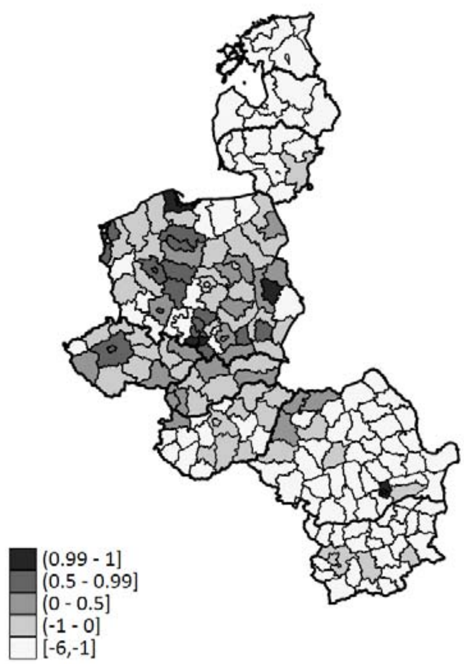
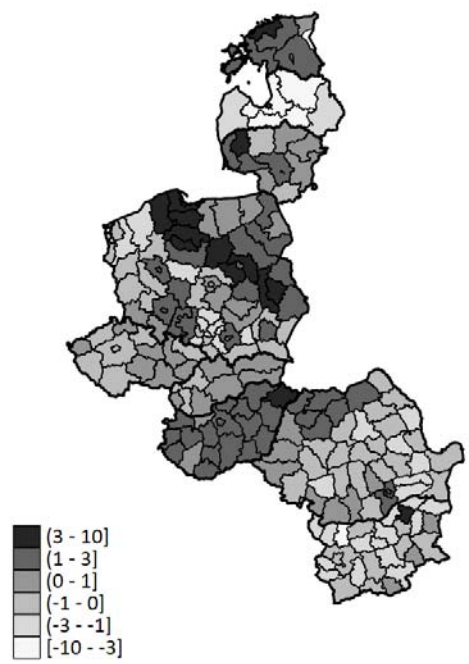
Map 1. Regional resistance – CEE as a counterfactual	Map 2. Regional recoverability – CEE as a counterfactual
	

Figure 4: CEE Regional Resistance and Recovery vis a vis National Average

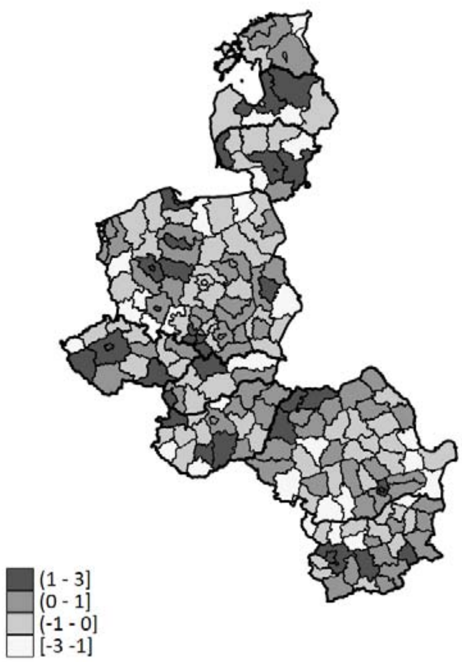
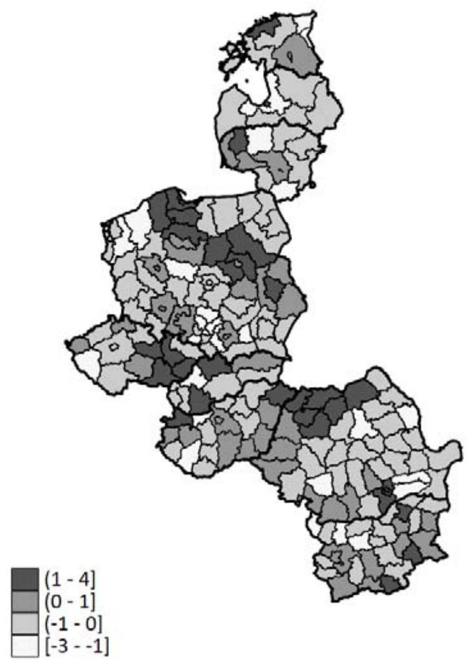
Map 3. Spatial distribution of regional resistance to the 2008 crisis - home country as reference	Map 4. Spatial distribution of regional recoverability after the 2008 crisis – home country as reference
	

Table 1. Descriptive statistics

Variable	Obs	Mean	S.D.	Min	Max	*Moran's I (p-val)* Contiguity matrix: cross-border spillovers	Contiguity matrix: no cross-border spillovers	Inverse distance matrix: cross-border spillovers	Inverse distance matrix: no cross-border spillovers
Resilience	**199**	**0.000**	**1.008**	**- 3.191**	**2.140**	**0.001**	**0.009**	**0.087**	***0.109***
Recoverability	**199**	**- 0.020**	**0.997**	**- 2.078**	**3.896**	**0.000**	**0.000**	**0.000**	**0.000**
Productivity, 2007	**199**	**0.906**	**0.176**	**0.537**	**1.543**	**0.000**	**0.001**	**0.000**	**0.000**
Specialization index, 2007	**199**	**0.233**	**0.108**	**0.043**	**0.685**	**0.012**	**0.004**	**0.002**	**0.000**
Employment share in agriculture, 2007	**199**	**0.186**	**0.143**	**0.002**	**0.629**	**0.000**	**0.000**	**0.000**	**0.000**
Employment share in industry, 2007	**199**	**0.255**	**0.076**	**0.085**	**0.446**	**0.000**	**0.000**	**0.000**	**0.000**
Lilien index of GVA structural change between 2008 and 2010	**199**	**1.433**	**0.921**	**0.171**	**4.126**	**0.000**	**0.000**	**0.000**	**0.000**
Lilien index of employment structural change between 2008 and 2010	**199**	**1.146**	**0.588**	**0.355**	**3.318**	**0.000**	**0.000**	**0.000**	**0.000**

Table 2. Maximum likelihood estimation results – resistance (SDM Model)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*	*(9)*	*(10)*	*(11)*	*(12)*
direct effects												
Productivity	**2.221*** **	**2.210*** **	**2.126*** **	**2.077*** **	**1.993*** **	**1.982*** **	**1.734*** **	**1.699*** **	**2.232*** **	**2.233*** **	**2.036*** **	**2.002*** **
	[4.98]	**[4.97]**	**[4.83]**	**[4.66]**	**[5.05]**	**[5.08]**	**[4.39]**	**[4.21]**	**[5.38]**	**[5.45]**	**[4.96]**	**[4.79]**
Employment share in agriculture	**0.773**	**0.706**	**1.168***	**1.122**								
	[1.08]	**[0.99]**	**[1.65]**	**[1.58]**								
Employment share in industry					**-1.443**	**-1.622**	**-1.730***	**-1.670***				
					[-1.46]	**[-1.64]**	**[-1.80]**	**[-1.73]**				
Specialization index									**-1.251***	**-1.259***	**-1.356***	**-1.331***
									[-1.78]	**[-1.80]**	**[-1.95]**	**[-1.91]**
indirect effects												
Productivity	**0.047**	**0.146**	**0.918** **	**0.461** **	**0.174**	**0.268**	**0.925** **	**0.465** **	**0.108**	**0.19**	**0.840** **	**0.416***
	[0.22]	**[0.76]**	**[2.42]**	**[2.11]**	**[0.79]**	**[1.37]**	**[2.44]**	**[2.13]**	**[0.51]**	**[1.01]**	**[2.27]**	**[1.95]**
total effects												
Productivity	**2.268*** **	**2.356*** **	**3.044*** **	**2.537*** **	**2.167*** **	**2.250*** **	**2.659*** **	**2.164*** **	**2.340*** **	**2.423*** **	**2.877*** **	**2.418*** **
	[4.49]	**[4.90]**	**[5.47]**	**[5.45]**	**[4.51]**	**[5.03]**	**[5.50]**	**[5.41]**	**[4.72]**	**[5.21]**	**[5.72]**	**[5.74]**
Employment share in agriculture	**0.773**	**0.706**	**1.168***	**1.122**								
	[1.08]	**[0.99]**	**[1.65]**	**[1.58]**								
					-1.443	**-1.622**	**-1.730***	**-1.670***				

Employment share in industry					**[-1.46]**	**[-1.64]**	**[-1.80]**	**[-1.73]**				
Specialization index									**-1.251***	**-1.259***	**-1.356***	**-1.331***
									[-1.78]	**[-1.80]**	**[-1.95]**	**[-1.91]**
Intercept	**-1.993*****	**-2.033*****	**-2.323*****	**-1.930*****	**-1.446****	**-1.438****	**-1.465****	**-1.100***	**-1.621*****	**-1.663*****	**-1.738*****	**-1.397****
	[-3.31]	**[-3.43]**	**[-3.89]**	**[-3.32]**	**[-2.37]**	**[-2.39]**	**[-2.47]**	**[-1.82]**	**[-2.84]**	**[-2.97]**	**[-3.18]**	**[-2.56]**
W*productivity	**0.0569**	**0.202**	**2.678****	**2.994****	**0.21**	**0.372**	**2.700****	**3.023****	**0.13**	**0.264**	**2.452****	**2.702***
	[0.22]	**[0.76]**	**[2.42]**	**[2.13]**	**[0.79]**	**[1.37]**	**[2.44]**	**[1.95]**	**[0.51]**	**[1.01]**	**[2.27]**	**[1.95]**
type of W	**contig**	**contig**	**inv dist**	**inv dist**	**contig**	**contig**	**inv dist**	**inv dist**	**contig**	**contig**	**inv dist**	**inv dist**
cross-border spillovers	**yes**	**no**	**yes**	**no**	**yes**	**no**	**yes**	**no**	**yes**	**no**	**yes**	**no**
country effects	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**
N	**199**	**199**	**199**	**199**	**199**	**199**	**199**	**199**	**199**	**199**	**199**	**199**
Pseudo R2	**0.119**	**0.121**	**0.144**	**0.138**	**0.123**	**0.129**	**0.146**	**0.14**	**0.128**	**0.131**	**0.148**	**0.143**

t-statistics in brackets *p<0.10, **p<0.05, ***p<0.01

Table 3. Maximum likelihood estimation results – recoverability (SDM Model)

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
direct effects								
resistance	**0.176*****	**0.177*****	**0.206*****	**0.207*****	**0.186*****	**0.187*****	**0.217*****	**0.217*****
	[2.64]	**[2.68]**	**[3.06]**	**[3.10]**	**[2.77]**	**[2.81]**	**[3.28]**	**[3.31]**
lilien - GVA	**0.334****	**0.321****	**0.377****	**0.372****				
	[2.05]	**[1.99]**	**[2.30]**	**[2.27]**				
lilien - employment					**0.290***	**0.290***	**0.317****	**0.304****
					[1.92]	**[1.94]**	**[2.12]**	**[2.05]**
indirect effects								
resistance	**0.096***	**0.107****	**0.567**	**0.211**	**0.105****	**0.118****	**-0.395**	**-0.075**
	[1.93]	**[2.00]**	**[0.90]**	**[1.11]**	**[1.99]**	**[2.07]**	**[-1.40]**	**[-0.47]**
lilien - GVA	**0.182***	**0.195***	**1.037**	**0.377**				
	[1.68]	**[1.70]**	**[0.88]**	**[1.08]**				
lilien - employment					**0.164**	**0.184**	**-0.577**	**-0.105**
					[1.58]	**[1.63]**	**[-1.24]**	**[-0.46]**
total effects								
resistance	**0.272****	**0.284*****	**0.773**	**0.418***	**0.292*****	**0.306*****	**-0.178**	**0.143**
	[2.55]	**[2.57]**	**[1.17]**	**[1.85]**	**[2.67]**	**[2.68]**	**[-0.67]**	**[0.84]**
lilien - GVA	**0.516****	**0.516****	**1.415**	**0.749***				
	[2.02]	**[1.96]**	**[1.13]**	**[1.67]**				
lilien - employment					**0.454***	**0.474***	**-0.259**	**0.199**
					[1.88]	**[1.89]**	**[-0.65]**	**[0.81]**
intercept	**-0.249***	**-0.232**	**-2.29**	**-0.199**	**-0.310***	**-0.300***	**-0.235**	**-0.191**
	[-1.66]	**[-1.57]**	**[-1.48]**	**[-1.29]**	**[-1.74]**	**[-1.72]**	**[-1.30]**	**[-1.05]**
W*recoverability	**0.428*****	**0.438*****	**0.518*****	**0.530*****	**1.992*****	**3.807*****	**2.472*****	**4.272*****
	[4.10]	**[4.23]**	**[4.83]**	**[4.99]**	**[4.04]**	**[6.49]**	**[4.07]**	**[6.90]**
type of W	**contiguity**	**contiguity**	**inv dist**	**inv dist**	**contiguity**	**contiguity**	**inv dist**	**inv dist**
cross-border spillovers	**yes**	**no**	**yes**	**no**	**yes**	**no**	**yes**	**no**
country effects	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**	**yes**
N	**199**	**199**	**199**	**199**	**199**	**199**	**199**	**199**
Pseudo R2	**0.0823**	**0.0835**	**0.0607**	**0.049**	**0.0725**	**0.0719**	**0.0671**	**0.112**

t-statistics in brackets *p<0.10, **p<0.05, ***p<0.01