MODERN ECONOMETRIC TECHNIQUES APPLIED TO THREE ESSAYS IN SPATIAL ECONOMICS

by

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DEDICATION

To my husband, my son, my parents, my grandparents and my arriving daughter.

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ABSTRACT

For Chapter 1: This paper offers a meta-regression analysis of the controversial impact of EU structural funds on the growth of the recipient regions. It identifies the factors that explain the heterogeneity in the size of 323 estimates of their impact recorded in 17 econometric studies. Heterogeneity comes from the publication status, the period examined, controlling for endogeneity, from the presence of several regressors but not from differences in functional forms.

For Chapter 2: Recent spatial econometric contributions call for theory-driven spatial models and W matrices capturing actual and time-varying interregional linkages. This paper answers this call by developing theoretically Griliches' well-known knowledge production function to add knowledge externalities to it. They capture how human and private capital originating from one region benefit the creation of innovation elsewhere. Furthermore, we measure interregional interaction based on the actual flows of patent creation-citation and of migration of the educated workers. They have the advantage of capturing clearly the direction of the knowledge transfers. Their presence in the theoretical model leads to a reduced-form spatial cross-regressive model which differentiates better the role of each type of externality – and displays a better goodness of fit – than the spatially lagged model where spillovers depend on geographical proximity only. Both models are estimated on spatial panel data covering the dynamics of innovation across US states over the 1986–1999 period.

For Chapter 3: The Ricardian framework is increasingly used for the study of the impact of climate change on farmland values. While most of the Ricardian studies assume no interaction between the geographical units under study, the few that do rely on traditional proximity-based dependence. In this paper we argue that since the larger share of agricultural goods produced by a state is not for its own local market, including interregional trade in the Ricardian framework provides new perspectives, avoids a missing variable bias and prevents erroneous conclusions. Our new framework is applied to the system of the U.S. states over the four most recent censuses (1997-2012) and demonstrate that climate and socio-economic conditions experienced in a state's trade partners have a significant role on that state's local farmland values.

CHAPTER 1 META-ANALYSIS OF THE IMPACT OF EUROPEAN UNION STRUCTURAL FUNDS ON REGIONAL GROWTH

1.1 Introduction

In the European Union, every programming period sees around 1/3 of the budget devoted to various regional cohesion policies. Since their implementation in the 1970's, a large set of studies measure their impact on the economy of the recipient localities, regions, and countries. They are selected because of their low levels of relative per capita GDP, high unemployment rate, low density, and recessive industry. While some contributions in the academic literature are generally supportive of the continuation of such policies (e.g. CAPPELEN *et al*., 2003; ESPOSTI and BUSSOLETTI, 2008), others cast doubts about their actual efficacy (e.g. DALL'ERBA and LE GALLO, 2008; and some estimates of DALL'ERBA and LE GALLO, 2007, and of BOUAYAD-AGHA *et al.,* 2011), highlight their conditional efficacy (e.g. EDERVEEN *et al*., 2002, 2006; RODRIGUEZ-POSE and FRATESI, 2004; DALL'ERBA and LE GALLO, 2007), or conclude that they act negatively on growth (FAGERBERG and VERSPAGEN, 1996; and some estimates of PUIGCERVER-PEÑALVER, 2007, and of BOUAYAD-AGHA *et al*., 2011). Understanding what factors explain the differences in the estimated impact of regional policies and whether actual practical changes can be implemented is especially important now that sluggish economic growth among European Union members and recent rounds of bailouts have undermined the availability of public funding for regional cohesion purposes.

This paper relies on a literature that econometrically estimates the regional growth impact of structural funds and identifies the sources of heterogeneity in the estimated impact. The focus is solely on econometric studies for homogeneity purposes. Moreover, some other papers are not considered because they do not rely on a sufficiently homogenous definition of the funds (e.g. they use proxy or dummies). As a result, the meta-database is composed of 17 manuscripts offering 323 estimates in total. The meta-analysis framework was first introduced by GLASS (1976). It has the capacity to combine the results of several existing studies and summarize their outcome. In addition, it controls for differences/similarities within and between studies and identifies whether the former come from sampling (e.g. size and time period of the sample) or non-sampling (e.g. estimation process and regressors used) characteristics. Estimation takes place in the frame of meta-regressions which measure the role of the study characteristics by explaining the differences among study outcomes. Hence it allows a more complete picture of an existing literature than traditional qualitative or narrative approaches.

The remainder of this paper is organized as follows: section 2 begins with a short description of the theory commonly used to measure the impact of EU structural funds. It continues with a description of some of the econometric challenges met in this literature. Section 3 reports the way the primary estimates have been collected from the existing literature. Section 4 presents the meta-regression models as well as the selected moderators. Section 5 reports the estimation results and discusses the factors that significantly affect the magnitude of the estimated impact of the funds. In addition, an ordered probit model uncovers the factors that influence the probability of estimating a significantly positive return of the funds. Finally, section 6 concludes.

1.2 Growth theories and econometric methods

1.2.1. Theories

Three strands of economic growth theory are commonly used to understand the role of public investments in stimulating growth. The traditional approach is the neoclassical growth framework that relies on the assumptions of decreasing returns to capital and constant and exogenous rate of technological progress. Structural funds correspond to public investments allocated to a capital scarce region, hence they increase the growth rate of the recipient area which experiences faster convergence towards its steady-state level but for a short period of time only (SOLOW, 1956). The growth rate does not change in the long-run due to the decreasing nature of the returns to capital. This holds true with investments in human capital as well (MANKIW *et al.*, 1992). In this framework, only changes in the exogenous rate of technological progress modify the steady-state growth rate. The second strand of the literature, the endogenous growth theory, is based on the assumptions of constant returns to capital (at the regional level), endogenous technological progress and local externalities. It assumes that new investments in public capital increase the marginal product of private capital. This fosters capital accumulation and growth in the recipient region in the long-run (ROMER, 1990; ASCHAUER, 1989). However, the empirical paradox pinpointed by JONES (1995a, 1995b) according to which total factor productivity remains constant in spite of new expenditure in R&D and human capital has given birth to the semi-endogenous growth theory (JONES, 1995b). Based on the idea of decreasing returns to scale in the production of knowledge, these models assume that total factor productivity growth depends on the exogenous growth rate of the population because it determines the R&D employment growth rate.

Neither the neoclassical nor the endogenous growth theories are specific enough about the type of public capital that is funded, yet the largest share of structural funds (around 1/3) finances transportation infrastructures. They reduce transportation costs, hence they have consequences on the economic growth of the recipient regions in ways that cannot be captured in any of the previous growth theories. As such, the third strand of economic growth theory, namely the new economic geography (KRUGMAN, 1991; FUJITA *et al*., 1999), has generated increasing interest. In this framework, new transportation infrastructures lead to different degrees of improvement in accessibility and economic development in the region(s) where they are implemented (VICKERMAN *et al*., 1999). When new (interregional) transportation infrastructures connect regions of different levels of income, companies and workers may delocate from the poor region to the rich one to benefit from agglomeration economies (KRUGMAN, 1991). This process can be self-reinforcing when the presence of localized technology spillovers is conducive to growth as indicated in the models of BALDWIN *et al*. (2004) who combine new economic geography and endogenous growth theories. In addition, since interregional transportation infrastructures are more often the rule than the exception in Europe, they will increase the accessibility of several regions, but the gains they generate will always be relatively higher in the richest one (VICKERMAN *et al*., 1999).

1.2.2. Econometric methods

In spite of these three strands of economic growth theory, the empirical literature of interest here relies almost exclusively on the neoclassical beta-convergence model à la BARRO AND SALA-I-MARTIN (1991). This feature is an advantage in a meta-analysis as it makes the estimates of the primary studies homogeneous conceptually. Specifically, the (cross-section) model most commonly used in the literature to measure the elasticity of the funds derives from the beta-convergence model specified in MANKIW *et al.* (1992, p. 423) but with variations in the number and specification of the regressors:

$$\frac{1}{T-t0}(\ln(y_T)-\ln(y_{t0})) = \alpha\iota_n + \beta_0 \ln(y_{t0}) + \beta_1 \ln(s) + \beta_2 \ln(n+g+\delta) + X\,\beta_3 + \beta_4 SF + \varepsilon with\ \varepsilon \sim N(0,\sigma_\varepsilon^2 I_n) \quad (1)$$

where the dependent variable is the annual growth rate of per capita GDP in region *i* over the period t0 – T, y_{t0} is the initial level of per capita GDP, *s* is the average gross domestic savings rate, *n* is the population growth rate, g is the exogenous rate of technological progress, δ is the rate of depreciation, *X* is a matrix of additional variables that maintain the steady state of each economy constant and *SF* stands for the structural funds. ε is the error term with the usual properties. Most studies report a significant negative estimate of β_0 which validates the convergence assumption brought to the fore by the neoclassical growth model. This paper focuses on the effect size of the average annual growth rate with respect to structural funds, i.e. the coefficient β_4.

Note that one gets a different marginal effect when an interaction term is added to specification (1). For instance, when EDERVEEN *et al.* (2006) evaluate whether the funds are *conditionally* effective on the quality of the institutions that rule the recipient region, they add a term such as $\beta_5 SF * institutions$ to the regressors of equation (1). The marginal effect then becomes $\partial g/\partial SF = \beta_4 + \beta_5 institutions$. In this situation, the effect at the mean of the interacted term is measured when possible (e.g. the mean of '*institutions*' in the case above).

While most of the studies measure the variables in the matrix X at the initial time period to prevent endogeneity, the funds are sometimes measured over the growth period. This leads to a problem of reverse causality as the funds are partially allocated based on past relative levels of regional per capita income (DALL'ERBA and LE GALLO, 2008). The more recent studies in the database have dealt with this issue by using past levels of structural funds (such as MOHL and HAGEN, 2010), instrumental variables (such as in DALL'ERBA and LE GALLO, 2008;) or ARELLANO and BOND's (1991) estimator (ESPOSTI and BUSSOLETTI, 2008). Differences in the treatment of endogeneity among primary studies will be treated in section 5 of this paper.

As access to structural funds data has become more available, several authors have decided to assess the impact of the funds in the frame of a panel data model. Such a specification provides them with more information and data variability. This allows control over unobserved heterogeneity and reduces problems of collinearity among the expanatory variables. No panel-data study uses a random effect approach which, in the frame of a neoclassical growth model, implies that the individual effects are correlated with some regressors. This would lead to endogeneity (ESPOSTI and BUSSOLETTI, 2008).

Increasing interest in new economic geography and advances in the field of spatial econometrics have led four studies to investigate the impact of the funds on both the targeted regions and on their neighbors (DALL'ERBA and LE GALLO, 2007, 2008; BOUAYAD-AGHA *et al*., 2011; MOHL and HAGEN, 2010). It allows them to proxy for interregional backward and forward linkages, technology spillovers, commuting across regions, and to refute the traditional assumption of independence of the error terms.

1.3 Primary studies

The collection process of the primary studies was performed to avoid missing any relevant empirical estimates and to reduce the potential biases due to any nonrandom selection. The following process was adopted: first, a search was made on the Economic Literature Index, ISI web of Knowledge and Google for any reference such as 'European growth', 'structural fund', and 'European regional cohesion'. Next, only the studies written in English were selected as the authors have limited capacity to extract information from other studies. Studies using proxies for structural funds were eliminated. The studies using dependent variables other than per capita income growth, using a theoretical framework other than the neoclassical growth model or relying on a different modeling framework were also eliminated. Some studies and measurements were also removed because they do not use the actual amounts of structural funds. For instance, some use a binary variable for recipients vs. non-recipients (BECKER *et al*., 2010; ESPOSTI, 2007) or use different growth regressions by eligibility status (RAMAJO *et al*., 2008). Here, only the measurements of ESPOSTI (2007) based on the actual allocation of the funds are kept. The latter contribution demonstrates clearly that using a dummy variable or actual expenses leads to different results.

Furthermore, some estimates in PUIGCERVER-PEÑALVER (2007) were disgarded because they are based on the regional allocation of the funds relatively to the Community average. Note also that econometric studies providing local estimates, as LE

GALLO *et al*. (2011), or focusing on the regions of one country only could not be considered since all the other studies measure the overall impact on the sample of EU regions.

Studies that appear in the bibliography of the relevant articles were individually checked too. Working papers that have led to a publication have naturally been removed from the sample. It leads to a meta-database composed of 17 studies of which two had estimates calculated over a five-year growth process that needed to be adjusted to a *yearly* growth rate. Secondly, the functional forms needed more homogeneity. While most of the studies rely on a linear model or on a log-log model (9 and 5 articles respectively), 2 articles use a log-lin model and 1 uses a lin-log model. The latter two cases report few estimates and the semi-elasticity they represent ($(\Delta Y/Y)/\Delta X$) or $\Delta Y/(\Delta X/X)$) can be transformed to an elasticity ($(\Delta Y/Y)/(\Delta X/X)$) when the average value of X (for log-lin) or Y (for lin-log) is reported. This process guarantees the completeness, homogeneity and comparability of the population under investigation, i.e., 323 estimates of the impact of structural funds on regional growth. The studies used in the metadatabase and some of the characteristics of the collected estimates appear in Table 1.1 below.

Table 1.1 Characteristics of the primary studies

Study	Pub. type	No. of est.	Functional form	Effect size estimate						
				Min	Max	Mean	St. dev.	% sig. &Neg.	% Non-sig	% sig. &Pos.
Akcomak S. (2008)	T	12	Lin-Lin	0.004	0.080	0.044	0.029	0.0	91.7	8.3
Bahr C. (2008)	PD	13	Lin-Lin	-0.001	0.157	0.063	0.040	0.0	38.5	61.5
Beugelsdijk M. and Eijffinger S. (2005)	PD	4	Lin-Lin	-1.431	0.32	-0.258	0.815	0.0	75	25
Bouayad-Agha S., Turpin N. and Vedrine L. (2011)	PD	18	Log-Log	-0.005	0.020	0.006	0.008	16.7	83.3	0.0
Bouvet F. (2005)	T	4	Log-Log	0.020	0.270	0.105	0.113	0.0	25	75
Cappelen, A., Castellacci, F., Fagerberg, J., and Verspagen, B.(2003)	PD	3	Lin-Lin	0.005	0.007	0.006	0.001	0.0	0.0	100
Dall'erba S. and Le Gallo J. (2008)	PD	3	Lin-Lin	-0.010	0.002	-0.004	0.006	0.0	100	0.0
Dall'erba S. and Le Gallo J. (2007)	PD	28	Lin-Lin	-0.002	0.007	0.000	0.002	14.3	71.4	14.3
Ederveen, S., Gorter, J., Mooij, R. and Nahuis, R (2002)	WP	3	Log-Lin	-0.350	0.700	0.123	0.533	33.3	33.3	33.3
Ederveen, S., de Groot, H. and Nahuis, R. (2006)	PD	31	Log-Log	-0.026	0.062	0.008	0.022	0.0	100	0.0
Esposti R. (2007)	PD	8	Lin-Lin	0.000	0.000	0.000	0.000	0.0	62.5	37.5
Esposti R. and Bussoletti S. (2008)	PD	4	Log-Log	0.139	0.414	0.226	0.129	0.0	100	0.0
Fagerberg J. and Verspagen B. (1996)	PD	2	Lin-Lin	-0.417	-0.225	-0.321	0.136	100	0.0	0.0
Mohl P. and Hagen T. (2010)	PD	90	Log-Log	-0.009	0.011	0.000	0.004	18.9	54.4	26.7
Puigcerver-Peñalver M.-C. (2007)	PD	6	Log-Lin	-1.343	0.001	-0.448	0.602	50	50	0.0
Rodriguez-Pose A. and Fratesi U. (2004)	PD	92	Lin-Lin	-7.586	6.294	0.484	2.184	3.2	85.9	10.9
Rodriguez-Pose A. and Novak K. (2013)	PD	2	Lin-Log	0.021	0.369	0.195	0.247	0.0	50	50
Total		323		-7.586	6.294	0.174	1.504	10.2	71.5	18.3

Notes: PD stands for published papers, WP stands for working papers, T for thesis

Among them, 77 are marginal effects based on an interaction term such as $\partial growth/\partial SF = \beta_4 + \beta_5 z$. Since the primary studies report the measurement of the mean of the interacted term *z* in 65 cases, the total effect evaluated at the mean is β_4 in 258 cases and it is $\beta_4 + \beta_5 z$ in 65 cases.

1.4 Fixed-effects model, mixed-effects model and hierarchical model

The fixed effects and mixed effects regression models are commonly used in meta-analysis to control for the heterogeneity in the primary estimates. The fixed effects model assumes that the variability among the effect sizes can be fully explained by a set of moderators that account for differences in the characteristics across study *i*:

$$T_i = \beta_0 + \beta_1 x_{i,1} + \cdots + \beta_k x_{i,k} + \varepsilon_i \text{ with } \varepsilon_i \sim N(0, \mathrm{v}_i) \quad (2)$$

where x_1 ... x_k are the study characteristics, β_1 ... β_k are the regression coefficients, ε_i is the error term andv_i is the estimated variance of the effect sizes collected from the primary studies, *i* = 1,2,…,k are indices for the estimated effect sizes.

In the mixed effect model the variability beyond the sampling error is derived partly from a systematic factor and partly from random sources:

$$T_i = \beta_0 + \beta_1 x_{i,1} + \cdots + \beta_k x_{i,k} + \mu_i + \varepsilon_i \text{ with } \varepsilon_i \sim N(0, \mathrm{v}_i) \text{ and } \mu_i \sim N(0, \tau^2) \quad (3)$$

Both the fixed-effects and the mixed-effects models allow the true effect size and its precision to vary across regressions. However, the mixed effects model also assumes that not all heterogeneity is observable. It allows for the presence of residual heterogeneity by assuming that the underlying effects follow a normal distribution around the effects predicted by the covariates (SUTTON *et al*., 2000).

One potential drawback of the above models is their assumption that the estimated effect sizes are independently distributed no matter what study they come from. The traditional assumption of independence can be violated when two (or more) effect size estimates come from the same study. This means they are based on the same sample of data, which introduces dependence at the sampling level but it can easily be accounted for by appropriate estimation of the sampling covariance matrix. Here, the 323 observations in the meta-analysis database are not from 323 independent studies since they are all nested within 17 studies. In order to verify if accounting for this type of dependence modifies the conclusions, the above models are complemented with a two-level hierarchical model that considers first the within-study variation and second the between-study variation (GOLDSTEIN, 2003).

Following the notation used by DOMINICIS *et al.* (2008), the two-level hierarchical model is:

$T_{ij} = \beta_{0j} + \beta_1 x_{i,1} + \cdots + \beta_k x_{i,k} + \varepsilon_{ij}$,

$\beta_{0j} = \beta_0 + \mu_j$, with $\varepsilon_{ij} \sim N(0, \mathrm{v}_i)$ and $\mu_j \sim N(0, \tau^2)$ (4)

where i is the individual observations nested in study j, ε_{ij} represents the error term at measurement level, v_i is the estimated variance of the effect sizes from the collected studies,

μ_j is the error term at the study level shared by all measurements within the same study.

As in DOBSON *et al.* (2006), this paper finds that it would be impossible to take into account all the conditioning variables given the limited size of the sample and that several of them can be found in some individual studies only. As a result, the focus is on the most commonly used conditioning variables while differences in data and estimation characteristics are captured by dummies. Controlling for all sources of heterogeneity is anyway unnecessary as it would only capture study differences that are already taken into account in the study fixed effects of the hierarchical model.

There are three classes of moderators. The first class concerns the *data characteristics,* which include information about:

-the publication status (published or unpublished), as it may be a source of heterogeneity (EGGER *et al.,* 1997).

- the degree of freedom.

- the area of study (more or less than EU12) as studies performed on a sample that excludes the Southern and East European countries generally conclude to a greater degree of cohesion and efficiency of the funds.

-the type of spatial unit used (country vs. regions) as it is well-known the spatial scale used for the analysis influences the conclusions

- the definition of the funds (fund/GDP vs. other) in order to differentiate the ways the primary studies normalize the allocation of the funds.

- the functional form used (linear, semi-elasticity vs. elasticity) as the three forms are found in the primary studies. These two functional forms constitute the bulk of the estimates (see Table 1.1).

-whether the funds are for objective 1 regions as historically the largest share of structural funds has been allocated to so-called objective 1 regions selected upon their level of per capita GDP being below 75% of the European average.

- the time lag between the average allocation of the funds and the average of the growth period as several primary studies use a lag to remove potential problems of simultaneous causation and recognize that public investments do not act instantaneously on growth.

- the number of years included in the allocation of the funds. Studies based on an average of several years are less sensitive to the cyclical effect of each year's allocation.

- initial year of the growth period (pre- vs. post-1994). It allows us to test the existence of a structural break in the capacity of the funds to promote growth. 1994 is chosen as it corresponds to the beginning of the 1994-1999 programming period during which more than 2.5 times the previous (1989-1993) level of funds was allocated.

- whether the study was written/published before or after the median year (2007) of the sample. This variable allows us to test whether more recent studies benefit from the experience built in the past literature. For instance, more recent studies pay a much greater degree of attention to issues of endogeneity of the funds and spatial autocorrelation than earlier studies. If not controlled for, both issues affect the magnitude and precision of the estimates.

The second class of moderators concerns the *estimation characteristics*, that is information on the estimation methods. Distinguishing the least squares methods (OLS, GLS, LSDV) from the others (ML, GMM, 2SLS) is necessary. While OLS and ML are equivalent in most simple regressions, they are not equivalent in the presence of spatial autocorrelation. This means ML is not part of the reference group. The other two moderators in this class indicate whether instruments (IV) were used to account for the endogeneity of the funds and whether a fixed effect approach was used. As mentioned in section 2, panel data studies cannot use a random effect approach in a neoclassical growth model. Finally, the role of controlling for spatial dependence is tested as it is increasingly recognized that the funds have effects beyond the boundaries of the recipient areas. It is a dummy with value 1 when the presence of externalities and feedback effects has been accounted for by spatial econometric means in the primary study.

The third class of moderators refers to the *presence of regressors* other than structural funds. The estimated effectiveness of the funds is also conditional upon such characteristics in the primary studies (EDERVEEN *et al*., 2002, 2006; RODRIGUEZ-POSE and FRATESI, 2004; ESPOSTI and BUSSOLETTI, 2008). They include the presence/absence of a national dummy variable, of the initial per capita GDP, of variables capturing the characteristics of the economic structure (e.g. share of workers in agriculture), employment or population, public investments or infrastructure stock, human capital or investments in education or research and development, corruption/institutional quality and the presence of an interaction term.

In essence, the results will suggest that the use of the above data characteristics, estimation characteristics and moderators produce smaller/greater estimates of β_4 on average in the primary studies. Except for the few continuous variables present here, the estimates can also be understood as measuring the bias that exist from excluding the associated control or choosing the alternative (in parenthesis in Table 1.2) in the primary study.

Note that the interpretation of some of the above dummy variables is not necessarily the same for different studies. For example, which country- or region-specific characteristics are captured by 'Fixed effects' depends on which other regressors are already included in the primary study. Similarly, the type of IV used is conditional upon other existing regressors. However, it is impossible to account for such a large degree of heterogeneity across primary studies without compromising the degree of freedom and the quality of the estimates.

1.5 Meta-regression results

Table 1.2 presents the results of the regressions for the fixed effect model (column 1) and the mixed effect model (column 2) where the 323 estimates are considered independent and for the hierarchical linear model where they are not (column 3). Indeed, the study fixed effects included in the latter model controls for differences across studies.

Table 1.2 Meta-regression results

Moderator variables	Fixed effects	Mixed effects	Hierar-chical	Ordered probit
Constant	0.187 (0.003)	0.187 (0.003)	0.187 (0.003)	
Data characteristics				
Publication status: published (unpublished)	-0.047 (0.045)	-0.047 (0.045)	-0.047 (0.045)	1.453 (0.052)

Degree of freedom†	-0.001 (0.180)	-0.001 (0.178)	-0.001 (0.180)	0.726 (0.081)
Area of Study: Less than EU12 (EU12 or more)	0.037 (0.008)	0.037 (0.008)	0.037 (0.008)	0.037 (0.008)
Spatial units: country (regions)	0.006 (0.560)	0.006 (0.562)	0.006 (0.560)	0.914 (0.377)
Fund definition: Fund/GDP (other)	0.068 (0.044)	0.068 (0.044)	0.068 (0.044)	2.224 (0.050)
Functional form: lin-lin (log-log)	-0.002 (0.639)	-0.002 (0.639)	-0.002 (0.639)	-2.502 (0.022)
Functional form: semi-elasticity (log-log)	0.003 (0.912)	0.003 (0.913)	0.003 (0.912)	-1.948 (0.014)
Recipient regions: Objective 1 regions (other)	0.000 (0.002)	0.000 (0.003)	0.000 (0.002)	0.100 (0.606)
Time lag: number of years†	-0.001 (0.000)	-0.001 (0.000)	-0.001 (0.000)	0.253 (0.004)
Years of allocation †	-0.001 (0.826)	-0.001 (0.826)	-0.001 (0.826)	0.186 (0.083)
Initial year of growth period: pre-1994 (post-1994)	-0.098 (0.001)	-0.098 (0.001)	-0.098 (0.001)	-0.214 (0.593)
Early study: written pre-2007 (recent study: written post-2007)	-0.026 (0.019)	-0.026 (0.019)	-0.026 (0.019)	-1.547 (0.171)
Estimation characteristics				
Estimation method: other (least squares methods)	0.031 (0.341)	0.031 (0.341)	0.031 (0.341)	-1.817 (0.066)
Endogeneity (no endogeneity)	-0.002 (0.001)	-0.002 (0.001)	-0.002 (0.001)	-0.250 (0.355)
Fixed effects approach (no effect)	-0.023 (0.348)	-0.023 (0.348)	-0.023 (0.348)	0.334 (0.611)
Spatial autocorrelation	-0.031 (0.339)	-0.031 (0.339)	-0.031 (0.339)	1.935 (0.040)
Presence of regressors				
National dummy variable	0.000 (0.232)	0.000 (0.233)	0.000 (0.232)	-0.262 (0.563)
Initial per capita GDP	-0.033 (0.494)	-0.033 (0.494)	-0.033 (0.494)	-0.506 (0.328)
Economic structure	0.000 (0.055)	0.000 (0.058)	0.000 (0.055)	1.958 (0.011)
Employment or population	0.022 (0.307)	0.022 (0.307)	0.022 (0.307)	-2.025 (0.006)
Public investment or infrastructure stock	-0.002 (0.537)	-0.002 (0.537)	-0.002 (0.537)	0.285 (0.652)
Human capital or investment in education or R&D	-0.102 (0.000)	-0.102 (0.000)	-0.102 (0.000)	-0.916 (0.202)
Corruption/Institutional quality	0.040 (0.000)	0.040 (0.000)	0.040 (0.000)	1.106 (0.082)

Interaction term	0.010 (0.000)	0.010 (0.000)	0.010 (0.000)	0.863 (0.086)
Threshold from 'Positive significant' to 'Negative significant'				-0.699 (0.516)
Threshold from 'Negative significant' to 'Non-significant'				-0.274 (0.799)
n	323			
Log-Likelihood	473.392	473.392	473.392	-208.73
AIC	-896.785	-894.785	-894.785	469.459
R*	0.163	0.163	0.163	0.357

Notes: The fixed effect model is estimated by Maximum Likelihood, the mixed effect mode is estimated by Restricted ML, the hierarchical model is estimated by Iterative Restricted ML. In the latter model, level-1 number of estimates is 323; level-2 number of studies is 17. The ordered probit model is estimated by Maximum Likelihood. All moderator variables enter the regression as dummies, except those labeled with a '†' which are continuous variables. The omitted category for dummy variable appears in brackets below the name of the moderator variable. The p-values are reported in parenthesis below the coefficient estimates.

The magnitude, sign and precision level of the estimates are comparable across all three models. The results indicate that the first significant moderator is 'publish'. It is a dummy variable that takes 1 when the primary study is published and 0 if not. The coefficient indicates that, on average, published studies report an impact that is lower than unpublished studies. The second significant moderator is 'area of study'. It is a dummy variable that takes the value 1 when the area of study is less than EU12 and 0 if not. The coefficient indicates that, on average, the impact of the funds on growth is greater in samples considering 'less than EU12' countries than in samples based on 'EU12 or more' countries. This result is not surprising considering that the poor regions of the Southern countries that enlarged the European Union from 9 to 12 members consumed a large share of the structural funds, yet they did not necessarily catch-up with their average national income or with the European average (DALL'ERBA and LE GALLO, 2008). While no significant difference between studies performed at the country or regional level is found, there is one between estimates based on the funds/GDP vs. any other form of normalization (funds/population or just funds). The former leads to estimates that are slightly higher on average.

No significant difference due to the functional form is found, which supports our choice of working with the whole sample. The next significant moderator is 'objective 1'. It is a dummy variable that takes value 1 when the funds are explicitly allocated to objective 1 regions. The difference in the estimated impact of such funds compared to non-objective 1 funds is significant but is very small (less than 0.000). The results indicate also that the immediate impact of the funds is greater than its delayed impact although not by much. This argument is in tune with BOLDRIN and CANOVA (2001) where these authors see, at least in the first rounds of EU cohesion policies, a strategy targeted more towards short-term income support and redistribution than long-term sustainable development. The number of years included in the allocation of the funds has no significant impact on heterogeneity. However, both the initial year of the growth period and the year of composition/publication of the primary study matter. They are dummy variables with value 1 for early periods and 0 for the more recent periods. Several factors could explain the role of the beginning of the growth period: the presence of business cycles that render the funds more efficient over some periods of time, an increase in the amounts allocated over each programming period (following the enlargement to the South, the 1994-1999 period saw a significant increase in funding for regional development compared to the past), or the presence of a 'learning effect' in the allocation and use of the funds as advanced by RODRIGUEZ-POSE and NOVAK (2013) recently. The authors justify it with a 'more appropriate expenditure of the Cohesion funds, due to a progressive shift in their expenditure priorities' as well as a 'strengthening of the principle of partnership' with local and regional authorities (p.32). The significant presence of a time trend in the year of publication or composition of the manuscript indicates a 'learning effect' too, although of a different nature. More recent studies can rely on a larger literature providing additional expertise on the topic and on the appropriate statistical techniques to pay attention to, among other, spatial autocorrelation and the endogenous nature of the funds. Both effects can affect the magnitude and the precision of the estimates.

Next, this paper tests whether several estimation characteristics used in the primary studies influence the estimated impact of the funds on growth. It appears that controlling for the endogeneity of the funds leads to estimates that are lower on average. It is the only significant characteristic in the second class of moderators.

Finally, the role of the regressors included in the primary studies is tested. They correspond to a dummy variable with value 1 when it is present in the primary study and 0 otherwise. Three moderators are significant at the 5% level. They are 'human capital or investment in education or R&D', 'corruption/institutional quality' and 'interaction term'. The first variable leads to an effect size that is lower on average. Its presence across many studies reflects the dominance of the augmented Solow growth model that includes the presence of a proxy for human-capital accumulation (MANKIW *et al*., 1992). EDERVEEN *et al*. (2006) is the contribution that explores the role of the second variable the most among the four studies that do so. Not surprisingly, they conclude that the effectiveness of the funds is conditional upon the level of corruption/institutional quality of the recipient area. Compared to studies that do not control for this characteristic, their estimates conclude to a lower effect size on average. Finally, when it comes to the 'interaction term', the reader should refer to the primary studies to find the exact definition of the 17 variables the funds have been interacted with in 77 cases. On average, the presence of an interaction term leads to a higher estimated impact of the funds in the primary studies.

When comparing the three models, it turns out that the coefficient estimates are very similar in magnitude and precision. It is confirmed in the similarity of the models' fit values (log-likelihood, AIC and R* - the Pearson correlation test between the fitted and observed values) and can be explained by the value of τ^2 being zero in the mixed and hierarchical models[1]. As a result, the heterogeneity detected in the distribution of the effect sizes is entirely observable whether it comes from the differences in study design, estimation processes, moderators used in the primary studies or from the variance of the effect sizes they estimate.

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[1] The hierarchical model shows the same results when the studies written by the same author(s) are considered as one. There are still 323 estimates in this case but only 12 independent studies.

Finally, the above models are complemented by an ordered probit model that presents the advantage of accounting for *both* the effect size of the dependent variable and whether it is significant or not in the primary studies (CARD *et al.*, 2010). In this approach, the dependent variable takes on a value of 0 for the 'significant positive estimates' (when $T_i/\sqrt{v_i}$ is greater than 1.96), 1 for the 'significant negative estimates' (when $T_i/\sqrt{v_i}$ is smaller than -1.96) and 2 for the 'non-significant estimates' (when $|T_i/\sqrt{v_i}|$ is smaller than 1.96). In this model the errors are assumed to be normally distributed with variance 1 (GREENE, 2012, p. 788). The results appear in the last column of Table 1.2. All the significant and negative estimated coefficients indicate the variables that increase Prob (y=0 | x). They also decrease Prob (y=2 | x) while their impact on the middle category, Prob (y=1 | x), is more ambiguous as described in GREENE (2012, p.789). The opposite can be said about the significant and positive estimated coefficients. The results indicate that the variables that increase the probability of a positive and significant estimated impact of the funds are the use of a functional form other than elasticity and the presence of a variable controlling for the level of 'Employment or population' in the primary study. The probability of concluding to an efficient impact of the funds is found to decrease with increasing years of lag between allocation and growth, which indicates the immediate rather than long-run impact of EU cohesion policies (BOLDRIN and CANOVA, 2001); when the funds are divided by GDP; when spatial autocorrelation is controlled for (DALL'ERBA and LE GALLO, 2008) and when the original model captures the 'economic structure' of the recipient area.

1.6 Conclusion

The capacity of structural funds to promote regional economic growth has been controversial for decades. Both economic theory and empirical applications are not unanimous about their role on growth; yet structural funds are an important part of the European integration project and the evaluation of their impact matters for both the recipients and the payers. This paper takes stock of the large number of studies that measure econometrically the impact of the funds on growth and select among them those that offer comparable effect sizes. It leads to 17 studies that offer 323 marginal effects.

The sources of their heterogeneity is examined by means of several weighted regression models (fixed-effects model, mixed-effects model and hierarchical model). While they all assume that part of the heterogeneity is due to differences in the data characteristics, estimation methods and choice of regressors in the primary studies, they each model the variance of the omitted variables differently. Yet, they all lead to very similar estimates, which proves the robustness of the results and that all the heterogeneity detected among the effect sizes is observable. They indicate that several differences in the data characteristics are at the origin of the heterogeneity found in the primary estimates. Among them, the publication status is found to influence the size of the estimates. A 'learning effect' is also present because studies focusing on more recent years conclude to a larger impact of the funds, which suggests the way of allocating and using them has become more efficient. Furthermore, the results indicate that the differences in functional forms used in the primary studies do not have a significant impact on the size of the estimates.

Controlling for endogeneity and for three types of regressors ('human capital or investment in education or R&D', 'institutional quality' and 'interaction term') in the original studies also leads to significant differences in the primary estimates. The latter are characteristics of the recipient regions that condition the effectiveness of the funds.

Finally, this study complements the usual meta-analytic approach by running an ordered probit model to uncover the factors that affect the probability of estimating a significantly positive impact of the funds. To our knowledge, this endeavor had never been done before.

These results suggest that future researchers working on EU regional development policies should be aware of the possible econometric bias and associated erroneous conclusions that come with their choice of study design and regressors. On the other hand, it is now clear that there are many aspects of the study such as the functional form and some estimation characteristics they should not be too worried about since they do not affect significantly the size of the estimates on average. In addition, future researchers will be able to rely on a larger literature than the first contributors to this field and this 'learning effect' has proven not negligible.

Given the long-lasting interest for improving the effectiveness of the funds, future contributions should devote more attention to estimating the impact of the funds in the frame of theories and models other than the neoclassical beta-convergence model. For instance, DALL'ERBA *et al.* (2009) offer an approach based on an endogenous growth model but many more contributions are needed. Another exciting development in the evaluation of the funds is the use of a counterfactual methodological approach based on the regression discontinuity design as in BECKER *et al*. (2010, 2013) and PELLEGRINI *et al*. (2013). The authors build on the allocation rule of Objective 1 funds to compare the effect on the regions with a per capita GDP level just below the eligibility threshold (75% of EU average) with the per capita GDP of the regions just above since they did not get this type of funding. Last but not least, more attention could be given to locally weighted estimates of the funds as in LE GALLO *et al.* (2011). Their main contribution is to provide coefficient estimates for every single region, as opposed to the average impact for the entire sample, as is currently done in the literature. It helps them identify the regions where the funds have had a positive and significant impact and allows them to reconsider the ‘one size fits all’ approach that has dominated the allocation process and the empirical literature so far.

CHAPTER 2 ON DERIVING SPATIAL ECONOMETRIC MODELS FROM THEORY AND W FROM OBSERVATIONS– AN APPLICATION TO THE U.S. REGIONAL KNOWLEDGE PRODUCTION FUNCTION

2.1 Introduction

A number of recent contributions (e.g. Corrado and Fingleton, 2012; Pinske and Slade, 2010; McMillen, 2012) has called for more attention to two intrinsically related and recurrent issues in spatial econometrics. The first one deals with the common use of diagnostic and goodness-of-fit tests to determine the appropriate form of spatial autocorrelation. We will demonstrate in this chapter that spatially explicit reduced form models can be derived from substantive economic theory when the spatial processes at work are motivated theoretically and can be directly embedded in the foundations of the model. A previous application of this approach can be seen in Ertur and Koch (2007), Fischer (2011) and Dall'erba and Llamosas-Rosas (2014) who study the role of interregional knowledge externalities in a Cobb-Douglas production function of regional income dynamics. This chapter focuses on a different application, namely the regional knowledge production function (henceforth KPF) derived from Griliches (1979) for which, to our knowledge, no prior extension of this sort is available.

The second challenge relates to the W matrix of spatial weights being almost consistently based on some degree of geographical proximity as if the strength of interregional interactions were to depend on that factor only (Fingleton and Le Gallo, 2008). While geographical distance is unambiguously exogeneous, it does not change with time nor allow to identify clearly the direction of the flows or their asymmetric nature. As a result, some contributions have proposed alternatives such as, among many others, the transportation cost (e.g. Conley and Ligon, 2002), economic distance (Fingleton, 2001, 2008; LeSage and Pace, 2008), or technological proximity (Parent and LeSage, 2008) across regions. These specifications permit the relative distance between any pair of regions to be asymmetric, but the direction of the transactions is still missing and they only offer a proxy of the actual interregional flows. As such, in this chapter we prefer to work with a W based on observed flows (such as Eliste and Fredriksson, 2004, and Chen and Haynes, 2014, who use trade flows, or Kang and Dall'erba, 2015, who rely on flows of patent creation-citation respectively) that evolve over time, are measured in the past to guarantee their exogeneity and, more importantly, support theory.

In order to illustrate how to implement these increasingly popular directions in the field of spatial econometrics, this chapter offers to reconsider the traditional theoretical development of the regional KPF and provides an application to the measurement of interregional knowledge spillovers across U.S. states. While the large majority of empirical evaluations of the KPF are performed at the firm level (such as David *et al.,* 2000; Cefis and Orsenigo, 2001; Cho *et al*., 2008), a growing number of studies evaluate it at the regional level (Audretsch and Feldman, 1996; Crescenzi*et al*., 2007; Rodriguez-Pose, 2001; Acs and Armington, 2004; Adams, 2002; Ó hUallacháin and Leslie, 2007; Sonn and Park, 2011; Anselin *et al*., 1997). This trend is, in part, motivated by the concern that regional economies have to compete nationally and internationally to attract the factors at the origin of innovation and maintain their technological edge over their competitors.

Among the studies focusing on knowledge production at the regional level, the investigation of *knowledge spillovers* has received an increasing amount of attention.

Knowledge spillovers take place when firms, industries, or regions benefit from the knowledge created by other firms, industries or regions without bearing the cost associated to its creation (Fischer *et al*. 2009). While the role of spillovers in knowledge creation has been well documented in the theoretical literature (Marshall, 1920; Jacobs, 1969; Jaffe, 1986; Glaeser *et al*., 1992; Fung and Chow, 2002; Asheim and Isaksen 2002; Henderson, 2003), their appropriate measurement remains a challenge. For instance, a large amount of knowledge spillovers takes place through face-to-face interactions (Jaffe, 1986; Jaffe *et al*., 1993; Audretsch and Feldman, 1996; Rodríguez-Pose, 2001; Sonn and Storper, 2008) and this process is not documented clearly. We do not know how often nor where the agents of one company meet agents from another company to exchange ideas. As a result, regional KPF often deal with this type of undocumented spillovers as if they are limited spatially. Empirical evidence confirms this point. For example, Jaffe *et al*. (1993) find that patents produced in one state are more likely to be cited within the same state. At the same time, other contributions indicate that knowledge spillovers may well reach companies located beyond the boundaries of the locality they originate from. This statement is in line with Anselin *et al*. (1997) who uncover that university research leads to innovation in high technology companies located within the same region and in neighboring ones. The previous study is the first one to have used the formal tools of spatial econometrics to measure these spillovers. Many more have followed since then with applications to many different areas of the world. For instance, Bode (2004) highlights the role of interregional knowledge spillovers in West Germany while Parent and LeSage (2008) do so for all the European regions. Several other studies focus on the system of the US regional economies, as we do in this paper. Among them, Parent (2012) examines the determinants of growth in state-level patents using a dynamic space-time model and a panel data sample covering 49 US states over the 1994–2005 period. Mukherji and Silberman (2013) demonstrate that a metropolitan area's ability to absorb external knowledge has a positively significant impact on its innovation capacity.

Previous studies define interregional interactions based on geographical proximity. As an attempt to address the more general and more appropriate intellectual interactions among regions, Jaffe (1986) specifies the knowledge externalities for any considered pair of firms by using a Pearson correlation coefficient. Numerical vectors describing the distribution of firm-level patents over several technological fields are first constructed and the correlation between any pair of vectors is used as a proxy for the firms' interaction. The distance that separates them is thus disregarded. Parent and LeSage (2008) have recently extended his approach by weighting Jaffe's firm-level technology spillovers by the relative size of a region's economic activity or its distance to its partners. Autant-Bernard *et al*. (2007) use a model of cooperation choice to test the presence of spatial effects relative to network effects by using data on collaborative projects submitted to the European Union 6th Framework Program. Their results show that the firms' position within a network matters more than their geographical location. Johnson *et al*. (2006) show that, in the US, the average distance between patent collaborators has increased from 117 miles in 1975 to 200 miles in 1999. The problem with *all* the previous approaches is that the *direction* of the flows, hence the *causality* associated to the creation of knowledge (from input to output), cannot be captured.

Fortunately, other routes of long-distance spillovers have been suggested in the literature. For instance, Ponds *et al*. (2010) focus on how networks stemming from university-industry collaborations support the impact of academic research on innovation across NUTS 3 Dutch regions over 1999-2001. Another explicit mechanism of spillovers is a matrix of interregional flows of patents created by a company and cited by another. This approach has been used first by Sonn and Storper (2008) who analyze 20 Metropolitan Statistical Areas and conclude that the proportion of local citations has increased over the 1975-1999 period. However, when Kang and Dall'erba (2015) extend this matrix to all the US counties and to a more recent period (1995- 1999), they conclude that on average patents created in remote locations (more than 50 miles away) have a greater role on a county's patenting activities than patents created locally (less than 50 miles away). Miguelez *et al*. (2010) focus on 269 European NUTS2 regions. Their results indicate that distant knowledge spillovers can take place through additional mechanisms, such as market transactions (e.g., the purchase of knowledge services from specialists, the purchase of knowledge products from suppliers and labour mobility), the monitoring of competitors, through foreign direct investments and firm spin-offs. However, we are not aware of a study measuring the role of these flows in the interregional innovation system of the US.

One type of knowledge flow that has been disregarded in the regional KPF literature is the spillovers of human capital embodied in the migration of highly-skilled workers. Yet, some articles have already highlighted the contribution of mobile inventors on the diffusion of knowledge across firms or regions. The phenomenon has mostly been studied in the context of international migrants coming to the US. For example, Kerr (2013) points out that highly-skilled immigrants account for about 25 percent of the workers in the most innovative and entrepreneurial U.S. industries, and they are responsible for a somewhat similar share of output measures like patents or firm start-ups. Chellaraj *et al.* (2005) find that both international graduate students and skilled immigrants have a significant and positive impact on future patent applications as well as on future patents awarded to university and non-university institutions. More precisely, a 10 percent increase in the number of foreign graduate students would raise patent applications by 4.7 percent, university patent grants by 5.3 percent, and non-university patent grants by 6.7 percent. Yet, to the best of our knowledge, no previous contribution has examined the role of the internal migration of the highly-skilled workers on innovation differentials across US regions. This paper intends to fill this gap.

Another contribution of this paper consists in offering a spatial panel data model which has the advantage over cross-sectional models commonly used in the regional KPF literature to increase the efficiency of the estimates. To our knowledge, only four contributions have measured interregional knowledge spillovers in a spatial panel context. The first one is Peri (2005) who estimates cross-regional citation flows and plug the estimated fitted values into a spatial weight matrix that captures the diffusion of knowledge flows across a panel of 113 European and North American regions over 22 years. Then come Autant-Bernard and Lesage (2011) who examine the spatial spillovers associated to public and private research expenditures by industry from 1992 to 2000 over a sample of 94 French regions. Their spatial weight matrix reflects the assumed degree of regional connectivity based on Jaffe's (1986) approach. Parent (2012) investigates a KPF across the

49 US states over 1994-2005 where the spatial weight scheme is the degree of technological proximity of the k-nearest neighbors measured on the averaged technological proximity indices (Jaffe, 1986) over the 1963-1993 period. Finally, Parent and LeSage (2012) analyze the dynamics of European patenting over 1989-1999 based on a sample of 320 regions taken from nine European countries. Their weight matrix is more traditional than previous approaches in that spillovers emanate from the five nearest-neighbors selected by the distance across the main administrative city of each region. All of the above contributions use a weight matrix that is constant over time and conclude to a positive and significant effect of interregional spillovers on the local production of innovation. In this paper, we challenge the assumption of a constant interregional weighting scheme by relying on a matrix of yearly migration of the highly-educated over 1986-1999 and a matrix of interstate flows of patent creation-citation over the same period.

Taking stock of the previous literature, this paper continues in section 2 with a theoretical model that extends Griliche's (1979) traditional KPF to a regional approach where the production of external knowledge and its role on local knowledge is theoretically founded. Compared to previous contributions, we emphasize the role of migration of the educated workers and of patent creation-citation as channels to transmit knowledge over space. The derivation of the theoretical model to a reduced-form model appears in this section too. The variables we use in our panel of 49 states (continental states and Washington D.C.) over the 1986–1999 period are described in section 3. The estimated results are reported and discussed in Section 4. Finally, Section 5 summarizes the results and offers some concluding remarks.

2.2. The spatial panel KPF

Our starting point is a knowledge production function (Griliches, 1979) measured for each region *i* at time *t* as follows:

$$Y_{i,t} = K_{i,t} C_{i,t}^{\alpha_1} H_{i,t}^{\alpha_2} L_{i,t}^{1-\alpha_1-\alpha_2}, \tag{1a}$$

where $0 \leq \alpha_1, \alpha_2 < 1$ and $\alpha_1 + \alpha_2 < 1$.

The production of knowledge $Y_{i,t}$ is a function of the current state of technical knowledge $K_{i,t}$[2], the level of private reproducible physical capital $C_{i,t}$, the level of human capital $H_{i,t}$ and the level of labor $L_{i,t}$. As usual in a Cobb-Douglas production function, the coefficients α are positive or null and below 1, reflecting the decreasing returns to physical and human capital, and the returns to scale are assumed decreasing.

All the variables above evolve in continuous time. As usual in the neoclassical literature, $L_{i,t}$ is assumed to grow exogenously at rates η_i while the stock of physical and human capital grows as follows (the dot represents the derivative of a variable with respect to time):

$$\dot{C}_{i,t} = s_i^C Y_{i,t} - \delta C_{i,t} \tag{1b}$$

$$\dot{H}_{i,t} = s_i^H Y_{i,t} - \delta H_{i,t} \tag{1c}$$

where s_i denotes the investment rate for each type of capital while δ is the depreciation rate that is common to both of them.

Finally, $K_{i,t}$ is assumed to grow at an exogenous rate *g* that is similarly experienced in all locations. This assumption has been challenged by Ertur and Koch (2007), Fischer (2011)

[2] We follow Griliches (1979) notations here. The stock of knowledge or of technology is usually written $A_{i,t}$ in a Cobb-Douglas production function.

and Dall'erba and Llamosas-Rosas (2014) who propose to model the aggregate level of knowledge as follows:

$$K_{i,t} = \Omega_t c_{i,t}^{\theta_1} h_{i,t}^{\theta_2} \prod_{j \neq i}^{N} K_{j,t}^{\rho w_{i,j}} \tag{2a}$$

where the elements that compose it can be described as:

-Ω_t is an exogenous stock of knowledge that is shared by all entities as predicted by the neoclassical growth model (Solow, 1956; Swan, 1956).

- as in the endogenous growth framework (Romer, 1986; Lucas, 1988), the levels of physical and human capital per worker available in region *i* increase the stock of knowledge available to all firms in region *i* by a value $\theta_1$and θ_2 respectively (with $0 \leq \theta_1, \theta_2 < 1$).

- finally, the last term captures the knowledge externalities that originate from all the regions *j* (with *j*≠ *i*) and spill over to *i* (as emphasized in the new economic geography theory; Fujita *et al*., 1999; Boarnet, 1998). The coefficient ρ ($0 < \rho < 1$) measures the average degree of interregional dependence. The latter term originates from the new economic geography literature.

In the present paper we depart from the previous model for two important reasons: 1) while the spillovers are assumed to take place instantaneously and over pure geographical contiguity only in (2a), we pay attention here to the fact that R&D efforts do not lead instantaneously to the creation of knowledge (Griliches, 1979) so that a time lag in the input variables is needed. Moreover, 2) the spillovers of physical and human capital are assumed here to originate from two distinct sources: the flows of patent creation-citations ($p_{i,j}$) and the migration flows from *i* to *j* ($m_{i,j}$). These two elements lead to a reformulation of (2a) as follows:

$$K_{i,t} = \Omega_t c_{i,t-1}^{\delta_1} h_{i,t-1}^{\delta_2} \prod_{j \neq i}^{N} c_{j,t-1}^{\tau_c P_{i,j} + \sigma_c M_{i,j}} h_{j,t-1}^{\tau_h P_{i,j} + \sigma_h M_{i,j}} \tag{2b}$$

where P denotes the patent creation-citation weight matrix and M denotes the migration weight matrix.

When we re-write equation (1a) in per capita terms, we get:

$y_{i,t} = K_{i,t}c_{i,t}^{\alpha_1}h_{i,t}^{\alpha_2}$

and applying a log transformation: $\ln y_{i,t} = \ln K_{i,t} + \alpha_1 \ln c_{i,t} + \alpha_2 \ln h_{i,t}$ (3)

Log transformation of (2a) leads to,

$$\ln K_{i,t} = \ln \Omega_t + \theta_1 \ln c_{i,t} + \theta_2 \ln h_{i,t} + \rho \sum_{j\neq i}^{N} W_{i,j} \ln K_{j,t} \quad (4a)$$

which in matrix format can be rewritten as:

$$\ln K = \ln \Omega + \theta_1 \ln \mathrm{c} + \theta_2 \ln \mathrm{h} + \rho W \ln K$$

$$\ln K = (\mathrm{I} - \rho W)^{-1}(\ln \Omega + \theta_1 \ln \mathrm{c} + \theta_2 \ln \mathrm{h})$$

$$\ln K = (\mathrm{I} - \rho W)^{-1} \ln \Omega + \theta_1 (\mathrm{I} - \rho W)^{-1} \ln \mathrm{c} + \theta_2 (\mathrm{I} - \rho W)^{-1} \ln \mathrm{h}$$

and in the case of (2b),

$$\ln K_{i,t} = \ln \Omega_t + \delta_1 \ln c_{i,t-1} + \delta_2 \ln h_{i,t-1} + \tau_c \sum_{j\neq i}^{N} P_{i,j} \ln c_{j,t-1} +$$

$$\sigma_c \sum_{j\neq i}^{N} M_{i,j} \ln c_{j,t-1} + \tau_h \sum_{j\neq i}^{N} P_{i,j} \ln h_{j,t-1} + \sigma_h \sum_{j\neq i}^{N} M_{i,j} \ln h_{j,t-1} \quad (4b)$$

For each region i combining (3) and (4a) and multiplying by $(\mathrm{I} - \rho W)$ leads to:

$$\ln y_{i,t} = \ln \Omega_t + (\theta_1 + \alpha_1) \ln c_{i,t} + (\theta_2 + \alpha_2) \ln h_{i,t} - \alpha_1 \rho \sum_{j\neq i}^{N} W_{i,j} \ln c_{i,t} -$$

$$\alpha_2 \rho \sum_{j\neq i}^{N} W_{i,j} \ln h_{i,t} + \rho \sum_{j\neq i}^{N} W_{i,j} \ln y_{j,t} \quad (5a)$$

Whereas multiplying by $(\mathrm{I} - \rho W)$ and combining (3) and (4b) for each region i leads to:

$$\ln y_{i,t} = \ln \Omega_t + \alpha_1 \ln c_{i,t} + \alpha_2 \ln h_{i,t} + \delta_1 \ln c_{i,t-1} + \delta_2 \ln h_{i,t-1} +$$

$$\tau_c \sum_{j\neq i}^{N} P_{i,j} \ln c_{j,t-1} + \sigma_c \sum_{j\neq i}^{N} M_{i,j} \ln c_{j,t-1} + \tau_h \sum_{j\neq i}^{N} P_{i,j} \ln h_{j,t-1} + \sigma_h \sum_{j\neq i}^{N} M_{i,j} \ln h_{j,t-1}$$

(5b)

Since the per capita production function has decreasing returns to scale, the output level converges to a steady state, leading to constant capital productivity in per worker terms (i.e., g). Taking this property into (5a) leads to the following equation (see appendix A for details):

$$\ln y_{i,t}^{*} = \ln \Omega_t + (\theta_1 + \alpha_1) \ln s_i^c + (\theta_2 + \alpha_2) \ln s_i^h - (\theta_1 + \alpha_1 + \theta_2 + \alpha_2) \ln(\delta + \eta_i + \mathrm{g}) + (\theta_1 + \alpha_1 + \theta_2 + \alpha_2) \ln y_{i,t}^{*} - \alpha_1 \rho \sum_{j \neq i}^{N} W_{i,j} \ln s_i^c - \alpha_2 \rho \sum_{j \neq i}^{N} W_{i,j} \ln s_i^h + (\alpha_1 \rho + \alpha_2 \rho) \sum_{j \neq i}^{N} W_{i,j} \ln(\delta + \eta_i + \mathrm{g}) + (1 - \alpha_1 - \alpha_2) \rho \sum_{j \neq i}^{N} W_{i,j} \ln y_{j,t}^{*} \quad (6a)$$

or

$$\ln y_{i,t}^{*} = \frac{1}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)} \ln \Omega_t + \frac{\theta_1+\alpha_1}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)} \ln s_i^c + \frac{\theta_2+\alpha_2}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)} \ln s_i^h - \frac{(\theta_1+\alpha_1+\theta_2+\alpha_2)}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)} \ln(\delta + \eta_i + \mathrm{g}) - \frac{\alpha_1 \rho}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)} \sum_{j \neq i}^{N} W_{i,j} \ln s_i^c - \frac{\alpha_2 \rho}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)} \sum_{j \neq i}^{N} W_{i,j} \ln s_i^h + \frac{\alpha_1 \rho + \alpha_2 \rho}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)} \sum_{j \neq i}^{N} W_{i,j} \ln(\delta + \eta_i + \mathrm{g}) + \frac{(1-\alpha_1-\alpha_2)\rho}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)} \sum_{j \neq i}^{N} W_{i,j} \ln y_{j,t}^{*}$$

(7a)

where spending in physical and human capital across neighboring locations is assumed to lead instantaneously to the creation of knowledge in region *i*. The empirical counterpart of (6a) is defined as follows:

$$\ln y_{i,t}^{*} = \beta_0 + \beta_1 \ln(\delta + \eta_i + g) + \beta_2 \ln s_i^c + \beta_3 \ln s_i^h + \gamma_1 \sum_{j \neq i}^{N} W_{i,j} \ln(\delta + \eta_i + \mathrm{g}) + \gamma_2 \sum_{j \neq i}^{N} W_{i,j} \ln s_i^c + \gamma_3 \sum_{j \neq i}^{N} W_{i,j} \ln s_i^h + \gamma_4 \sum_{j \neq i}^{N} W_{i,j} \ln y_{j,t}^{*} + \epsilon_i, \text{ where } \epsilon_i \sim N(0, \sigma^2)$$

(8a)

following the theoretical predictions, the following two restrictions should hold: $-\beta_1 = \beta_2 + \beta_3$ and $-\gamma_1 = \gamma_2 + \gamma_3$.

On the other hand, equation (5b) leads to :

$$\ln y_{i,t}^{*} = \ln \Omega_t + \alpha_1 \ln s_{i,t}^{c} + \alpha_2 \ln s_{i,t}^{h} - (\alpha_1+\alpha_2)[\ln(\delta+\eta_{i,t}+g) - \ln(\delta+\eta_{i,t-1}+g)]$$

$$+ (\alpha_1+\alpha_2)\ln y_{i,t}^{*} + \delta_1 \ln s_{i,t-1}^{c} + \delta_2 \ln s_{i,t-1}^{h} + (\delta_1+\delta_2)\ln y_{i,t-1}^{*}$$

$$+ \tau_c \sum_{j\neq i}^{N} P \ln s_{j,t-1}^{c} + \delta_c \sum_{j\neq i}^{N} M_{i,j} \ln s_{j,t-1}^{c} + \tau_h \sum_{j\neq i}^{N} P_{i,j} \ln s_{j,t-1}^{h}$$

$$+ \delta_h \sum_{j\neq i}^{N} M_{i,j} \ln s_{j,t-1}^{h}$$

$$- (\tau_c+\tau_h)[\sum_{j\neq i}^{N} P_{i,j} \ln(\delta+\eta_{j,t-1}+g) - \sum_{j\neq i}^{N} P_{i,j} \ln y_{j,t-1}^{*}] + (\delta_c$$

$$+ \delta_h)[\sum_{j\neq i}^{N} M_{i,j} \ln(\delta+\eta_{j,t-1}+g) - \sum_{j\neq i}^{N} M_{i,j} \ln y_{j,t-1}^{*}$$

(6b)

or

$$\ln y_{i,t}^{*} = \frac{1}{1-(\alpha_1+\alpha_2)}\ln \Omega_t + \frac{-(\alpha_1+\alpha_2)}{1-(\alpha_1+\alpha_2)}\ln(\delta+\eta_{i,t}+g) + \frac{\alpha_1}{1-(\alpha_1+\alpha_2)}\ln s_{i,t}^{c}$$

$$+ \frac{\alpha_2}{1-(\alpha_1+\alpha_2)}\ln s_{i,t}^{h} + \frac{-(\delta_1+\delta_2)}{1-(\alpha_1+\alpha_2)}\ln(\delta+\eta_{i,t-1}+g)$$

$$+ \frac{\delta_1}{1-(\alpha_1+\alpha_2)}\ln s_{i,t-1}^{c} + \frac{\delta_2}{1-(\alpha_1+\alpha_2)}\ln s_{i,t-1}^{h}$$

$$+ \frac{(\delta_1+\delta_2)}{1-(\alpha_1+\alpha_2)}\ln y_{i,t-1}^{*} + \frac{-(\tau_c+\tau_h)}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} P_{i,j}\ln(\delta+\eta_{j,t-1}+g)$$

$$+ \frac{-(\sigma_c+\sigma_h)}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} M_{i,j}\ln(\delta+\eta_{j,t-1}+g) + \frac{\tau_c}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} P \ln s_{j,t-1}^{c} +$$

$$\frac{\sigma_c}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} M_{i,j}\ln s_{j,t-1}^{c} + \frac{\tau_h}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} P_{i,j}\ln s_{j,t-1}^{h} +$$

$$\frac{\sigma_h}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} M_{i,j}\ln s_{j,t-1}^{h} + \frac{(\tau_c+\tau_h)}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} P_{i,j}\ln y_{j,t-1}^{*} +$$

$\frac{(\sigma_c+\sigma_h)}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} M_{i,j}\ \ln y_{j,t-1}^{*}$

(7b)

In this specification, spending in physical and human capital in partner locations defined by the interregional flows of patent creation-citation and of migration leads to knowledge production in region *i* after a lag of one year.

The empirical counterpart of (6b) is defined as follows:

$$\ln y_{i,t}^{*} = \beta_0 + \beta_1 \ln\big(\delta + \eta_{i,t} + g\big) + \beta_2 \ln s_{i,t}^{c} + \beta_3 \ln s_{i,t}^{h} + \beta_4 \ln\big(\delta + \eta_{i,t-1} + g\big) + \beta_5 \ln s_{i,t-1}^{c} + \beta_6 \ln s_{i,t-1}^{h} + \beta_7 \ln y_{i,t-1}^{*} + \gamma_1 \sum_{j\neq i}^{N} P_{i,j} \ln\big(\delta + \eta_{i,t-1} + \mathrm{g}\big) + \gamma_2 \sum_{j\neq i}^{N} M_{i,j} \ln\big(\delta + \eta_{j,t-1} + \mathrm{g}\big) + \gamma_3 \sum_{j\neq i}^{N} P_{i,j} \ln s_{j,t-1}^{c} + \gamma_4 \sum_{j\neq i}^{N} M_{i,j} \ln s_{j,t-1}^{c} + \gamma_5 \sum_{j\neq i}^{N} P_{i,j} \ln s_{j,t-1}^{h} + \gamma_6 \sum_{j\neq i}^{N} M_{i,j} \ln s_{j,t-1}^{h} + \gamma_1 \sum_{j\neq i}^{N} P_{i,j} \ln y_{j,t-1}^{*} + \gamma_2 \sum_{j\neq i}^{N} M_{i,j} \ln y_{j,t-1}^{*} + \epsilon_i, \text{ where } \epsilon_i \sim N(0,\sigma^2). \quad (8b)$$

for which the following restrictions should hold: $-\beta_1 = \beta_2 + \beta_3, -\beta_4 = \beta_5 + \beta_6,\ \beta_7 = -\beta_4, -\gamma_1 = \gamma_3 + \gamma_5, -\gamma_2 = \gamma_4 + \gamma_6, \gamma_7 = -\gamma_1, \gamma_8 = -\gamma_2$.

2.3 Description of the data

We perform our estimation based on the 48 continental states plus Washington D.C. The primary data are county-level data from Kang and Dall'erba (2015). For instance, like them we use the ratio of utility patent applications per employee in manufacturing as a proxy for the innovation output (***Patent)***. Patent application data is used because the year when the application is made is closer to the time when knowledge is created. Patent application data comes from the US Patent and Trademark Office (USPTO, 2010). The dataset has been used by Jaffe and Lerner (2004), Crescenzi *et al*. (2007), and Sonn and Park (2011). We choose the sample of patents applied between 1986 to 1999 whose inventors are residents of the 48 continental states and Washington, D.C. We divide this number by the number of employees in the manufacturing sector because the patent citation data are available for the manufacturing sectors only (Chemical, Drug & Medicals, Mechanical, Computer & Communication, Electrical & Electronic, and the other manufacturing sectors). Data on the number of employees by state and manufacturing sector is available from the Bureau of Economic Analysis.

Spending in reproducible physical capital devoted to innovation ($C_{i,t}$) and spending in human capital for innovation purposes ($H_{i,t}$) are the primary inputs in the knowledge production function. However, we are not aware of data that would distinguish these two inputs clearly. Instead, we offer to distinguish between private and academic R&D spending. Both types of R&D spending fund physical capital and human capital devoted to innovation although we can argue that academic R&D investments finance a relatively greater share of human capital than private R&D investments.

In this paper, we will measure the latter as the ratio of private R&D expenditure divided by the number of employees in the manufacturing sector and note it (**c**). It is measured on a yearly basis over 1986-1999. The private expenditure data come from Standard and Poor's Compustat database which provides annual and monthly data for more than 14,650 active U.S. and Canadian companies (Standard and Poor’s, 2001). Compustat draws its R&D data from the documents of the Securities & Exchange Commission among other sources. We extract the R&D expenditures from Compustat for each fiscal year and aggregate them by state.

The contribution of academic R&D in the creation of innovation is measured through the ratio of the aggregated expenditures at universities and colleges per employee in the manufacturing sector (**h**) for each year from 1986 to 1999. We prefer this variable than the usual amount of spending for education or number of workers with a high-level of education because our dependent variable is not the usual aggregated output level (as in Mankiw *et al*., 1992; Holtz-Eakin, 1993; Lall and Yilmaz, 2001; Garofalo and Yamarik, 2002). Instead, we measure the *innovation* output so that the only investments in human capital that are of relevance to us are those of which aim is innovation. Yet, not all investments in education, especially those targeting low levels of education or supporting labor force training programs are intended to yield to innovation. Furthermore, the share of graduate degree holders in the local workforce only captures the stock of readily available educated workers, not the level of *investment* in human capital, and even if the two concepts are closely related theoretically they can lead to different elasticities empirically (see Dall'erba and Llamosas, 2015). Secondly, not all graduate degree holders work or desire to work in innovation-producing sectors. As such, the amount of R&D spent in the academia is more closely related to our dependent variable. Institution-level microdata come from the Higher Education research and development survey produced by the National Science Foundation and are aggregated at the state level to match our sample.

As obvious from equations (8a-b), three spatial weights matrices are used in our study:

1) We use a queen contiguity weight matrix (W) in equation (8a). W indicates whether two states share a common boundary or not and it is column-standardized to be consistent with the standardization process used in the other two weight matrices:

$$\Psi_{i,j} = \begin{cases} 1, & if\ region\ i\ \cap region\ j \neq \emptyset \\ 0, & if\ region\ i\ \cap region\ j = \emptyset \end{cases}$$

$$W_{i,j} = \frac{\Psi_{i,j}}{\Psi_{\cdot j}}$$

Where $\Psi_{\cdot j}$ is the sum of all elements in column j.

2) We rely on the NBER US Patent Citation Data File (Hall *et al.*, 2001) for the construction of the patent creation-citation weight matrix (P). This data file contains information about any utility patents granted between 1963 and 1999 along with the citation records associated to the 1975-1999 period. Therefore, we can construct the patent creation-patent citation relationship at the US state level. However, since a patent is usually associated with several inventors, we follow the fractional counting method proposed by Jaffe *et al.* (1993) and Sonn and Storper (2008), i.e. a patent with N inventors citing another patent (previously) deposited by M inventors leads to (N×M) flows of information and each of them records 1/(N×M) fraction of the patent. Once these fractional flows are summed up, they capture the origin, destination and intensity of the inter-state patent creation – patent citation routes. Because we use a panel approach, these flows are measured on a yearly level over 1986-1999. Finally, note that we column-standardize P to capture the portion of knowledge created in state *j* that spills over to the recipient state *i* as in Kang and Dall'erba (2015).

3) We capture the inter-state migration flows of the highly educated workers in matrix M by constructing a series of spatial weights matrices based on the residence they occupy

every other year. While the literature traditionally uses the share of graduate degree holders, the flow of migrants with this level of education is not available in our database (Integrated Public Use Micro-data Series - IPUMS). As a result, we choose the highest education level available and it is Bachelor's degree holders or equivalent. As above, the flows are measured every year over 1986-1999 and a column standardization process is applied.

Figure 2.1 Median value and interquartile range of the variables (in log) over time

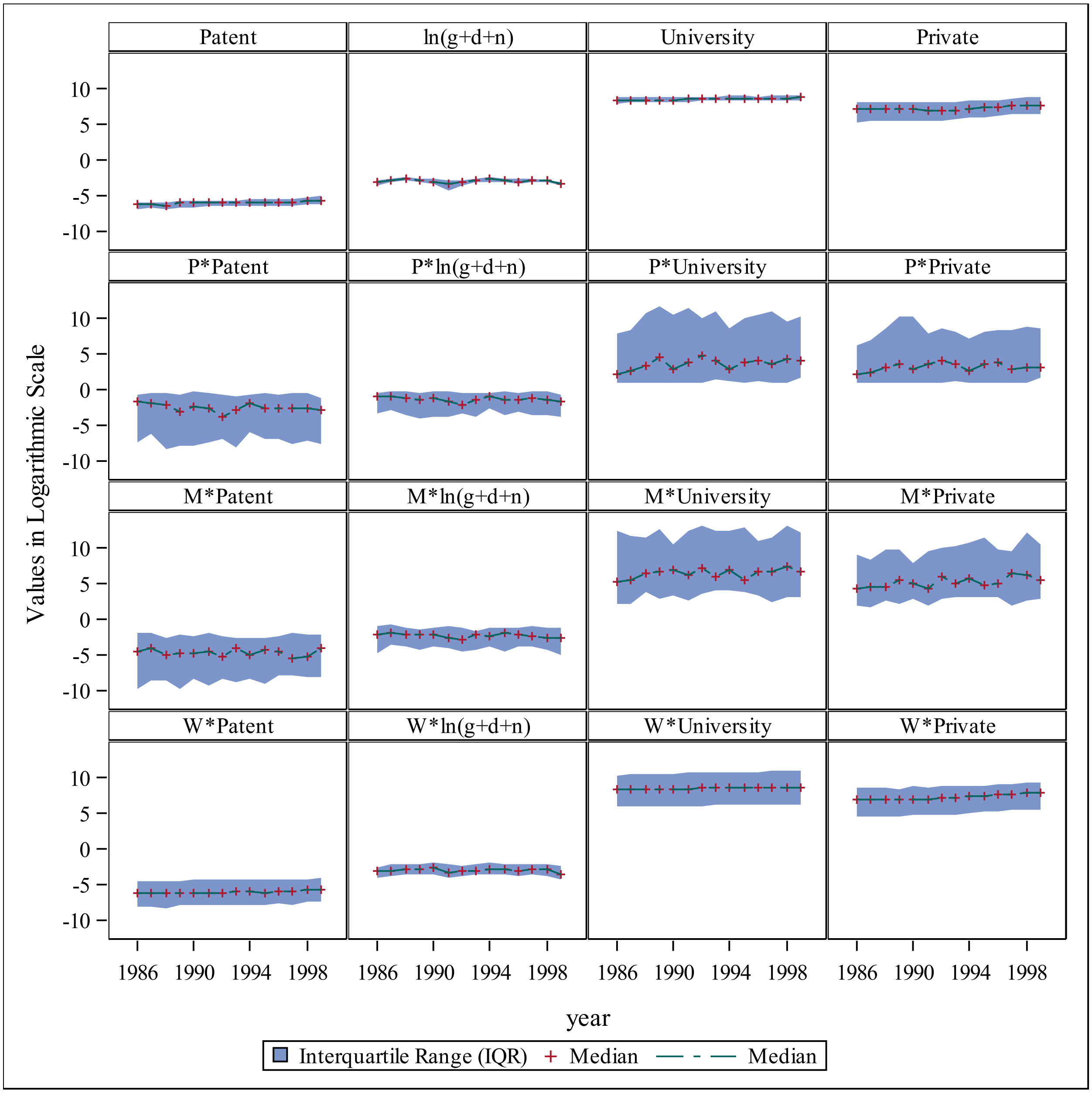
Patent
ln(g+d+n)
University
Private
P*Patent
P*ln(g+d+n)
P*University
P*Private
M*Patent
M*ln(g+d+n)
M*University
M*Private
W*Patent
W*ln(g+d+n)
W*University
W*Private
Values in Logarithmic Scale
10
5
0
-5
-10
1986 1990 1994 1998
year
Interquartile Range (IQR)
Median
Median

Table 2.1 Summary statistics. All variables are in log value.

	Mean	SD	Min	Q1	Median	Q3	Max
ln(Patent)	-6.077	0.682	-8.192	-6.529	-5.989	-5.587	-4.194
ln($\delta + \eta_{i,t} + g$**)**	-2.945	0.865	-8.638	-3.259	-2.908	-2.599	0
ln(c**)**	7.087	1.801	1.29	5.814	7.291	8.324	11.148
ln(h**)**	8.688	0.706	7.099	8.263	8.605	9.003	11.431
P.ln(Patent)	-5.413	8.091	-58.147	-7.43	-2.565	-0.535	1
P.ln($\delta + \eta_{i,t} + g$**)**	-2.583	4.069	-34.478	-3.453	-1.263	-0.286	1
P.ln(c**)**	6.699	9.504	0.033	1	3.12	8.468	77.344
P.ln(h**)**	8.032	11.545	0.031	1	3.77	10.257	91.657
M.ln(Patent)	-6.035	5.161	-30.898	-8.536	-4.648	-2.121	-0.061
M.ln($\delta + \eta_{i,t} + g$**)**	-2.925	2.493	-14.376	-4.114	-2.198	-1.04	-0.028
M.ln(c**)**	7.034	5.981	0.083	2.519	5.251	10.063	34.004
M.ln(h**)**	8.625	7.352	0.103	3.124	6.674	12.349	42.637
W.ln(Patent)	-6.077	2.237	-11.393	-7.805	-6.003	-4.265	-1.855
W.ln($\delta + \eta_{i,t} + g$**)**	-2.945	1.124	-6.889	-3.688	-2.943	-2.096	-0.524
W.ln(c**)**	7.087	2.612	1.739	5.082	7.265	8.878	13.715
W.ln(h**)**	8.688	3.011	2.736	6.148	8.587	10.935	15.456

While Table 2.1 offers several summary statistics of our variables pooled across states and years, Figure 1.1 displays their median over 1986-1999. The shaded areas indicate the Inter Quartile Range (IQR) so that it is clear that nearby states (W matrix) display a somewhat similar but less heterogenous level of input and output knowledge levels than the states connected to each other through patenting (P matrix) or migration (M matrix). Furthermore, we find that the median level of patent creation in the states educated workers and patents originate from is greater than the median level across the states (log values are -4.6 and -2.5 vs. -5.9) while the opposite is true for the median level of inputs (university and private R&D). It indicates that the states at the origin of the interregional flows are able to generate larger returns on their investments than the median state. The following section will highlight which of the knowledge input variables generate the largest returns.

2.4. Results

Model (7a) corresponds to a Spatial Durbin model that we estimate by Maximum Likelihood. In that purpose, we use the package *spdep* (Bivand *et al*., 2014) in R (R, 2015). LeSage and Pace (2009) note that its β-parameters cannot be interpreted as if they reflect linear regression slope coefficients. Their suggestion is to provide scalar summary measures of the Jacobian matrices containing the partial derivatives. That is, the mean of the main diagonal elements of these matrices produces a scalar summary of the direct effects while the mean of the sum of the off- diagonal elements from each row produces the scalar summary of the indirect effects. On the other hand, model (7b) can be estimated as a traditional panel data model, i.e. with either state fixed effects or random effects. Their goodness of fit is compared based on the ML results computed with the the *plm* package (Croissant *et al*., 2013) in R. The model with state fixed-effect dummy (SD) can be written as:

$$\ln y^*_{i,t} = \sum_{i=1}^{N} SD_i + \beta_1 \ln(\delta + \eta_{i,t} + g) + \beta_2 \ln s^c_{i,t} + \beta_3 \ln s^h_{i,t} + \beta_4 \ln(\delta + \eta_{i,t-1} + g)$$

$$+ \beta_5 \ln s^c_{i,t-1} + \beta_6 \ln s^h_{i,t-1} + \beta_7 \ln y^*_{i,t-1} + \gamma_1 \sum_{j\neq i}^{N} P_{i,j} \ln(\delta + \eta_{j,t-1} + g)$$

$$+\gamma_2 \textstyle\sum_{j\neq i}^{N} M_{i,j} \ln(\delta + \eta_{j,t-1} + g) + \gamma_3 \sum_{j\neq i}^{N} P \ln s^c_{j,t-1} + \gamma_4 \sum_{j\neq i}^{N} M_{i,j} \ln s^c_{j,t-1} +$$

$$\gamma_5 \textstyle\sum_{j\neq i}^{N} P_{i,j} \ln s^h_{j,t-1} + \gamma_6 \sum_{j\neq i}^{N} M_{i,j} \ln s^h_{j,t-1} + \gamma_7 \sum_{j\neq i}^{N} P_{i,j} \ln y^*_{j,t-1} + \gamma_8 \sum_{j\neq i}^{N} M_{i,j} \ln y^*_{j,t-1},$$

with the restrictions $-\beta_1 = \beta_2 + \beta_3$, $-\beta_4 = \beta_5 + \beta_6$, $\beta_7 = -\beta_4, -\gamma_1 = \gamma_3 + \gamma_5, -\gamma_2 = \gamma_4 + \gamma_6, \gamma_7 = -\gamma_1, \gamma_8 = -\gamma_2$.

The model with random effects would be the same as above but with $\beta_0 \ln \Omega_t$ instead of $\sum_{i=1}^{N} SD_i$.

Following LeSage and Pace's idea (2009), we report in Table 2.2 below the direct and indirect marginal effects of the Spatial Durbin model (7a). Their significance level is based on 500 random simulations of the parameters from the estimated variance–covariance matrix. While the direct effect of each regressor *r* captures the sum of the (spatial) feedback effects to the region of origin as well as the traditional effect within the region of interest ($\partial y_i/\partial x_{ri}$), the indirect effects represent the average value of the interregional spillovers ($\partial y_j/\partial x_{ri}$). In addition, we report the implied parameters and their significance level based on the delta method of Casella and Berger (2002) which builds on the estimated coefficient means and variance-covariance matrix.

Table 2.2 ML Estimation results of Model (7a). P-values in parenthesis.

	Restricted			**Unrestricted**		
	Estimates	**Direct Effects**	**Indirect Effects**	**Estimates**	**Direct Effects**	**Indirect Effects**
Effects						
Intercept	-7.927 (<0.001)			-15.507 (<0.001)		
ln(*h*)				0.500 (<0.001)	0.493 (<0.001)	0.377 (<0.001)
ln(*c*)				0.162 (<0.001)	0.164 (<0.001)	-0.075 (0.002)
$\ln(\delta + \eta_{i,t} + g)$				-0.006 (0.704)	-0.006 (0.612)	-0.003 (0.992)
$\ln(h) - \ln(\delta + \eta_{i,t} + g)$	0.124 (<0.001)	0.131 (<0.001)	0.183 (0.001)			
$\ln(c) - \ln(\delta + \eta_{i,t} + g)$	0.131 (<0.001)	0.126 (<0.001)	-0.137 (<0.001)			

W.ln(h)		0.443 (<0.001)
W.ln(c)		-0.066 (<0.001)
W.ln($\delta + \eta_{i,t}$ + g)		-0.003 (0.922)
W.(ln(h)-ln($\delta + \eta_{i,t}$ + g))	0.134 (0.011)	
W.(ln(c)-ln($\delta + \eta_{i,t}$ + g))	-0.140 (<0.001)	
Implied Parameters (Calculated using the Delta Method)		
α_1	-0.733 (0.131)	0.960 (<0.001)
α_2	0.766 (0.016)	-0.144 (0.036)
θ_1	0.634 (0.190)	-1.260 (<0.001)
θ_2	-0.870 (0.006)	0.046 (0.508)
ρ	0.146 (0.012)	-0.278 (<0.001)
Fit Statistics		
Log likelihood	-566.317	-378.922
AIC	1146.6	775.84
BIC	1178.35	816.622
R*	0.589	0.787
Jarque-Bera	0.541 (0.763)	46.997 (<0.001)
LR for restrictions	374.79 (<0.001)	
LM Tests		
LMERR test	0.102 (0.750)	0.006 (0.936)
Breusch-Pagan	61.45 (<0.001)	74.02 (<0.001)
Note: P-values calculated based on heteroscedasticity-consistent standard errors.		

As expected, we find that the direct effects of spending in R&D by private companies (**c**) as well as of spending in higher-education institutions (**h**) are positive and significant (Jaffe 1989; Audretsch and Feldman 1996; Ó hUallacháin and Leslie 2007) whether one focuses on the restricted or unrestricted model (the $-\beta_1 = \beta_2 + \beta_3$ and $-\gamma_1 = \gamma_2 + \gamma_3$ restrictions might not hold according to the result of the LR test). We also find that the spending in the academia that takes place across neighboring states is positively correlated with local innovation, which confirms the high degree of spatial association in education spending across the US States (Census Bureau, 2013). In addition, this result could reflect that at least part of the high-skilled workers migrates to nearby locations. While not focusing exclusively on the highly educated, Molloy *et al*. (2011) find that short-distance migration occurs more frequently than long-distance migration in the US. Our findings indicate also a negative effect of the neighbors' spending in private R&D. This result is in contradiction with the expectations of the literature (e.g. Bode, 2004; Anselin *et al*., 1997, 2000) and more especially Kang and Dall'erba (2015) who also explores the role of spatial externalities of private R&D spending. Indeed, their findings highlight the significant role of both proximity-based spillovers and actual long-distance spillovers on innovation production. The latter type of externality is obviously not included in the current model. Combined with a relatively low R* statistic which measures the Pearson correlation coefficient between the response variable and the fitted values, the results of Table 2.2 suggest that model (7a) is misspecified. We explore next whether Model (7b) that offers a different specification and a definition of inter-state spillovers that it not based on geographical contiguity can improve the results.

We estimate Model (7b) with fixed effects and random effects and we report their results in Table 2.3 below. In addition to a spatial weighting scheme that is closer to the actual data generation process, the reduced form model derived from theory includes the effect of past levels of investment in the state of interest and in the states it interacts with through in-migration and patent citation. Furthermore, the current model does not contain the spatial lag of the dependent variable as in (7a), so that the interpretation of the estimated marginal effect is direct. The log-likelihood, AIC, and BIC indicate that this model performs better than model (7a) in terms of goodness of fit. A closer look indicates also that the fixed effect model achieves a better fit than the random effect model, which is confirmed by the significant p-value of the Hausman test for both the restricted and unrestricted models. The results of the LR test indicate that the theoretical restrictions might not hold ($-\beta_1 = \beta_2 + \beta_3, -\beta_4 = \beta_5 + \beta_6,\ \beta_7 = -\beta_4, -\gamma_1 = \gamma_3 + \gamma_5, -\gamma_2 = \gamma_4 + \gamma_6, \gamma_7 = -\gamma_1, \gamma_8 = -\gamma_2$), however, the restricted model has the theoretical property that unrestricted model doesn't have, we still focus our interpretation of the results on the estimates of the fixed effect restricted model.

Table 2.3 Random Effects and Fixed Effects Estimation results for Model (7b). P-values in parenthesis.

	Restricted Model		**Unrestricted Model**	
	Fixed Effects Model (1)	**Random Effects Model (2)**	**Fixed Effects Model (3)**	**Random Effects Model (4)**
Effects				
Intercept		-6.745 (<0.001)		-2.590 (<0.001)
$\ln(h)_t - \ln(\delta + \eta_{i,t} + g)$	-0.029 (0.348)	-0.025 (0.415)		
$\ln(c)_t - \ln(\delta + \eta_{i,t} + g)$	0.078 (0.009)	0.076 (0.011)		
$\ln(h)_{t-1} - \ln(\delta + \eta_{i,t-1} + g) + y^*_{i,t-1}$	-0.045 (0.153)	-0.030 (0.337)		
$\ln(c)_{t-1} - \ln(\delta + \eta_{i,t-1} + g) + y^*_{i,t-1}$	0.093 (0.001)	0.086 (0.004)		
$\mathrm{P}.\ln(h)_{t-1} - \mathrm{P}.\ln(\delta + \eta_{i,t-1} + g) + \mathrm{P}.y^*_{i,t-1}$	-0.008 (0.168)	-0.008 (0.163)		
$\mathrm{M}.\ln(h)_{t-1} - \mathrm{M}.\ln(\delta + \eta_{i,t-1} + g) + \mathrm{M}.y^*_{i,t-1}$	-0.029 (<0.001)	-0.029 (<0.001)		

$P.\ln(c)_{t-1} - P.\ln(\delta + \eta_{i,t-1} + g) + P.y^{*}_{i,t-1}$	0.022 (0.005)	0.022 (0.005)		
$M.\ln(c)_{t-1}$ - $M.\ln(\delta + \eta_{i,t-1} + g) + M.y^{*}_{i,t-1}$	0.047 (<0.001)	0.045 (<0.001)		
$\ln(h)_t$			0.479 (<0.001)	0.440 (<0.001)
$\ln(c)_t$			0.012 (0.545)	0.007 (0.684)
$\ln(h)_{t-1}$			-0.255 (0.003)	-0.330 (0.001)
$\ln(c)_{t-1}$			0.046 (0.017)	0.039 (0.016)
$P.\ln(h)_{t-1}$			0.003 (0.672)	0.004 (0.550)
$M.\ln(h)_{t-1}$			-0.017 (0.138)	-0.014 (0.146)
$P.\ln(c)_{t-1}$			0.010 (0.128)	0.008 (0.064)
$M.\ln(c)_{t-1}$			0.017 (0.020)	0.015 (0.032)
$\ln(\delta + \eta_{i,t} + g)$			-0.011 (0.104)	-0.011 (0.043)
$\ln(\delta + \eta_{i,t-1} + g)$			0.011 (0.112)	0.010 (0.072)
$y^{*}_{i,t-1}$			0.684 (<0.001)	0.781 (<0.001)
$P.\ln(\delta + \eta_{i,t-1} + g)$			0.023 (0.029)	0.024 (<0.001)
$P.y^{*}_{i,t-1}$			0.003 (0.673)	0.003 (0.647)
$M.\ln(\delta + \eta_{i,t-1} + g)$			0.010 (0.275)	0.012 (0.055)
$M.y^{*}_{i,t-1}$			-0.009 (0.424)	-0.008 (0.364)

Implied Parameters (Calculated using the Delta Method)				
α_1	-0.028 (0.349)	-0.024 (0.415)	0.321 (<0.001)	0.304 (<0.001)
α_2	0.074 (0.009)	0.072 (0.010)	0.008 (0.542)	0.005 (0.682)
δ_1	-0.043 (0.152)	-0.029 (0.336)	-0.171 (<0.001)	-0.228 (<0.001)
δ_2	0.089 (0.002)	0.082 (0.004)	0.031 (0.021)	0.027 (0.018)
τ_c	-0.007 (0.168)	-0.007 (0.163)	0.002 (0.672)	0.003 (0.549)
τ_h	-0.028 (<0.001)	-0.027 (<0.001)	-0.011 (0.137)	-0.010 (0.151)
σ_c	0.021 (0.005)	0.021 (0.005)	0.007 (0.128)	0.006 (0.065)
σ_h	0.044 (<0.001)	0.043 (<0.001)	0.011 (0.021)	0.010 (0.035)
Fit Statistics				
Log likelihood	103.921	79.952	402.983	387.683
AIC	-93.843	-191.843	-677.966	-745.367
BIC	160.193	-156.189	-392.733	-678.515
R*	0.953	0.949	0.982	0.981
Jarque-Bera	97.774 (<0.001)	78.878 (<0.001)	79.506 (<0.001)	94.184 (<0.001)
LR for restrictions	598.124 (<0.001)	615.462 (<0.001)		
LM Tests				
Hausman's test	45.243 (<0.001)		27.122 (0.028)	
Breusch-Pagan test	5.842 (0.558)	8.639 (0.374)	10.536 (0.722)	31.795 (0.007)
LMERR test	0.166 (0.684)	3.419 (0.064)	0.649 (0.421)	0.290 (0.590)
Note: P-values calculated based on heteroscedasticity-consistent standard errors in model (4).				

The implied parameters indicate that spending in private R&D expenditure does not have a significant impact on innovation output whether ones focuses on this year's or last year's spending (parameters α_1 and δ_1 respectively). It is possible that additional time lags would be needed to discover a significant impact as it is well-known R&D expenditure takes time to produce any innovative output (Griliches, 1979, 1992). However, current and last year's R&D expenditure at universities and colleges are enough to display a statistically significant impact on innovation promotion. It confirms the results of Anselin *et al.* (1997) and Kang and Dall'erba (2015). When it comes to the spatial externalities, our findings indicate that spending in private and academic R&D in the states recent migrants come from has a positive and significant role on innovation production (parameters σ_c and σ_h respectively), which indicates that their experience and educational background are beneficial to the recipient area as we expected. On the other hand, academic R&D spending that takes place at time *t-1* in the states where patents are originally created is negatively correlated with the production of innovation at time *t* in the states that cite these patents (parameter τ_h). One possible explanation is that a patent-citing state may, intentionally or not, reduce its marginal spending in academic R&D in its own location if it is known that other states, the patent-creating states, are already bearing the costs of academic R&D. Since spending in academic R&D has a positive marginal effect on local innovation, the marginal effect of this "free-rider" behavior leads to a negative effect on local innovation. Another channel that could explain this negative relationship is that, on average, the states where patents are created are more innovative than those where the patents are cited so they may cite their locally-created patent themselves numerous times (Jaffe *et al*., 1993), hence increasing the degree of competition for innovation among states. A similar negative effect is found for private R&D spending taking place from patent-creating to patent-citing states (parameter τ_c), although the effect is not statistically significant. Kang and Dall'erba (2015) found a positive relationship for these latter two parameters when estimated across counties located more than 50 miles apart and in a cross-section setting. However, since the degree of industrial specialization is usually larger at the county- than at the state-level, it may be that, in the current study, the complementarity in the innovative process usually experienced at the county level is masked by the competitive effect that takes place at the state level. An approach combining the sectoral and the spatial dimensions of the flows of patent creation-citation would shed some light on this conundrum, but it is left for future research.

2.5. Conclusion

This study offers a spatial panel knowledge production function to analyze the impact of spending in private R&D, in academic R&D, as well as of knowledge spillovers on the production of innovation across US sates. Our approach brings new insights in this literature for several reasons. First, we expand the traditional theoretical knowledge production function of Griliches (1979) to include explicit knowledge externalities in it. It allows us to derive the reduced-form model from theory instead of following the usual approach by which the form of externalities is chosen ad-hoc or suggested through spatial statistics applied to the distribution of the errors. Second, in order to capture the role of interregional knowledge spillovers, we derive two specifications from theory. One controls for spillovers through pure geographical contiguity while in the other one spillovers take place through existing interregional flows of patent creation-citation and of migration of the highly educated workers. Naturally, the latter two matrices see changes in the intensity and direction of the interregional flows across years, a characteristic that has seldom been used in the spatial econometric literature in general and been completely overlooked in the regional KPF literature in particular.

The specification based on a W defined on proximity leads to a spatial lag model where the direct and indirect marginal effect of the inputs (spending in academic and private R&D) corresponds for the most part to our expectations. A better model fit is obtained in the specification with Ws defined on interregional migration and patent flows. The results of the spatial cross-regressive model it leads to indicate that the current and last year's R&D expenditure at universities and colleges support local innovation while private R&D may require more time to show the same effect. Our findings indicate also that past levels of R&D in the states migrants come from benefit the state they move to thus confirming the transfer of knowledge embedded in labor migration (Almeida and Kogut, 1999). The flows of patent creation-citation lead to a more novel result by which academic R&D spending that takes place at time *t-1* in the states where patents are originally created is negatively correlated with the production of innovation at time *t* in the states that cite these patents. While some "free-rider" and/or competitive behavior among the innovative agents may explain this result, it contradicts what the recent contribution of Kang and Dall'erba (2005) found. However, the latter study focuses on the U.S. counties for which the degree of industrial specialization is more often than not greater than at the state level so that the complementarity in the innovative process usually experienced at the county level could be masked by the competitive effect that takes place at the state level.

This chapter, like the bulk of regional KPF literature, has focused on a sectorally aggregated scheme. While some contributions have already touched upon the sectoral KPF approach (Jaffe, 1989; Anselin *et al*., 2000; Autant-Bernard and LeSage, 2011), none of them provides an estimate of the marginal effect of intra- vs. inter-sectoral spillovers by sector, rely on models derived from theory or on W matrices based on actual interregional knowledge flows. Further developments examining the interregional and sectoral nature of the transfer of knowledge are thus certainly needed.

CHAPTER 3 THE RICARDIAN MODEL OF CLIMATE CHANGE IMPACT MEETS THE RICARDIAN MODEL OF INTERREGIONAL TRADE: THEORY AND EVIDENCE

3.1. Introduction

The attention generated by the impact of the Summer 2012 drought on the Corn Belt exemplifies how vital it is for the US agricultural sector to understand climate change and how to mitigate and/or adapt to it. While there is little controversy about whether agriculture is sensitive to changes in climatic conditions, significant uncertainty exists with respect to future climate's impact on agriculture. It is anticipated that some regions will be winners and others losers, but it is still unclear whether climate change will bring a net gain or a net loss for the US agriculture as a whole (Adams, 1989; Mendelsohn *et al*., 1994; Deschênes and Greenstone, 2007), as production currently spans a variety of climate zones over all the lower 48 states and occupies up to 42% of US territory. Among the studies of climate impacts on US agriculture, three types of models can be identified. The first is the crop growth simulation model (e.g. Nordhaus, 1991; Tol, 1995; Mendelsohn and Neumann, 1999; Nelson *et al.*, 2009) which is based on agronomic (biophysical) models and focuses on simulating crop growth over the life cycle of a plant exposed to the full range of weather outcomes including extreme events. The second type of model uses standard econometric techniques to estimate the impact of climate and other exogenous inputs (such as soil quality) on one type of crop (e.g. McCarl *et al.,* 2008; Lobell *et al.,* 2008; and Schlenker and Roberts, 2009). Finally, the third theoretical framework called the Ricardian approach and initiated by Mendelsohn *et al.* in 1994 offers a different approach in that it explicitly account for adaptation. Landowners, well aware of their local production conditions, are expected to allocate their land to the most rewarding use. This framework has attracted much attention when analyzing the US agricultural sector (e.g. Schlenker *et al*., 2005, 2006; Deschênes and Greenstone, 2007; Dall'erba and Dominguez, 2015), partly because decisions on which crop to plant, how much of each input to use and what tillage/management technique to adopt are determined endogenously and will reflect in the value of farmland or agricultural profits, the usual dependent variables in a Ricardian regression framework (Kelly *et al*., 2005).

In this paper, we follow the latter approach for several reasons. First, empirical evidence clearly demonstrates that adaptation at the farm level is already taking place in the US. The 1996 report of Schimmelpfennig *et al.* indicates that “some of the alternatives considered are adoption of later maturing cultivars, change of crop mix, and a timing shift of field operations to take advantage of longer growing seasons”. Adaptation does not limit itself to crop-producers. Schimmelpfennig *et al.* (1996) report that “the growth of dairy in the South is a testament to the creativity of farmers in finding ways to cool animals in hot climates (for example, shading, wetting, circulating air, and air conditioning). Other adaptations include herd reduction in dry years, shifting to heat-resistant breeds, and replacing cattle with sheep”. Furthermore, the crop production approach treats each crop individually when crops are actually mutually dependent through factors such as crop rotation (practiced for 85% of the corn and 75% of the wheat of the US over 1990-1997, Padgitt *et al.,* 2000) or access to inputs (land, water, fertilizers, and government subsidies) whether they share the latter or compete for them.

Finally and more importantly for this current paper, the recognition that trade is going to act as an adaptation mechanism to climate change is growing (Julia and Duchin, 2007; Stephan and Schenker, 2012; Schenker, 2013; Zhang et al., 2014). Indeed, short-run production losses following a sudden drought or a flood for instance can be substituted for imports. Moreover, long-run climate changes should lead the production of some agricultural products to shift to countries which will then experience a competitive advantage compared to current producers.

Our paper offers important contributions to this literature for several reasons. First, while the contributions above have all focused on trade at the international level, ours focuses on the system of the US states only so that the traditional trade barriers can be ignored. Second, in spite of the growing spatial econometric literature that emphasizes the role of spatial dependence in the crop production function or Ricardian framework (Polsky, 2004; Seo, 2008; Lippert et al., 2009), dependence is always limited to geographical proximity. We argue that trade flows are more appropriate as they capture more substantive forms of dependence and their intensity and direction vary for each pair of partners. Third, we develop the reduced-form spatial model directly from theory instead of relying on the usual Lagrange Multiplier tests of Anselin *et al.* (1996) to select the right spatial model. Last but not least, we control for the role of spatial heterogeneity by relying on a nested hierarchical structure whereby the climate zones the US states belong to are explicitly modeled. It allows us to generate consistent estimates (Greene, 2000) and to account for within-group and between-group interactions (Moulton, 1986). A hierarchical approach is also used in Overmars and Verburg (2006) when considering field-level and village-level data or in Van Cauwenbergh *et al*. (2007) who deal with parcel-, farm- and landscape/region/state-level data when assessing agricultural systems sustainability. In the literature quoted earlier, the focus has primarily been on generating different coefficient estimates by groups to model spatial heterogeneity (Schlenker et al., 2005, split counties by irrigation level while Dall'erba and Dominguez, 2015, split them by elevation).

In order to shed new lights on the role of agricultural trade across US states in a Ricardian model of climate change, we start in section 2 with a review of the literature using spatial econometric techniques to deal with spatial dependence. We develop a theoretical Ricardian model with trade in section 3 where the data used for our empirical work is also described. Section 4 focuses on the estimation of the reduced-form spatial model and the interpretation of its results. Finally, section 5 summarizes the results and provides some concluding remarks.

3.2. Literature review

The recent surge in Ricardian contributions that acknowledge and model explicitly the role of spatial dependence is motivated by three factors. First, the mismatch in the location and boundaries of the physical (weather and soil data) and administrative (e.g. income, land value) data that enter the model is a clear example of ecological fallacy at the origin of spatial dependence in the error terms (Anselin and Cho, 2000). Second, spatial autocorrelation is intrinsic in the distribution of a Ricardian model's data because nearby places experience similar temperature and rainfall (Ezcuerra *et al*., 2008) and spillover effects across neighbors emanate from communication between farmers (Polsky 2004, Munshi 2004, Kumar 2011), technology and investment spillovers (McCunn and Huffman 2000, Chatzopoulos and Lippert 2016), a similar policy environment (Polsky 2004) and the distance between the source of irrigated water and the location of its use (Dall'erba and Dominguez, 2015). Third, the spatial econometric literature has now provided ample evidence that ignoring spatial autocorrelation present in a model leads to biased and inconsistent or inefficient estimates (Anselin, 1988; Le Sage and Pace, 2009) even when traditional spatial fixed effects are included in the model (Baltagi *et al*., 2007; Kapoor *et al*., 2007; Anselin and Arribas-Bel, 2013).

Table 3.1 Papers using spatial econometrics in Ricardian literature

	Study Region	Data Structure	Weighting Matrix	Spatial Model ***	Decision Rule	Estimation Method ****
Polsky (2004)	Great Plains (U.S.)	Panel data	Rook (1st order)	SAR	Unclear	MLE
Schlenker et al. (2006)	U.S. Counties	Panel data	Rook & Queen	SEM	Unclear	GMM
Deschenes and Greenstone (2007)	U.S. Counties	Panel data	Distance Circle (240km)	Nonparametric	---	Conley SHAC
Fisher et al. (2012)	U.S. Counties	Panel data	Distance Circle (240km)	Nonparametric	---	Conley SHAC
Dall'Erba and Dominguez (2015)	Southwest U.S.	Cross sectional	Revised Distance Circle *	SLX & SAR	Theory-based	GS2SLS
Seo (2008)	South America	Panel data	Not standard	SAR & SEM	Unclear	MLE
Kumar (2011)	India	Panel data	Rook (1st order)	SAR & SEM	Robust LM tests	MLE
Lippert et al. (2009)	Germany	Cross sectional	Rook (1st order)	SEM	Unclear	MLE
Schmidtner et al. (2015)	Germany	Cross sectional	Queen (1st order)	SEM	Robust LM tests	MLE
Chatzopoulos and Lippert (2016)	Germany	Cross sectional	Nearest Neighbor (6) **	SAR-IV & SARAR-IV	Unclear	GS2SLS

* 240 km distance cut-off matrix. Nonzero element is weighted by agricultural output ratio.
** 6 nearest neighbor matrix. Nonzero element is weighted by inverse distance.
*** SARAR stands for spatial autoregressive model with autoregressive disturbance. SEM stands for spatial error mode. Nonparametric means no parametric type spatial regression model is assumed. SLX stands for spatial lag of X model. SAR stands for spatial autoregressive model. SAR-IV (SARAR-IV) is SAR (SARAR) model with endogenous exploratory variables.
**** MLE stands for maximum likelihood estimator. Most of the authors uses Lesage and Pace (2009)'s MATLAB routines for MLE. GMM stands for Kelejian and Prucha (1999)'s GMM estimator for spatial correlation coefficient. Conley SHAC stands for Conley (1999)'s

nonparametric spatial heteroscedasticity autocorrelation consistent error estimator. GS2SLS stands for generalized spatial two-stage least square estimators developed by Kelejian and Prucha (1998, 1999, 2010) and Drukker et al. (2013).

Table 3.1 provides detailed information on the Ricardian contributions that have used a spatial econometric approach[3]. Two main shortcomings of the existing literature become clear. First, most of studies define the spatial weight matrix based on geographical proximity only. They choose either contiguity or great circle distance in order to do so. Even though geographical proximity has been used many times to approximate for the spatial interactions between different regions, some contributions argue that spatial weight matrices based on actual flow data are more appropriate theoretically and empirically as they change over time, they are non-symmetric and they provide a clear idea of directionality. Contributions along these lines are Eliste and Fredriksson (2004), Chen and Haynes (2014) who use trade flows and Kang and Dall'erba (2015) and Sonn and Storper (2008) who rely on actual flows of patent creation-citation.

Second, it is also clear that the model selection strategy is either arbitrary or, at best, based on the Lagrange Multiplier tests, their robust version and the decision rule described in Anselin and Florax (1995) and Anselin *et al.* (1996). It is well-known that it is limited to choosing between a spatial lag model (SAR) and a spatial error model (SEM) when other spatial model specifications are available. The earliest example is Polsky (2004) who runs a spatial lag model with group-wise heteroskedasticity across counties of the U.S. Great

[3] A spatial econometric approach has also been used in related literatures (see Holloway et al., 2007, and Brady and Irwin, 2011 for a thorough survey) such as the crop production function (Anselin et al., 2004; Schlenker and Roberts, 2009; Delbecq et al., 2012), and hedonic models of farmland value (Plantinga et al., 2002; Patton and McErlean, 2003; Huang et al., 2007; Maddison, 2009; Cotteleer et al., 2011).

Plains. Two articles published shortly after (Schlenker et al., 2006; Deschenes and Greenstone, 2007) choose to deal with spatial dependence through Conley's (1999) heteroskedasticity and spatial error autocorrelation consistent standard errors. Fisher *et al.* (2012) uses the same approach. However, this approach has been criticized for various reasons. Kelejian and Prucha (2007) indicate that Conley's (1999) estimator does not allow for Cliff-Ord type spatial feedback effects and it is defined for continuous space when these empirical works use discrete spatial units. Furthermore and more importantly, the authors assume that spillover effects are absent in their model. Indeed, as in the OLS case, the marginal effect of a change in region i following a change in region j, $\partial y_i/\partial x_j$, is zero in this approach. Dall'erba and Dominguez (2015) demonstrate that it is not appropriate when focusing on the US agriculture. For instance, the rainfall and snowpack of one locality can provide water for irrigation elsewhere and part of the agricultural goods produced in one location will be consumed elsewhere (for instance, only 30% of Arizona-produced agricultural goods consumed within the state, IMPLAN, 2010).

Some recent contributions formally model spillovers by standard spatial econometric means but their Ricardian analysis is not applied to the US case. Seo (2008) estimates both a SAR and a SEM in a study using South American agricultural household data. In a Ricardian study on India agriculture, Kumar (2011) uses the robust Lagrange Multiplier test (Anselin et al. 1996) to select the preferred spatial weighting matrix and model specification. Lippert *et al.* (2009), Schmidtner *et al.* (2015) and Chatzopoulos and Lippert (2016) focus on agriculture in Germany and use a two-stage least-squares (2SLS) approach to account for the endogeneity of the spatially lagged dependent variable

(Kelejian and Prucha, 1998). Dall'Erba and Dominguez (2015) offer a 2SLS approach too but discover that local spillovers (in a model with the spatial lag of some covariates, SLX) are more appropriate than the global spillovers embedded in a SAR model. Furthermore, their weight matrix combines proximity with the relative output of each pair of region to avoid symmetric flows.

In light of the existing literature, our contribution consists in deriving the reduced-form spatial model from theory and to rely on actual trade flows of agricultural goods to identify the role of interregional spillovers. Both elements are described further in the next section.

3.3 Theory, Spatial-Panel Model and Data Used

Our open-economy Ricardian model builds on the closed economy model that has dominated the literature so far. The profit $\pi_{i,k}$ associated with the *k*th potential use of farmer *f* 's land in location *i* depends on a set of local attributes $x_{i,c}$ that farmer *f* can control (such as irrigation and fertilizer) and of attributes $x_{i,nc}$ that he cannot control (soil characteristics, climate, local demand). However, in an open-economy framework, the latter attributes are complemented by a set of similar attributes $x_{j,c}$ and $x_{j,nc}$ that take place among all trade partners $j \neq i$, hence on which *i* has no control. The process by which the farmer located in *i* maximizes the value of the profit function is written as:

$$\max \pi_{i,k} = p_k q_{i,k}\left(x_{i,k,c}, x_{i,k,nc}, \sum_{k=1}^{\infty} \sum_{j \neq i} x_{j,k,c}\,, \sum_{k=1}^{\infty} \sum_{j \neq i} x_{j,k,nc}\right) - c_{i,k}\left(x_{i,k,c}, x_{i,k,nc}\right) - P_{i,k} L_i\left(x_{i,k,c}, x_{i,k,nc}\right) \quad (1)$$

where p_k=(p_1, …, p_{N_k}) is the vector of output prices associated with k*th* use of land. This factor does not change by location as each individual farmer is assumed to be a price-taker since each individual produces too little to have any influence on prices. $q_{i,k}$ is the vector of the quantity of good *k* produced in location *i*. It is a function of locally controllable and non-controllable inputs as well as of similar inputs located in trade partners *j* used for the production of goods similar to or other than *k*. Finally, $c_{i,k}$=($c_{i,1}, \dots, c_{i,N_k}$) is the vector of input prices bar the cost (or rent) $P_{i,k}$ of land in location *i* used for *k* applied to the quantity of land L_i. The farmer is assumed to maximize his profit by selecting the optimal level of attributes $q_{i,k}, x_{i,k,c}$ and L_i given the level of all the attributes it cannot control ($x_{i,k,nc}$, $\sum_{k=1}^{\infty}\sum_{j\neq i} x_{j,k,c}$ and $\sum_{k=1}^{\infty}\sum_{j\neq i} x_{j,k,nc}$).

From an econometric viewpoint, a linear or semilog equation can approximate for the (per acre) profit envelope of the *k* (1, …, N_k) possible land uses by assuming that land in any location is put to its most profitable use at any time *t* as follows:

$$\left(\frac{\pi_i}{L_i}\right)_t = g(x_{i,c}, x_{i,nc}, \textstyle\sum_{j\neq i} x_{j,c}, \sum_{j\neq i} x_{j,nc}) \qquad (2)$$

where *g* is a possible transformation of the attributes farmer *f* can control ($x_{i,c}$) and has no control over ($x_{i,nc}, \sum_{j\neq i} x_{j,c}, \sum_{j\neq i} x_{j,nc}$). The reduced form model that derives from (2) is therefore a SLX model written as below:

$$y = \alpha\iota_n + X\beta + WX\theta + \varepsilon \quad \text{with } \varepsilon \sim N(0, \sigma^2 I_n) \qquad (3)$$

where, for any regressor r, $\partial y/\partial x_r = \beta + W\theta_r$. The second element refers to local spillovers that capture how changes in the conditioning variables of the importing states affect profits in the exporting states.

Model (3) is applied to the 48 U.S. continental states over the U.S. Agriculture Census years of 1997, 2002, 2007 and 2012. All the economic variables have been converted to constant 2012 USD using the corresponding Consumer Price Index (CPI). Our dependent variable is agricultural profit (the difference using agricultural income minus agricultural expense) per acre and it comes from the U.S. Department of Agriculture (USDA). Agricultural profit generally increases from west to east and increases significantly through the years.

Our independent variables capture a set of local and interregional conditions that we now describe. The North American Regional Reanalysis (NARR) (Mesinger *et al.,* 2006) is used as the proxy for observations of past climate data as it assimilates observed precipitation and temperature. NARR data are available for the conterminous US and are at a 32-km spatial resolution, 3-hourly temporal resolution for the period 1979-present. Hence, we used a spatial interpolation method to calculate a state's values and aggregate, at first, the data to the monthly level. In addition to temperature and precipitation, we use their squared values to capture their non-linear effect. Because the effect of climate varies across seasons, we separate the effect to each of the four seasons: March through May is Spring, June through August is Summer, September through November is Fall, December to February is Winter. We include both linear and quadratic terms for the weather variables. The linear term reflects the marginal value of weather evaluated at the grand mean across all 48 states for 5 time points, while the quadratic term shows how that marginal effect will change as one moves away from the grad mean. We also included variables reflecting the proportions (percentages) of farmlands having severe drought (drought) and severe wet (flood) conditions averaged across all months for each state and each year.

The variable indicated as the “human intervention” is the total demand (i.e. final and intermediate demand) for commodities with SCTG codes 1-7 (in million dollars) for each state and each year. A brief description of the SCTG codes can be found in Table 3.2. These data come from the Regional Economic Accounts developed by the Bureau of Economic Analysis (BEA). Furthermore, we rely on the percentage of farmland using fertilizer and the percentage of farmland using irrigation to control for the usual inputs in the agricultural production process. These data are found from USDA. The summary statistics of our data are reported in Table 3.3 below.

Table 3.2 Standard Classification of Transported Goods (SCTG) Commodity Codes

Code	Contents
01	Animals and Fish (live)
02	Cereal Grains (including seed)
03	Agricultural Products Except for Animal Feed (other)
04	Animal Feed and Products of Animal Origin
05	Meat, Fish, and Seafood and Their Preparations
06	Milled Grain Products and Preparations, and Bakery Products
07	Other Prepared Food Stuffs, and Fats and Oils

Table 3.3 Summary Statistics for Response and Explanatory Variables

Variable	Mean	Std	Min	Q1	Median	Q3	Max
Agricultural Profit	90.676	96.731	-124.043	22.097	66.8	125.604	596.349
Share of Irrigation (%)	6.483	7.817	0.055	1.201	3.336	10.229	35.584
Log Fertilizer	14.542	1.723	9.509	13.501	14.987	15.816	16.793
Total demand	12096.234	16911.823	0	2406.483	6927.149	16617.021	109035
Spring Temp	12.213	5.423	1.889	8.06	11.452	16.368	25.301
Summer Temp	24.767	3.844	17.364	21.533	24.984	27.678	34.013
Fall Temp	13.553	4.343	5.944	10.116	13.078	16.676	24.793
Winter Temp	0.944	6.268	-12.386	-3.969	0.553	5.034	18.455

Spring Temp^2	178.414	143.909	3.568	64.96	131.164	267.906	640.117
Summer Temp^2	628.1	191.897	301.493	463.689	624.214	766.094	1156.878
Fall Temp^2	202.436	127.22	35.331	102.35	171.034	278.075	614.692
Winter Temp^2	13.701	68.677	-153.422	-15.754	0.305	25.344	340.599
Spring Prec	7.103	3.423	0.319	4.86	7.221	9.346	15.966
Summer Prec	6.985	3.355	0.205	4.559	7.26	9.102	20.062
Fall Prec	6.173	3.05	0.9	3.778	6.067	8.096	16.766
Winter Prec	6.063	3.409	0.433	3.193	6.372	8.264	16.188
Spring Prec^2	62.106	53.959	0.101	23.624	52.139	87.352	254.907
Summer Prec^2	59.998	52.717	0.042	20.789	52.702	82.839	402.479
Fall Prec^2	47.367	43.621	0.81	14.274	36.81	65.543	281.109
Winter Prec^2	48.318	48.094	0.188	10.2	40.604	68.294	262.048
W*Share of Irrigation (%)	7.449	5.197	0.624	4.315	5.812	8.08	28.71
W*Log Fertilizer	15.249	0.968	11.999	15.013	15.451	15.847	16.589
W*Total demand	24794.562	13995.736	3895.488	17106.96	21222.424	26604.17	84396.063
W*Spring Temp	12.387	3.233	3.679	9.939	12.478	14.815	19.613
W*Summer Temp	24.881	2.334	19.429	23.392	24.874	26.486	30.964
W*Fall Temp	13.679	2.266	6.896	12.177	13.489	15.38	20.309
W*Winter Temp	0.948	3.336	-9.258	-1.087	1.18	3.081	8.258
W*Spring Temp^2	178.743	82.232	13.533	114.642	172.409	238.056	400.953
W*Summer Temp^2	632.051	116.758	379.105	554.351	624.972	710.445	968.431
W*Fall Temp^2	203.161	64.522	47.561	158.929	194.214	249.902	417.471
W*Winter Temp^2	12.105	29.919	-94.642	-3.202	11.656	29.054	80.935
W*Spring Prec	7.146	1.971	2.378	5.694	7.157	8.514	11.943
W*Summer Prec	6.954	2.273	0.92	5.35	7.577	8.583	13.3
W*Fall Prec	6.113	1.81	2.328	4.804	6.166	7.181	10.375
W*Winter Prec	6.084	1.69	0.993	5.263	6.277	7.159	9.989
W*Spring Prec^2	61.071	30.608	7.977	35.182	57.776	82.026	150.938
W*Summer Prec^2	60.469	28.276	1.124	38.508	63.663	81.011	177.123
W*Fall Prec^2	44.548	24.248	5.552	27.034	40.829	55.204	113.07
W*Winter Prec^2	46.347	20.81	0.994	34.26	44.655	58.429	115.102
Ave. % of Severe Drought	12.609	19.319	0	0	2.728	17.986	86.516
Ave. % of Severe Wet	4.16	6.978	0	0	0.704	4.883	46.661
W*Ave. % of Severe Drought	10.996	10.479	0.001	1.384	8.481	17.237	47.315
W*Ave. % of Severe Wet	5.462	3.973	0.542	3.081	4.742	7.009	34.707

While a set of soil characteristics is often used to capture differences in the level of fertility across spatial units in a cross-section setting, a state fixed effect can capture them in a panel data model since they do not change over time. Furthermore, we account for the first time in the Ricardian literature for the hierarchical nature of our data. State-level weather observations are dependent on the climate zone they belong to. We rely on the data from NOAA (National Oceanic and Atmospheric Administration) to allocate the states across climate zones and on a hierarchical structure depicted as follows to capture their role:

$$y_{ijt} = \alpha + X'_{ijt}\beta + (W_t X_{ijt})'\theta + \tau_{ij} + \mu_i + \varepsilon_{ijt} \quad \text{with } \varepsilon_{ijt} \sim N(0, \sigma_\varepsilon^2) \tag{4}$$

where index i is for climate zones (i = 1,…, 9) and index j is for the states nested within climate zone i (See Table 3.4 for the list of states within each climate zone). Note that, the parameter β and parameter θ are invariant to *states j* in climate zone i as indicated in Equation (4). This shows the climate zone will give an impact on the overall intercept α by putting additional effect upon the state level effect. The climate zone effect will not have impact on the slope parameters such as β and θ. Furthermore, since the climate zone dummy μ_i and the state dummy τ_{ij} are time-invariant, this gives light to use a fixed effect panel model which removes these time-invariant effects.

Table 3.4 Climate Zones for 48 U.S. Continental States

Region	States
Central	Illinois (IL)
	Indiana (IN)
	Kentucky (KY)
	Missouri (MO)
	Ohio (OH)
	Tennessee (TN)
	West Virginia (WV)
East North Central	Iowa (IA)
	Michigan (MI)
	Minnesota (MN)
	Wisconsin (WI)
Northeast	Connecticut (CT)
	Delaware (DE)
	Maine (ME)
	Maryland (MD)

	Massachusetts (MA)
	New Hampshire (NH)
	New Jersey (NJ)
	New York (NY)
	Pennsylvania (PA)
	Rhode Island (RI)
	Vermont (VT)
Northwest	Idaho (ID)
	Oregon (OR)
	Washington (WA)
South	Arkansas (AR)
	Kansas (KS)
	Louisiana (LA)
	Mississippi (MS)
	Oklahoma (OK)
	Texas (TX)
Southeast	Alabama (AL)
	Florida (FL)
	Georgia (GA)
	North Carolina (NC)
	South Carolina (SC)
	Virginia (VA
Southwest	Arizona (AZ)
	Colorado (CO)
	New Mexico (NM)
	Utah (UT)
West	California (CA)
	Nevada (NV)
West North Central	Montana (MT)
	Nebraska (NE)
	North Dakota (ND)
	South Dakota (SD)
	Wyoming (WY)

Our spatial weight matrix corresponds to the actual flows of interstate trade of agriculture goods for the four census years starting in 1997. Data come from Commodity Flow Survey (CFS) from the US census. After removing the diagonal values that capture the (the trade flows within each state), we decide to column standardize the trade weight matrix so that a fixed portion of demand in state *j* increases agricultural profit in state *i*.

Assuming there are unique attributes of state-level effects and climate zone level effects that are not the results of random variation and that do not vary across time [(as stated in Equation (4)], then the fixed effect panel model is used. This is also called the "Least Squares Dummy Variable Model" (LSDVM), because the time-invariant dummy variables are added for the hierarchical structure. The fixed effect panel model is proposed to be used because of its nice property to allow both state and climate zones to be time-invariant, however, the fixed effect panel model are usually not as efficient as the random effect panel model. A Hausman's test is thus performed to compare between the fixed effect panel model and the random effect panel model. Furthermore, we will also test the hypothesis of a significant time lagged dependent variable y_{ijt-1} in our model. In that purpose, we use the Arellano and Bond (1991) difference generalized methods of moment (GMM) estimator first proposed by Holtz-Eakin, Newey and Rosen (1988). Results for these various model settings are presented in the next section.

3.4 Results

Only the random effect panel model estimates associated to the state and climates zones are reported in Table 3.5. Other model estimates, such as fixed effects panel model (which provides very similar results) and pooling panel model are not reported but they are available from the authors upon request.

Table 3.5 Random effect panel model results

Type of variable	Variable name	Intrastate effects		Interstate effects	
		Estimate	P-value	Estimate	P-value
Human Intervention	Intercept	-727.877	0.361	N/A	N/A
	Share of Irrigation (%)	11.332	0.040	-2.008	0.492
	Log Fertilizer	5.610	0.476	17.249	0.534
	Total demand	0.001	0.326	-0.002	0.124

Weather					
	Spring Temp	28.222	0.016	-66.563	0.016
	Summer Temp	18.108	0.585	36.550	0.639
	Fall Temp	-28.379	0.173	-3.043	0.950
	Winter Temp	-8.583	0.272	-12.104	0.170
	Spring Temp^2	-0.897	0.044	2.214	0.058
	Summer Temp^2	-0.045	0.947	-0.914	0.583
	Fall Temp^2	0.626	0.362	0.464	0.779
	Winter Temp^2	0.463	0.297	1.680	0.090
	Spring Prec	5.671	0.555	35.438	0.013
	Summer Prec	6.642	0.499	-25.730	0.277
	Fall Prec	3.998	0.536	-20.177	0.315
	Winter Prec	6.093	0.601	58.721	0.051
	Spring Prec^2	0.077	0.850	-2.174	0.024
	Summer Prec^2	-0.353	0.463	-0.021	0.987
	Fall Prec^2	-0.046	0.887	1.154	0.356
	Winter Prec^2	-0.290	0.621	-3.531	0.076
	Ave. % of Severe Drought	0.471	0.321	-2.752	0.021
	Ave. % of Severe Wet	-0.237	0.790	-2.022	0.293
LM test					
	Breusch-Pagan test	93.643 (0.0002)			
	Test for serial correlation	51.385 (<0.001)			
	Test for spatial dependence	0.004 (0.9512)			
Fit statistics					
	AIC	2087.756			
	BIC	2257.146			
	Log-likelihood	-991.878			
	Adj R^2	0.3085			

Comparing the fixed effect panel model with the random effect panel model, the Hausman's test shows the chi-squares test statistic of 7.097 with degree of freedom of 42 and p-value >0.999. This concludes that the random effect panel model is more efficient than the fixed effect panel model while also not losing the consistency of the estimates. Because of this, the random effect panel model is used. In conventional Ricardian analysis, the square terms for the weather variables are included in the model. This was not clear if in a SLX setting the square terms should also be included. To illustrate this, we perform a likelihood ratio test comparing the full model (including the squared spatially lagged weather variables) with the corresponding reduced model (removing the squared spatially lagged weather variables). The chi-squares test statistic is 18.462 with degrees of freedom of 8 and p-value of 0.018. Therefore, the full model has significantly better fit than the reduced model and the squared spatially lagged weather variables are included in the final model.

For the weather variables, in general, we see the unweighted variables are likely to be non-significant and were smaller in magnitude compared to their weighted version, which tend to be significant and have much bigger magnitude. This general phenomenon shows strong spillover effects through trade flows, or in other words, relationship between profit and these exogenous variables might be better explained through trade flows. Specifically, for the weather variables, the estimates from the fixed panel model shows that unweighted seasonal temperatures (see the shaded cells in Table 3.5) have more impact on profit than the unweighted seasonal precipitation. It predicts that the profit will be increased by about \$28M if the average temperatures in spring increases by one degree. The linear terms for other seasons are non-significant. The spring temp^2 also shows significant result, however, the magnitudes (only about \$0.9M decrease) are much smaller than its linear correspondences. The other quadratic terms are non-significant. Interestingly, only temperature in spring is significant, also the significant quadratic terms shows the relationship is non-linear, however, the magnitude of the quadratic term shows such non-linear relationship is not very different from linear. The unweighted precipitation variables are less interesting as all of them are non-significant. Besides the precipitation variables, we also find that the average proportion of extreme drought farmland and average proportion of extreme wet farmland are also both non-significant.

For the unweighted human intervention variables, as expected, the main player is the share of the irrigated farmland. The unit for it is the percentage, as showed in Table 3.5. The random effect panel model reports that the profit is expected to be increased by approximately \$11M if the share of the irrigated farmland is increased by 1%. The log of the fertilizer usage and total value of agricultural commodity (total demand) don't show the significance effect from the random effect panel model.

The results from the unweighted variables reflect the relationship between the explanatory variables and profit locally (i.e., intrastate effect). The results from the weighted variables reflect the spillover effects on those explanatory variables from other states through the trade flows (i.e., interstate effect). For the seasonal temperature variables, the first impression is that, again, only weighted spring temperature showed significant result, but with negative sign. This is different from what we see earlier for its unweighted version, that the sign was positive. The random effect panel model reports about \$67M drop in profit when spatially lagged spring temperature is increased by 1 degree. This shows that through spatial weighting, higher temperature in spring will decrease the profit. Such decreasing effect has more impact on the profit since the magnitude of the weighted spring temperature is higher than the unweighted one. All the other terms are non-significant including the quadratic terms (weighted spring^2 is significant at 0.1 level), showing that the relationship between weighted seasonal temperature and profit is more likely to be linear. This is different from the conventional quadratic relationship between temperature and profit reflected from the analysis of the unweighted temperature.

Comparing to spatially lagged seasonal temperature, spatially lagged seasonal precipitation is perhaps more relevant to profit. The total precipitation in cold seasons (spring and winter) are generally lower than that in warm seasons (summer and fall), therefore, spring and winter are generally “dry seasons” for continental states in the U.S. and summer and fall are generally “rain seasons” for continental states in the U.S. The first impression from the weighted seasonal precipitation is that the signs are positive for dry seasons and the signs are negative for wet seasons. This shows that in general, precipitation will help to increase the profit if precipitation is in need and excessive rainfall in wet seasons might decrease the profit. Interestingly, among the four seasons under consideration, again only spring shows significant results. The random effect panel model reports that the profit will be significantly increased by about \$35M when the spatially lagged total precipitation in spring increases by 1 unit. When the spatially lagged total precipitation in winter increases by 1 unit, the profit will be significantly increased by about \$59M (at 0.1 level of significance). Their corresponding quadratic term are also significant at 0.1 level showing such relationship might be non-linear, however, the magnitude of the quadratic terms shows that the quadratic relationship might not be very strong.

The spatially lagged average percentage of extreme drought farmland shows significant negative effect on the agricultural profit. The random effect model shows that the decrease is \$2.8M if the average proportion of severe drought is increased by 1%.

In terms of model fit, log-likelihood, AIC, BIC, and adjusted R^2 are calculated for the random effect panel model, where R* is simply the correlation between the model prediction and the response variable.

The global Moran's I test for the profit of 48 states across 4 time points using the dynamic spatial-temporal weights matrix (this is a combined year-specific spatial weight matrix which construction process was discussed in the previous section) shows that the Moran's I statistic is 0.08 with expected value of -0.005 and variance of 0.001. The Z-statistic for Moran's I test is 2.4554 with p-value of 0.001. The significant positive value of the Z-statistic shows there is significant clustering effect for the profits regarding the overall dynamic spatial-temporal weights. This shows that the spatial-temporal consideration using the constructed weights matrix is necessary.

Lagrange-Multiplier (LM) test are performed for testing heteroscedasticity, spatial autocorrelation, and serial autocorrelations. The heteroscedasticity and serial autocorrelation are evidenced while the spatial autocorrelation is not significant. This suggests that a Heteroscedasticity and Autocorrelation (serial) Consistent (HAC) covariance matrix adjustment is needed for the variance estimates of the regression coefficients. As such, all the results reported in Table 3.5 are HAC adjusted.

Table 3.6 General Methods of Moments Panel Model Results

Type of Variable	Variable name	Intrastate effects		Interstate effects	
		Estimat e	p-value	Estimat e	p-value

	Agricultural Profit (Lag 1)	0.295	<0.0001	N/A	N/A
Human Intervention					
	Share of Irrigation (%)	11.568	<0.0001	-5.110	0.065
	Log Fertilizer	0.096	0.984	2.176	0.913
	Total demand	0.003	0.001	-0.001	0.301
Weather					
	Spring Temp	54.295	<0.0001	-90.408	<0.0001
	Summer Temp	-66.265	0.028	109.417	0.061
	Fall Temp	-53.590	0.006	24.664	0.472
	Winter Temp	-17.275	0.005	-7.567	0.174
	Spring Temp^2	-0.920	0.003	1.847	0.011
	Summer Temp^2	1.330	0.011	-1.858	0.084
	Fall Temp^2	1.621	0.016	-0.493	0.626
	Winter Temp^2	0.068	0.843	3.497	<0.0001
	Spring Prec	7.501	0.321	34.650	0.004
	Summer Prec	20.776	0.015	26.515	0.128
	Fall Prec	19.549	<0.0001	-25.284	0.278
	Winter Prec	-3.563	0.712	20.777	0.439
	Spring Prec^2	0.004	0.990	-2.514	<0.0001
	Summer Prec^2	-1.346	<0.0001	-2.904	0.008
	Fall Prec^2	-1.187	<0.0001	2.080	0.154
	Winter Prec^2	0.787	0.166	-0.563	0.755
	Ave. % of Severe Drought	-0.213	0.404	-1.897	0.009
	Ave. % of Severe Flood	-0.209	0.790	5.915	<0.0001
Diagnostic tests					
	Sargan Test	7.074 (0.132)			
	Test for Autocorrelation	0.658 (0.5105)			

The GMM model differs from the random effect panel model by adding a temporally lagged profit (by one time point) as one additional explanatory variable and using higher order temporally lagged profit as instrument variables, as in Arellano and Bond (1991). Since the temporally lagged response variable is used as one of the explanatory variable, the conventional independence assumption in OLS estimates is violated, consequently, the model has to be estimated by using GMM. A benefit of adding temporally lagged profit is, however, making the model dynamic. In general, the GMM model estimates are more sensitive, i.e., it provides more significant findings than the random effect panel model. For the weather variables, the unweighted linear spring temperature is still significantly positive, but with higher magnitude (now, about $54M increase). The other seasons show negative impact on agricultural profit ranging from -$17M (winter) to -$66M (summer), respectively. The weighted spring temperature shows significant negative impact on agricultural profit with magnitude of -$90M, while the weighted summer temperature shows significant positive impact on agricultural profit with magnitude of $109M at 0.1 level of significance. For precipitation, the findings are similar from the random effect panel model. The unweighted summer and fall precipitation show significant positive effect on profit while the weighted spring precipitation shows significant positive effect. It is interesting to see that the precipitation all have positive impact on profit but the intrastate effect happens on rain seasons while the interstate effect happens in dry seasons. This shows that trade helps to increase the profit when more rain is needed in dry seasons while it won't help much in rain seasons. The weighted average percentage of severe drought farmland is significantly negative and the weighted average percentage of severe wet farmland is significantly positive. Again, when there is excessive rain fall, the trade will help to bring up the profit. For human intervention variables, significant positive results are found for share of irrigation and total demand, which echo the findings from the random effect panel model on share of irrigation but also additionally shows significant positive result for total demand. The spatially lagged share of irrigation is slightly negative compared to its unweighted version.

Because the GMM model is not based on likelihood, log-likelihood, AIC, and BIC are not calculated, instead standard diagnostic tests for panel GMM models are reported. As a standard procedure, Sargan's J test (Sargan, 1988) shows the model restriction is not over-identified. The tests of autocorrelation also shows non-significant autocorrelation is presented. There is no easy way to test for spatial autocorrelation under GMM SLX models currently.

3.5 Conclusions

While adaptation to future weather conditions is a well-documented feature of the Ricardian literature, the role of trade as a mechanism of adaptation has been investigated at the international level only (Julia and Duchin, 2007; Stephan and Schenker, 2012; Schenker, 2013; Zhang et al., 2014). Yet, there is no reason why one should not expect states within the US to also import more from other states after they got hit by an unexpected weather event such as a drought or for them to change the nature and direction of their trade of agricultural products based on new weather conditions. As such, this study fills this gap by studying the role of interstate trade in agricultural products on agricultural profits across the 48 U.S. continental states and the four census years of 1997-2012.

Starting with a theoretical Ricardian model where the weather conditions, farm inputs and local level of demand in the state of interest and in its trade partners act as control variables, we derive a reduced-form model taking the form of a SLX model. It implies that a change in the above conditions within the boundaries of the importing states will affect the level of per acre profit in the exporting state. Maximum Likelihood and GMM estimates are generated for a hierarchical model where states are nested within the climate zone they belong to and various types of individual effects are tested (pooled model, fixed effect model, random effect model, mixed effect model). Since various model results are generally consistent with each other, we mainly report the findings from the random effect panel model and the difference GMM because of their consistency and efficiency. They highlight, first, the non-linear relationship between unweighted weather variables and agricultural profit. We also find that unweighted spring temperature (also unweighted spring^2) have a significant impact (at 5% level) on agricultural profit. Local precipitation and extreme events are not found to affect profits significantly (by random effect panel model), which may be because irrigation mitigates their marginal effect. However, the weighted spring participation has significant positive impact on profit, and it seems to suggest that for dry seasons (spring and winter), more participation will lead to more profit through trade. We also find that some of the weather conditions (severe drought and severe flood) experienced in the importing states influence significantly profits in the exporting states. When it comes to the data capturing human intervention, the results confirm our expectations: more irrigation leads to higher profits.

APPENDIX A FOR CHAPTER 2

Taking the system of Equations (1b-1c), and dividing them by $L_{i,t}$, we have:

$$\frac{\dot{C}_{i,t}}{L_{i,t}} = s_i^c y_{i,t} - \delta c_{i,t}$$

(A1a)

$$\frac{\dot{H}_{i,t}}{L_{i,t}} = s_i^h y_{i,t} - \delta h_{i,t}$$

(A1b)

Since $\frac{\dot{L}_{i,t}}{L_{i,t}} = \eta_i$ and for any other input X:

$$\dot{x} \equiv \frac{d\left(\frac{X_{i,t}}{L_{i,t}}\right)}{dt} = \frac{\dot{X}_{i,t}}{L_{i,t}} - \frac{\dot{L}_{i,t}}{L_{i,t}}x$$

Implying $\dot{x} = \frac{\dot{X}_{i,t}}{L_{i,t}} - \eta_i x$

Rewriting (A1a-b), we have:

$$\dot{c}_{i,t} = s_i^c y_{i,t} - (\delta + \eta_i)c_{i,t}$$

(A2a)

$$\dot{h}_{i,t} = s_i^h y_{i,t} - (\delta + \eta_i)h_{i,t}$$

(A2b)

or in growth rate

$$\frac{\dot{c}_{i,t}}{c_{i,t}} = s_i^c \frac{y_{i,t}}{c_{i,t}} - (\delta + \eta_i)$$

(A3a)

$$\frac{\dot{h}_{i,t}}{h_{i,t}} = s_i^h \frac{y_{i,t}}{c_{i,t}} - (\delta + \eta_i)$$

(A3b)

Since we have diminishing return to scale in per capita terms, the growth rate for input X at steady state ($\frac{\dot{x}^*}{x^*}$) should be constant over time because δ, η_i and s in equations (A2a-b) are constant over time. It implies that at the steady state, $\frac{y_{i,t}^*}{x_{i,t}}$ is a constant, hence:

$$\frac{d(\frac{y_{i,t}^*}{x_{i,t}})}{dt} = 0 \qquad \text{(A4)}$$

Dividing both sides of equation (5a) by $\ln c_{i,t}$ leads to:

$$\ln \frac{y_{i,t}}{c_{i,t}} = \ln \Omega_t + (\theta_1 + \alpha_1 - 1) \ln c_{i,t} + (\theta_2 + \alpha_2) \ln h_{i,t} - \alpha_1 \rho \sum_{j \neq i}^{N} W_{i,j} \ln c_{i,t} - \alpha_2 \rho \sum_{j \neq i}^{N} W_{i,j} \ln h_{i,t} + \rho \sum_{j \neq i}^{N} W_{i,j} \ln y_{j,t}$$

(A5)

Equation (A3a) implies that the derivative of equation (A5) over time is:

$$\frac{d(\frac{y_{i,t}^*}{c_{i,t}})}{dt} = \frac{\dot{\Omega}_t}{\Omega_t} + (\theta_1 + \alpha_1 - 1)\frac{\dot{c}_{i,t}}{c_{i,t}} + (\theta_2 + \alpha_2)\frac{\dot{h}_{i,t}}{h_{i,t}} - \sum_{j \neq i}^{N} (\alpha_1 \rho W_{i,j} \frac{\dot{c}_{i,t}}{c_{i,t}} - \alpha_2 \rho \frac{\dot{h}_{i,t}}{h_{i,t}} + \rho \ln \frac{\dot{y}_{i,t}}{y_{i,t}}) = 0$$

(A6a)

By symmetry (A3b) implies:

$$\frac{d(\frac{y_{i,t}^*}{h_{i,t}})}{dt} = \frac{\dot{\Omega}_t}{\Omega_t} + (\theta_1 + \alpha_1)\frac{\dot{c}_{i,t}}{c_{i,t}} + (\theta_2 + \alpha_2 - 1)\frac{\dot{h}_{i,t}}{h_{i,t}} - \sum_{j\neq i}^N(\alpha_1\rho W_{i,j}\frac{\dot{c}_{i,t}}{c_{i,t}} - \alpha_2\rho W_{i,j}\frac{\dot{h}_{i,t}}{h_{i,t}} + \rho W_{i,j}\ln\frac{\dot{y}_{i,t}}{y_{i,t}}) = 0$$

(A6b)

Since $\frac{\dot{\Omega}_t}{\Omega_t} - \sum_{j\neq i}^N(\alpha_1\rho W_{i,j}\frac{\dot{c}_{i,t}}{c_{i,t}} - \alpha_2\rho W_{i,j}\frac{\dot{h}_{i,t}}{h_{i,t}} + \rho W_{i,j}\ln\frac{\dot{y}_{i,t}}{y_{i,t}})$ is present in both equations, it implies that

$$\frac{\dot{c}_{i,t}}{c_{i,t}} = \frac{\dot{h}_{i,t}}{h_{i,t}} = \frac{\dot{\Omega}_t}{\Omega_t} = \mathrm{g}$$

Substituting the last results into equation (A3), we have:

$$\frac{c_{i,t}^*}{y_{i,t}} = s_i^c/(\delta + \eta_i + \mathrm{g})$$

(A7a)

$$\frac{h_{i,t}^*}{y_{i,t}} = s_i^h/(\delta + \eta_i + \mathrm{g})$$

(A7b)

Taking equations (A7a-b) into equation (5a) allows us to find the steady-state for economy i:

$$\ln y_{i,t}^* = \ln\Omega_t + (\theta_1 + \alpha_1)\ln s_i^c + (\theta_2 + \alpha_2)\ln s_i^h + (\theta_1 + \alpha_1 + \theta_2 + \alpha_2)\ln(\delta + \eta_i + \mathrm{g}) + (\theta_1 + \alpha_1 + \theta_2 + \alpha_2)\ln y_{i,t}^* + \alpha_1\rho\sum_{j\neq i}^N W_{i,j}\ln s_i^c + \alpha_2\rho\sum_{j\neq i}^N W_{i,j}\ln s_i^h + (\alpha_1\rho + \alpha_2\rho)\sum_{j\neq i}^N W_{i,j}\ln(\delta + \eta_i + \mathrm{g}) + (1 - \alpha_1 - \alpha_2)\rho\sum_{j\neq i}^N W_{i,j}\ln y_{j,t}^*$$

(A8)

For the case with two weight matrices (patent creation-citation (P) and highly educated workers migration (M)), we can start from equation (5b). When we divide both sides of the equation by $\ln c_{i,t}$ we have:

$$\ln \frac{y_{i,t}}{c_{i,t}} = \ln \Omega_t + (\alpha_1 - 1) \ln c_{i,t} + \alpha_2 \ln h_{i,t} + \delta_1 \ln c_{i,t-1} + \delta_2 \ln h_{i,t-1} +$$

$$\tau_c \sum_{j \neq i}^{N} P_{i,j} \ln c_{j,t-1} + \sigma_c \sum_{j \neq i}^{N} M_{i,j} \ln c_{j,t-1} + \tau_h \sum_{j \neq i}^{N} P_{i,j} \ln h_{j,t-1} + \sigma_h \sum_{j \neq i}^{N} M_{i,j} \ln h_{j,t-1}$$

(A9)

Equation (A4) implies that the derivative of (A9) over time is

$$\frac{d(\frac{y_{i,t}^*}{c_{i,t}})}{dt} = \frac{\dot{\Omega}_t}{\Omega_t} + (\alpha_1 - 1) \frac{\dot{c}_{i,t}}{c_{i,t}} + \alpha_2 \frac{\dot{h}_{i,t}}{h_{i,t}} + \delta_1 \frac{\dot{c}_{i,t-1}}{c_{i,t-1}} + \delta_2 \frac{\dot{h}_{i,t-1}}{h_{i,t-1}} + \tau_c \sum_{j \neq i}^{N} P_{i,j} \ln \frac{\dot{c}_{j,t-1}}{c_{j,t-1}} +$$

$$\sigma_c \sum_{j \neq i}^{N} M_{i,j} \frac{\dot{c}_{j,t-1}}{c_{j,t-1}} + \tau_h \sum_{j \neq i}^{N} P_{i,j} \frac{\dot{h}_{j,t-1}}{h_{j,t-1}} + \sigma_h \sum_{j \neq i}^{N} M_{i,j} \frac{\dot{h}_{j,t-1}}{h_{j,t-1}} \quad =0$$

(A10a)

By symmetry we get the following equation for input H

$$\frac{d(\frac{y_{i,t}^*}{h_{i,t}})}{dt} = \frac{\dot{\Omega}_t}{\Omega_t} + \alpha_1 \frac{\dot{c}_{i,t}}{c_{i,t}} + (\alpha_2 - 1) \frac{\dot{h}_{i,t}}{h_{i,t}} + \delta_1 \frac{\dot{c}_{i,t-1}}{c_{i,t-1}} + \delta_2 \frac{\dot{h}_{i,t-1}}{h_{i,t-1}} + \tau_c \sum_{j \neq i}^{N} P_{i,j} \ln \frac{\dot{c}_{j,t-1}}{c_{j,t-1}} +$$

$$\sigma_c \sum_{j \neq i}^{N} M_{i,j} \frac{\dot{c}_{j,t-1}}{c_{j,t-1}} + \tau_h \sum_{j \neq i}^{N} P_{i,j} \frac{\dot{h}_{j,t-1}}{h_{j,t-1}} + \sigma_h \sum_{j \neq i}^{N} M_{i,j} \frac{\dot{h}_{j,t-1}}{h_{j,t-1}} = 0$$

(A10b)

Since $\frac{\dot{\Omega}_t}{\Omega_t} + \delta_1 \frac{\dot{c}_{i,t-1}}{c_{i,t-1}} + \delta_2 \frac{\dot{h}_{i,t-1}}{h_{i,t-1}} + \tau_c \sum_{j \neq i}^{N} P_{i,j} \ln \frac{\dot{c}_{j,t-1}}{c_{j,t-1}} + \sigma_c \sum_{j \neq i}^{N} M_{i,j} \frac{\dot{c}_{j,t-1}}{c_{j,t-1}} +$

$\tau_h \sum_{j \neq i}^{N} P_{i,j} \frac{\dot{h}_{j,t-1}}{h_{j,t-1}} + \sigma_h \sum_{j \neq i}^{N} M_{i,j} \frac{\dot{h}_{j,t-1}}{h_{j,t-1}}$ is common to both equations, it implies that:

$\frac{\dot{c}_{i,t}}{c_{i,t}} = \frac{\dot{h}_{i,t}}{h_{i,t}} = \frac{\dot{\Omega}_t}{\Omega_t} = g$, which implies that equations (A7a-b) hold true in this case too. When taken into equation (5b), the steady-state of the economy *i* can be written as follows:

$$\ln y_{i,t}^{*} = \ln \Omega_t + \alpha_1 \ln s_{i,t}^{c} + \alpha_2 \ln s_{i,t}^{h} - (\alpha_1 + \alpha_2) \ln\left(\delta + \eta_{i,t} + g\right) + (\alpha_1 + \alpha_2) \ln y_{i,t}^{*} + +\delta_1 \ln s_{i,t-1}^{c} + \delta_2 \ln s_{i,t-1}^{h} + (\alpha_1 + \alpha_2) \ln\left(\delta + \eta_{i,t-1} + g\right) + (\delta_1 + \delta_2) \ln y_{i,t-1}^{*} + \tau_c \sum_{j\neq i}^{N} P \ln s_{j,t-1}^{c} + \delta_c \sum_{j\neq i}^{N} M_{i,j} \ln s_{j,t-1}^{c} + \tau_h \sum_{j\neq i}^{N} P_{i,j} \ln s_{j,t-1}^{h} + \delta_h \sum_{j\neq i}^{N} M_{i,j} \ln s_{j,t-1}^{h} - (\tau_c + \tau_h) \sum_{j\neq i}^{N} P_{i,j} \ln\left(\delta + \eta_{j,t-1} + g\right) + (\delta_c + \delta_h) \sum_{j\neq i}^{N} M_{i,j} \ln\left(\delta + \eta_{j,t-1} + g\right) + (\tau_c + \tau_h) \sum_{j\neq i}^{N} P_{i,j} \ln y_{j,t-1}^{*} + (\delta_c + \delta_h) \sum_{j\neq i}^{N} M_{i,j} \ln y_{j,t-1}^{*}$$

(A11)

APPENDIX B FOR CHAPTER 2

Restricted model for Model (7a) in the main document:

$$\ln y_{i,t}^{*} = \frac{1}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\ln\Omega_t + \frac{\theta_1+\alpha_1}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\ln s_i^c + \frac{\theta_2+\alpha_2}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\ln s_i^h - \frac{(\theta_1+\alpha_1+\theta_2+\alpha_2)}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\ln(\delta+\eta_i+g) - \frac{\alpha_1\rho}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\sum_{j\neq i}^{N} W_{i,j}\ln s_i^c - \frac{\alpha_2\rho}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\sum_{j\neq i}^{N} W_{i,j}\ln s_i^h + \frac{\alpha_1\rho+\alpha_2\rho}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\sum_{j\neq i}^{N} W_{i,j}\ln(\delta+\eta_i+g) + \frac{(1-\alpha_1-\alpha_2)\rho}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\sum_{j\neq i}^{N} W_{i,j}\ln y_{j,t}^{*}$$

(B1a)

$$\ln y_{i,t}^{*} = \beta_0\ln\Omega_t + \beta_1\ln(\delta+\eta_i+g) + \beta_2\ln s_i^c + \beta_3\ln s_i^h + \gamma_1\sum_{j\neq i}^{N} W_{i,j}\ln(\delta+\eta_i+g) + \gamma_2\sum_{j\neq i}^{N} W_{i,j}\ln s_i^c + \gamma_3\sum_{j\neq i}^{N} W_{i,j}\ln s_i^h + \gamma_4\sum_{j\neq i}^{N} W_{i,j}\ln y_{j,t}^{*} \quad \text{(B2a)}$$

following the theoretical predictions, the following two restrictions should hold: $-\beta_1 = \beta_2+\beta_3$ and $-\gamma_1 = \gamma_2+\gamma_3$.

Although we can identify the parameters on interest, the interpretation of the marginal effects relies more on the direct and indirect effect displayed in table 2. The parameters are calculated as the follows.

From equation (B2a), imposing the restrictions $-\beta_1 = \beta_2+\beta_3$ and $-\gamma_1 = \gamma_2+\gamma_3$, we have new coefficients from our estimated model (by using R package ‘spdep’)as the following:

$\beta_1 = \frac{\theta_1+\alpha_1}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}$; $\beta_2 = \frac{\theta_2+\alpha_2}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}$;

and

$\gamma_1 = -\frac{\alpha_1}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\rho; \gamma_2 = -\frac{\alpha_2}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\rho;$

$$\gamma_3 = -\frac{1-\alpha_1-\alpha_2}{1-(\theta_1+\alpha_1+\theta_2+\alpha_2)}\rho$$

Solving for each parameter of interest: $\alpha_1, \alpha_2, \theta_1, \theta_2, \rho$, we have

$\alpha_1 = -\frac{\gamma_1}{\gamma_3-\gamma_1-\gamma_2},$

$\alpha_2 = -\frac{\gamma_2}{\gamma_3-\gamma_1-\gamma_2},$

and

$$\theta_1 = -\frac{\beta_1}{1+\beta_1+\beta_2} + \frac{\gamma_1}{\gamma_3-\gamma_1-\gamma_2}$$

$$\theta_2 = -\frac{\beta_2}{1+\beta_1+\beta_2} + \frac{\gamma_2}{\gamma_3-\gamma_1-\gamma_2}$$

$$\rho = \frac{\gamma_3-\gamma_1-\gamma_2}{1+\beta_1+\beta_2}$$

The variance is obtained using the delta method.

Restricted model for Model (7b) in the main document:

$$\ln y_{i,t}^* = \frac{1}{1-(\alpha_1+\alpha_2)}\ln\Omega_t + \frac{-(\alpha_1+\alpha_2)}{1-(\alpha_1+\alpha_2)}\ln(\delta+\eta_{i,t}+\mathrm{g}) + \frac{\alpha_1}{1-(\alpha_1+\alpha_2)}\ln s_{i,t}^c$$
$$+\frac{\alpha_2}{1-(\alpha_1+\alpha_2)}\ln s_{i,t}^h + \frac{-(\delta_1+\delta_2)}{1-(\alpha_1+\alpha_2)}\ln(\delta+\eta_{i,t-1}+\mathrm{g})$$
$$+\frac{\delta_1}{1-(\alpha_1+\alpha_2)}\ln s_{i,t-1}^c + \frac{\delta_2}{1-(\alpha_1+\alpha_2)}\ln s_{i,t-1}^h$$
$$+\frac{(\delta_1+\delta_2)}{1-(\alpha_1+\alpha_2)}\ln y_{i,t-1}^* + \frac{-(\tau_c+\tau_h)}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} P_{i,j}\ln(\delta+\eta_{j,t-1}+\mathrm{g})$$

$$+\frac{-(\sigma_c+\sigma_h)}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} M_{i,j}\ln(\delta+\eta_{j,t-1}+g)+\frac{\tau_c}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} P\ln s_{j,t-1}^{c}+$$

$$\frac{\sigma_c}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} M_{i,j}\ln s_{j,t-1}^{c}+\frac{\tau_h}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} P_{i,j}\ln s_{j,t-1}^{h}+\frac{\sigma_h}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} M_{i,j}\ln s_{j,t-1}^{h}+$$

$$\frac{(\tau_c+\tau_h)}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} P_{i,j}\ln y_{j,t-1}^{*}+\frac{(\sigma_c+\sigma_h)}{1-(\alpha_1+\alpha_2)}\sum_{j\neq i}^{N} M_{i,j}\ln y_{j,t-1}^{*} \qquad \text{(B1b)}$$

$$\ln y_{i,t}^{*}=\beta_0\ln\Omega_t+\beta_1\ln(\delta+\eta_{i,t}+g)+\beta_2\ln s_{i,t}^{c}+\beta_3\ln s_{i,t}^{h}+\beta_4\ln(\delta+\eta_{i,t-1}+g)$$

$$+\beta_5\ln s_{i,t-1}^{c}+\beta_6\ln s_{i,t-1}^{h}+\beta_7\ln y_{i,t-1}^{*}+\gamma_1\sum_{j\neq i}^{N} P_{i,j}\ln(\delta+\eta_{j,t-1}+g)$$

$$+\gamma_2\sum_{j\neq i}^{N} M_{i,j}\ln(\delta+\eta_{j,t-1}+g)+\gamma_3\sum_{j\neq i}^{N} P\ln s_{j,t-1}^{c}+\gamma_4\sum_{j\neq i}^{N} M_{i,j}\ln s_{j,t-1}^{c}+$$

$$\gamma_5\sum_{j\neq i}^{N} P_{i,j}\ln s_{j,t-1}^{h}+\gamma_6\sum_{j\neq i}^{N} M_{i,j}\ln s_{j,t-1}^{h}+\gamma_7\sum_{j\neq i}^{N} P_{i,j}\ln y_{j,t-1}^{*}+\gamma_8\sum_{j\neq i}^{N} M_{i,j}\ln y_{j,t-1}^{*}$$

(B2b)

following the theoretical predictions, the following restrictions should hold: $-\beta_1=\beta_2+\beta_3, -\beta_4=\beta_5+\beta_6,\ \beta_7=-\beta_4, -\gamma_1=\gamma_3+\gamma_5, -\gamma_2=\gamma_4+\gamma_6, \gamma_7=-\gamma_1, \gamma_8=-\gamma_2$.

From equation (B2b), imposing above restrctions, we have new coefficients from our estimated model as the following:

$\beta_1=\frac{\alpha_1}{1-(\alpha_1+\alpha_2)}$,

$\beta_2=\frac{\alpha_2}{1-(\alpha_1+\alpha_2)}$,

$\beta_3=\frac{\delta_1}{1-(\alpha_1+\alpha_2)}$,

$\beta_4=\frac{\delta_2}{1-(\alpha_1+\alpha_2)}$,

$\gamma_1=\frac{\tau_c}{1-(\alpha_1+\alpha_2)}$,

$\gamma_2=\frac{\sigma_c}{1-(\alpha_1+\alpha_2)}$,

$\gamma_3 = \frac{\tau_h}{1-(\alpha_{1+}\alpha_2)}$,

$$\gamma_4 = \frac{\sigma_h}{1-(\alpha_{1+}\alpha_2)}$$

Solving for each parameter of interest: α_1, α_2,δ_1, δ_2, τ_c, σ_c, τ_h, σ_h, we have

$\alpha_1 = \beta_1\left[1 - \frac{\beta_1+\beta_2}{1+\beta_1+\beta_2}\right]$,

$\alpha_2 = \beta_2\left[1 - \frac{\beta_1+\beta_2}{1+\beta_1+\beta_2}\right]$,

$\delta_1 = \beta_3\left[1 - \frac{\beta_1+\beta_2}{1+\beta_1+\beta_2}\right]$,

$\delta_2 = \beta_4\left[1 - \frac{\beta_1+\beta_2}{1+\beta_1+\beta_2}\right]$,

$\tau_c = \gamma_1\left[1 - \frac{\beta_1+\beta_2}{1+\beta_1+\beta_2}\right]$,

$\tau_h = \gamma_3\left[1 - \frac{\beta_1+\beta_2}{1+\beta_1+\beta_2}\right]$,

$\sigma_c = \gamma_2\left[1 - \frac{\beta_1+\beta_2}{1+\beta_1+\beta_2}\right]$,

$\sigma_h = \gamma_4\left[1 - \frac{\beta_1+\beta_2}{1+\beta_1+\beta_2}\right]$.

The variance can be obtained by using the delta method.

REFERENCE

Acs Z and Armington C (2004) Employment Growth and Entrepreneurial Activity in Cities. Regional Studies 38: 911-927

Acs Z, Anselin L, Varga A (20020 Patents and Innovation Counts as Measures of Regional Production of New Knowledge. Research Policy 31:1069–85.

Adams JD (2002) Comparative Localization of Academic and Industrial Spillovers. Journal of Economic Geography 2: 253-278

Adams R. (1989) Global Climate Change and Agriculture: An Economic Perspective, *American Journal of Agricultural Economics*, 71, 5, 1272–1279.

AKÇOMAK S.I. (2008) The Impact of Social Capital on Economic and Social Outcomes, PhD-Dissertation, Maastricht University.

Almeida P, Kogut B (1999) Localization of Knowledge and the Mobility of Engineers in Regional Networks. Management Science 45:905–17

Anselin L (1988) *Spatial econometrics: Methods and models*. Kluwer Academic Publishers, Dordrecht.

Anselin L, Attila V, Zoltan A (1997) Local Geographic Spillovers between University Research and High Technology Innovations. Journal of Urban Economics 42: 422-448

Anselin L, Florax RJGM (1995) Small sample properties of tests for spatial dependence in regression models. In: Anselin L, Florax RJGM (eds) New directions in spatial econometrics. Springer-Verlag, Berlin.

Anselin L, Varga A, Acs Z (2000) Geographical spillovers and university research: A spatial econometric perspective. Growth and Change 31**:** 501-515

Anselin L. and Arribas-Bel D. (2013) Spatial fixed effects and spatial dependence in a single cross-section, *Papers in Regional Science*, 92, 1, 3-17.

Anselin L., Bera A., Florax R.J.G.M., Yoon M. (1996) Simple Diagnostic Tests for Spatial Dependence, *Regional Science and Urban Economics,* 26, 77–104.

Anselin, L. and Cho, W.K.T. (2000) Spatial Effects and Ecological Inference, *Political Analysis*, 10, 276–297.

Arellano, M. and Bond, S. (1991) Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations, *The Review of Economic Studies*, 58(2), 1991, 227–297.

Aschauer D.A. (1989) Is Public Infrastructure Productive?, Journal of Monetary Economics, 23,177-200.

Asheim B and Arne I (2002) Regional Innovation Systems: The Integration of Local 'Sticky' and Global 'Ubiquitous' Knowledge. The Journal of Technology Transfer 27: 77-86

Audretsch DB and Maryann PF (1996) R&D Spillovers and the Geography of Innovation and Production. The American Economic Review 86: 630-640

Autant-Bernard C (2001) The geography of knowledge spillovers and technological proximity. Economics of innovation and new technology 10: 237-254

Autant-Bernard C and LeSage, JP (2011) Quantifying Knowledge Spillovers Using Spatial Econometric Models. Journal of Regional Science 51: 471-496

Autant-Bernard C, Billand P, Frachisse D et al (2007) Social distance versus spatial distance in R&D cooperation: empirical evidence from European collaboration choices in micro and nanotechnologies. Papers in Regional Science 86: 495-519

Autant-Bernard C, Mairesse J and Massard N (2007) Spatial knowledge diffusion through collaborative networks. Papers in Regional Science 86: 341-350

BÄHR C. (2008) How Does Sub-National Autonomy Affect the Effectiveness of Structural Funds?, Kyklos, 61, 3-18.

Baldwin R., Forslid R., Martin P., Ottaviano G., Robert-Nicoud F. (2004) Economic Geography and Public Policy, Princeton University Press.

Baltagi, B., Song, S.H., Jung, B.C. and Koh, W. (2007) Testing for Serial Correlation, Spatial Autocorrelation and Random Effects Using Panel Data, *Journal of Econometrics,* 140, 5–51.

Barro R.J. And Sala-I-Martin X. (1991) Convergence Across States and Regions, Brookings Papers on Economic Activity, 1, 107-182.

Becker S.O., Egger P.H. And Von Ehrlich M. (2010) Going NUTS: The Effect of EU Structural Funds on Regional Performance, Journal of Public Economics, 94, 578-590.

Becker S.O., Egger P.H. And Von Ehrlich M. (2013) Absorptive Capacity and the Growth and Investment Effects of Regional Transfers: A Regression Discontinuity Design with Heterogeneous Treatment Effects, American Economic Journal: Economic Policy, 5, 4, 29-77.

Beugelsdijk M. And Eijffinger S.C.W. (2005) The Effectiveness of Structural Policy in the European Union: An Empirical Analysis for the EU-15 in 1995–2001, Journal of Common Market Studies, 43, 37-51.

Boarnet MG (1998) Spillovers and the locational effects of public infrastructure. Journal of Regional Science 38: 381–400

Bode E (2004) The Spatial Pattern of Localized R&D Spillovers: An Empirical Investigation for Germany. Journal of Economic Geography 4: 43-64

Boldrin M. And Canova F. (2001) Inequality and Convergence in Europe's Regions: Reconsidering European Regional Policies, Economic Policy, 16, 207–253.

Bouayad-Agha S., Turpinn. And Védrine L. (2011) Fostering the Development of European Regions: A Spatial Dynamic Panel Data Analysis of the Impact of Cohesion Policy, Regional Studies, 47, 1573-1593.

Bouvet F. (2005) European Union Regional Policy: Allocation Determinants and Effects on Regional Economic Growth, PhD-thesis, Department of Economics, University of California, Davis.

Breschi S and Lissoni F (2009) Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. Journal of economic geography 9: 439-468

Cappelen A., Castellacci F. Fagerberg J. And Verspagen B. (2003) The Impact of EU Regional Support on Growth and Convergence in the European Union, Journal of Common Market Studies, 41, 621-644.

Card D., Jochen K. And Weber A. (2010) Active Labour Market Policy Evaluations: A Meta-Analysis, The Economic Journal, 120, F452-F477.

Casella G. and Berger R (2002) Statistical Inference, 2nd edn. Thomson Learning.

Cefis E and Orsenigo L (2001) The persistence of innovative activities: A cross-countries and cross-sectors comparative analysis. Research Policy 30: 1139-1158

Census Bureau (2013) Public Education Finances: 2013. US Dept. of Commerce, Washington DC

Chatzopoulos T. and Lippert C. (2016) Endogenous farm-type selection, endogenous irrigation, and spatial effects in Ricardian models of climate change, *European Review of Agricultural Economics*, 43, 2, 217-235.

Chellaraj G, Maskus KE and Mattoo A (2008) The Contribution of International Graduate Students to US Innovation. Review of international economics 16: 444-462

Chen Z and Haynes KE (2015) Spatial Impact of Transportation Infrastructure: A Spatial Econometric CGE Approach. In: Nijkamp P, Rose A and Kourtit K (ed) Regional Science Matters – Studies dedicated to Walter Isard. Springer International Publishing, Switzerland, p 163-186.

Conley TG and Ethan L (2002) Economic Distance, Spillovers and Cross Country Comparisons, Journal of Economic Growth 7: 157–187

Conley, T.G. (1999) GMM Estimation with Cross Sectional Dependence, *Journal of Econometrics,* 92, 1- 45.

Corrado L and Bernard F (2012) Where is the Economics in Spatial Econometrics? Journal ofRegional Science 52(2): 210–239

Crescenzi R, Rodríguez-Pose A and Storper M (2007) The Territorial Dynamics of Innovation: A Europe–United States Comparative Analysis. Journal of Economic Geography 7: 673-709

Dall'erba S and Llamosas-Rosas I (2015) The Impact of Private, Public and Human Capital on the US States Economies: Theory, Extensions and Evidence. In: Karlsson C, Andersson M, Norman T (ed) Handbook of Research Methods and Applications in Economic Geography. Edward Elgar, Northampton, p 436-467.

Dall'erba S. and Dominguez F. (2015) The Impact of Climate Change on Agriculture in the South-West United States: the Ricardian Approach Revisited, *Spatial Economic Analysis*, 11, 1, 1-19.

Dall'erba S., Guillain R. And Le Gallo J. (2009) Impact of Structural Funds on Regional Growth: How to Reconsider a 9 Year-Old Black-Box?, Région et Développement, 30,77-99.

Dall'erba S. And Le Gallo J. (2007) Cohesion Policy, the Convergence Process and Employment in the European Union, Czech Journal of Economics and Finance, 57, 324-340.

Dall'erba S. And Le Gallo J. (2008) Regional Convergence and the Impact of European

Structural Funds over 1989–1999: A Spatial Econometric Analysis, Papers in Regional Science, 87, 219-244.

De Dominicis L., Florax R.G.J.M. And De Groot H.L.F. (2008) A Meta-analysis on the Relationship between Income Inequality and Economic Growth, Scottish Journal of Political Economy, 55, 654-682.

Deschênes O. and Greenstone M. (2007) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather, *The American Economic Review,* 97, 1, 354–385.

Dobson, S., Ramlogan, C. And Strobl, E. (2006). Why Do Rates of β-Convergence Differ? A Meta-regression Analysis, Scottish Journal of Political Economy, 53, 2, 153–73.

Ederveen S., De Groot H.L.F. And Nahuis R. (2006) Fertile Soil for Structural Funds? A Panel Data Analysis of the Conditional Effectiveness of European Cohesion Policy, Kyklos, 59, 17-42.

Ederveen S., Gorter J., De Mooij R.A. And Nahuis R. (2002) Funds and Games: The Economics of European Cohesion Policy, CPB Netherlands Bureau for Economic Policy Analysis, The Hague, the Netherlands.

Egger M., Davey Smith G., Schneider M. And Minder C. (1997) Bias in Meta-analysis Detected by a Simple, Graphical Test, British Medical Journal, 315, 7109, 629–634.

Eliste P and Fredriksson PG (2004) Does Trade Liberalization Cause a Race-to-the-Bottom in Environmental Policies? A Spatial Econometric Analysis. In: Anselin L, Florax R and Rey SJ (ed) Advances in Spatial Econometrics: Methodology, Tools and Applications. Springer Berlin Heidelberg, Berlin, p 383-396.

Ertur C and Koch W (2007) Growth, technological interdependence and spatial externalities: theory and evidence. Journal of applied econometrics 22: 1033-1062

Esposti R. (2007) Regional growth and policies in the European Union: Does the Common Agricultural Policy have a counter-treatment effect? American Journal of Agricultural Economics, 89, 116-134.

Esposti R. And Bussoletti S. (2008) Impact of Objective 1 Funds on Regional Growth Convergence in the European Union: A Panel-data Approach, Regional Studies, 42, 159-173.

Ezcuerra, R., Iraizoz, B., Pascual, P. and Rapún, M. (2008) Spatial Disparities in the European Agriculture: a Regional Analysis, *Applied Economics*, 40, 13, 1669-1684.

Fagerberg J. And Verspagen B. (1996) Heading for Divergence? Regional Growth in Europe Reconsidered, Journal of Common Market Studies, 34, 431–448.

Fingleton B (2001) Equilibrium and Economic Growth: Spatial Econometric Models and Simulations. Journal of Regional Science 41: 117–147

Fingleton B (2008) A Generalized Method of Moments Estimator for a Spatial Model with Moving Average Errors, with Application to Real Estate Prices. Empirical Economics 34: 35–57

Fingleton B and Le Gallo J (2008) Estimating Spatial Models with Endogenous Variables, a SpatialLag and Spatially Dependent Disturbances: Finite Sample Properties. Papers in Regional Science 87: 319–339

Fischer MM (2011) A Spatial Mankiw–Romer–Weil Model: Theory and Evidence. The Annals of Regional Science 47: 419-436

Fischer MM, Scherngell T, and Reismann M (2009) Knowledge Spillovers and Total Factor Productivity: Evidence Using a Spatial Panel Data Model. Geographical Analysis 41: 204-220

Fisher A., Hanemann M., Roberts MJ., Schlenker W. (2012) The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather: Comment, *American Economic Review*, 102, 7, 3749-60.

Fujita M, Krugman P and Venables AJ (1999) The Spatial Economy: Cities, Regions and International Trade. The MIT Press, Cambridge

Fujita M., Krugman P. And Venables A.J. (1999) The Spatial Economy: Cities, Regions and International Trade, MIT Press, Cambridge.

Fung MK and William WC (2002) Measuring the Intensity of Knowledge Flow with Patent Statistics. Economics Letters 74: 353-358

Glaeser EL, Kallal HD, Scheinkman JA et al (1992) Growth in Cities. Journal of Political Economy 100: 1126-1152

Glass G. V. (1976) Primary, Secondary, and Meta-Analysis of Research, Educational Researcher, 5, 3-8.

Goldstein H. (2003) Multilevel Statistical Models (3rd edition). Edward Arnold, London.

Greene W. H. (2000). *Econometric Analysis* (4th edn.). Upper Saddle River, NJ: Prentice Hall International.

Greene W.H. (2012) Econometric Analysis, Seventh Edition, Prentice Hall, New Jersey, USA.

Griliches Z (1979) Issues in Assessing the Contribution of Research and Development to Productivity Growth. The Bell Journal of Economics 10: 92-116

Griliches Z (1992) The Search for R&D Spillovers. The Scandinavian Journal of Economics 94:29–47

Henderson JV (2003) Marshall's Scale Economies. Journal of Urban Economics 53: 1-28

Jacobs J (1969) The Economy of Cities. Random House, New York

Jaffe AB (1986) Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value. The American Economic Review 76: 984-1001

Jaffe AB (1989) Real Effects of Academic Research. The American Economic Review 79: 957-970

Jaffe AB, Trajtenberg M and Henderson R (1993) Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. The Quarterly Journal of Economics 108: 577-598

Johnson DK, Siripong A and Brown AS (2006) The Demise of Distance? The Declining Role of Physical Proximity for Knowledge Transmission. Growth and Change 37: 19-33

Jones C. I. (1995a) Time Series Test of Endogenous Growth Models. Quarterly Journal of Economics, 110, 2, 495-525.

Jones C. I. (1995b) R&D Based Models of Economic Growth. Journal of Political Economy, 103, 4, 759-784.

Julia R., Duchin F. (2007) World Trade as the Adjustment Mechanism of Agriculture to Climate Change, *Climatic Change* 82, 393-409.

Kang D and Dall'erba S (2015) An examination of the role of local and distant knowledge spillovers on the U.S. regional knowledge creation, International Regional Science Review. doi: 10.1177/0160017615572888

Kang D and Dall'erba S (2015) An examination of the role of local and distant knowledge spillovers on the U.S. regional knowledge creation, International Regional Science Review. doi: 10.1177/0160017615572888

Kapoor M, Kelejian HH, Prucha IR (2007). Panel Data Model with Spatially Correlated Error Components, *Journal of Econometrics,* 140, 1, 97-130.

Kelejian H. and Prucha I. (2007) HAC estimation in a spatial framework, *Journal of Econometrics*, 140, 131–154.

Kelejian HH. and Prucha IR. (1998) A Generalized Spatial Two-Stage Least Squares Procedure for Estimating a Spatial Autoregressive Model with Autoregressive Disturbances, Journal of Real Estate Finance and Economics, 17, 1, 99–121.

Kelly D.A., Kolstadb C.D., Mitchell G.T. (2005) Adjustment Costs from Environmental Change, *Journal of Environmental Economics and Management*, 50, 468–495.

Kerr W(2013) High-skilled immigration, domestic innovation, and global exchanges. NBER Report 4: 13-16

Krugman, P. (1991) Increasing Returns and Economic Geography, Journal of Political Economy, 99, 483-499.

Kumar K. (2011) Climate sensitivity of Indian agriculture: do spatial effects matter? *Cambridge Journal of Regions, Economy and Society*, 4, 2, 221-235.

Le Gallo J., Dall'erba S. And Guillain R. (2011) The Local vs. Global Dilemma of the Effects of Structural Funds, Growth and Change, 42, 466-490.

Le Sage J. and Pace K. (2009) *Introduction to Spatial Econometrics*, Taylor and Francis/CRC.

LeSage J and Pace RK (2008) Spatial Econometric Modeling of Origin-Destination Flows, Journalof Regional Science 48: 941–967

Lippert C., Krimly T., Aurbacher J. (2009) A Ricardian Analysis of the Impact of Climate Change on Agriculture in Germany, *Climatic Change*, 97, 593–610.

Lucas R (1988) On the mechanics of economic development. Journal of Monetary Economics 22: 3–42

Mankiw G. N., Romer D. And Weil D. N. (1992) A Contribution to the Empirics of Economic Growth, Quarterly Journal of Economics, 107, 407-437.

Marshall A (1920) Principles of Economics. Macmillan, London

McCarl B.A., Villavicencio X. and Wu X. (2008) Climate Change and Future Analysis: Is Stationarity Dying? *American Journal of Agricultural Economics,* 90, 5, 1241–1247.

McCunn A. and Huffman W.(2000) Convergence in U.S. Productivity Growth for Agriculture: Implications Of Interstate Research Spillovers For Funding Agricultural Research, American Journal of Agricultural Economics, 82, 2, 370-88.

McMillen DP (2012) Perspectives on Spatial Econometrics: Linear Smoothing with Structured Models. Journal ofRegional Science 52(2): 192–209

Mendelsohn R. and Neumann J.E. (1999), *The Impact of Climate Change on the United States Economy.* Cambridge, New York: Cambridge University Press.

Mendelsohn R., Nordhaus W.D. and Shaw D. (1994) The Impact of Global Warming on Agriculture: A Ricardian Analysis, *The American Economic Review*, 84, 4, 753-771.

Mesinger F., DiMego G., Kalnay E., Mitchell K., Shafran P.C., Ebisuzaki W., Jović D., Woollen J., Rogers E., Berbery E.H., Ek M.B., Fan Y., Grumbine R., Higgins W., Li H., Lin Y., Manikin G., Parrish D., Shi W. (2006) North American Regional Re-analysis, *Bulletin of the American Meteorological Society,* , 87, 343-360.

Miguélez E and Moreno R (2013) Do labour mobility and technological collaborations foster geographical knowledge diffusion? The case of European regions. Growth and change 44: 321-354

Miguélez E, Moreno R and Suriñach J (2010) Inventors on the move: tracing inventors' mobility and its spatial distribution. Papers in regional science 89: 251-274

MOHL P. and HAGEN T. (2010) Do EU Structural Funds Promote Regional Growth? New Evidence from Various Panel Data Approaches, Regional Science and Urban Economics, 40, 353-365.

Molloy R, Christopher LS and Abigail W (2011) Internal migration in the United States. Journal of Economic Perspectives 25(3): 173-96

Moulton, B.R. (1986) Random Group Effects and the Precision of Regression Estimates, *Journal of Econometrics,* 32, 385–397.

Mukherji N and Silberman J (2013) Absorptive capacity, knowledge flows, and innovation in US metropolitan areas. Journal of regional science 53: 392-417

Munshi K. (2004) Social learning in a heterogeneous population: technology diffusion in the

Nelson G.C., Rosegrant M.W., Koo J., Robertson R., Sulser T., Zhu T. and Ringler C. (2009) Climate *Change: Impact on Agriculture and Costs of Adaptation. Food Policy Report*. Washington, DC: International Food Policy Research Institute, September.

Nordhaus W. D. (1991) To Slow or Not to Slow: The Economics of the Greenhouse Effect, *Economic Journal,* 101, 407, 920–937.

Ó hUallacháin B and Leslie TF (2007) Rethinking the Regional Knowledge Production Function. Journal of Economic Geography 7: 737-752

Overmars K.P. and Verburg P.H. (2006) Multilevel Modelling of Land Use from Field to Village Level in the Philippines, *Agricultural Systems*, 89, 435–456.

Padgitt M., Newton D., Penn R. and Sandretto C. (2000) Production Practices for Major Crops in US Agriculture, 1990-1997, Statistical Bulletin No. (SB969) 114 pp, September.

Parent O (2012) A space-time analysis of knowledge production. Journal of Geographical Systems 14: 49-73

Parent O and LeSage JP (2008) Using the Variance Structure of the Conditional Autoregressive Spatial Specification to Model Knowledge Spillovers. Journal of Applied Econometrics 23: 235-256

Parent O and LeSage JP (2012) Determinants of knowledge production and their effects on regional economic growth. Journal of Regional Science 52: 256-284

Pellegrini G., Terribile F., Tarola O., Muccigrosso T. And Busillo F. (2013) Measuring the effects of European Regional Policy on economic growth: A regression discontinuity approach, Papers in Regional Science, 92, 1, 217-233.

Peri G (2005) Determinants of knowledge flows and their effect on innovation. The Review of Economics and Statistics 87: 308-322

Pinkse J and Slade ME (2010) The Future of Spatial Econometrics. Journal of Regional Science 50(1): 103–117

Polsky (2004) Putting space and time in Ricardian climate change impact studies: agriculture in the U.S. great plains, 1969-1992, *Annals of the Association of American Geographers*, 94, 3, 549-564.

Ponds R, Van Oort F and Frenken K (2010) Innovation, spillovers and university–industry collaboration: An extended knowledge production function approach. Journal of Economic Geography 10: 231-255

Puigcerver-Peñalver M. (2007) The Impact of Structural Funds Policy on European Regions' Growth: A Theoretical and Empirical Approach, The European Journal of Comparative Economics, 4, 179-208.

Ramajo J., Márquez M., Hewings G.J.D. And Salinas M.M. (2008) Spatial Heterogeneity and Interregional Spillovers in the European Union: Do Cohesion Policies Encourage Convergence Across Regions? European Economic Review, 52551–567.

Rodríguez-Pose A (2001) Is R&D investment in lagging areas of Europe worthwhile? Theory and empirical evidence. Papers in Regional Science 80: 275-295

Rodriguez-Pose A. And Fratesi U. (2004) Between Development and Social Policies: The Impact of European Structural Funds in Objective 1 Regions, Regional Studies, 38, 97-113.

Rodriguez-Pose A. And Novak K. (2013) Learning Processes and Economic Returns in European Cohesion Policy, Investigaciones Regionales, 25, 7-26.

Romer P.M. (1990) Endogenous Technological Change, Journal of Political Economy, 98, S71-S102.

Romer PM (1986) Increasing returns and long- run growth. Journal of Political Economy 94: 1002–1037

Sargan, J. D. (1988). *Lectures on Advanced Econometric Theory*. Oxford: Basil Blackwell. ISBN 0-631-14956-2.

Schenker O. (2013) Exchanging Goods and Damages: The Role of Trade on the Distribution of Climate Change Costs, *Environmental & Resource,* 54, 2, 61-282.

Schimmelpfennig D., Lewandrowski J., Reilly J., Tsigas M. and Parry I. (1996) Agricultural Adaptation to Climate Change: Issues of Long Range Sustainability, *Agricultural Economic Report,* No. (AER740) 68 pp, June.

Schlenker W. and Roberts M.J. (2009) Nonlinear Temperature Effects Indicate Severe Damages to U.S. Crop Yields Under Climate Change, *Proceedings of the National Academy of Science*, 106, 37, 15594–15598.

Schlenker W., Hanemann W. M. and Fisher A.C. (2005) Will U.S. Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach, *The American Economic Review*, 95, 1, 395 – 406.

Schlenker W., Hanemann W.M. and Fisher A.C. (2006) The Impact of Global Warming on U.S. Agriculture: an Econometric Analysis of Optimal Growing Conditions, *Review of Economics and Statistics*, 88, 1, 113–125.

Schmidtner EB., Dabbert S., Lippert C. (2015) Do different measurements of soil quality influence the results of a Ricardian analysis? : a case study on the effects of climate change on German agriculture, German journal of agricultural economics, 64, 2, 89-106.

Seo S.N. (2008) Assessing Relative Performance of Econometric Models in Measuring the Impact of Climate Change on Agriculture Using Spatial Autoregression, *The Review of Regional Studies,* 38, 2, 195–209.

Solow R (1956) A Contribution to the theory of economic growth. Quarterly Journal of Economics 70: 65–94

Solow R.M. (1956) A Contribution to the Theory of Economic Growth, Quarterly Journal of Economics, 70, 65-94.

Sonn JW and Park IK (2011) The Increasing Importance of Agglomeration Economies Hidden behind Convergence. Urban Studies 48: 2180-2194

Sonn JW and Storper M (2008) The Increasing Importance of Geographical Proximity in Knowledge Production: An Analysis of US Patent Citations, 1975 - 1997. Environment and Planning A 40: 1020-1039

Sonn, J. W., and M. Storper (2008) The Increasing Importance of Geographical Proximity in Knowledge Production: An Analysis of Us Patent Citations, 1975 – 1997, *Environment and Planning A* 40(5): 1020-39.

Stephan G. and Schenker O. (2012) International Trade and the Adaptation to Climate Change and Variability , Center for European economic Research, Discussion Paper No. 12-008.

Sutton A.J., Abrams K.R., Jones D.R., Sheldon T.A. And Song F. (2000) Methods for Meta-Analysis in Medical Research. John Wiley and Sons, New York.

Swan TW (1956) Economic growth and capital accumulation. Economic Record 32: 334-361

Tol R.S.J. (1995) The Damage Costs of Climate Change—towards More Comprehensive Calculations, *Environmental and Resource Economics,* 5, 4, 353–374.

Van Cauwenbergh N., Biala K., Brouckaert v., Franchois L., Garcia Cidad V., Hermy M., Mathijs E., Muys B., Reijnders J., Sauvenier X., Valckx J., Vanclooster M., Van der Veken B., Wauters E., Peeters A. (2007) SAFE—A Hierarchical Framework for Assessing the Sustainability of Agricultural Systems, *Agriculture, Ecosystems and Environment*, 120, 229–242.

Vickerman R., Klaus S. And Wegner M. (1999) Accessibility and Economic Development in Europe, Regional Studies, 33, 1–15.

Zhang Y., Cai Y., Beach RH., McCARL BA. (2014) Modeling Climate Change Impacts on the US Agricultural Exports, *Journal of Integrative Agriculture*, 13, 4, 666-676.