A spatial econometric production model, incorporating spill-over effects *

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Abstract

Regional economic models for production and consumption aim to describe interaction between, and magnitude of, produced/-consumed commodities and services. They have however been criticized for being weak and lack details. This constitutes a genuine problem since one of primary aims in regional science is to explain spatial spillovers, Partridge et al. (2012). Furthermore, these models suffer from scarcity of representative data, which

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leads to rareness of empirical studies that often share similar structure, same simplifying assumptions and reveal same type of shortcomings, see Partridge & Rickman (2010).

It is within this context that spatial econometric models can be advantageous compared to other modeling approaches. They have however been criticized for lacking theoretical justification since the relationship between economic activities and physical proximity can be rather obscured. There are however numerous applications, where the foundations of spatial interactions are designed in a theoretically sound manner and in accordance with valid economic theories, see Fingleton (2003), Fingleton & López-Bazo (2006) or Barde (2010).

Our aim in this research has been to assess capability of spatial interactions techniques in apprehending spatial dependencies. Separate Generalized Nesting Spatial models (GNS) has been constructed for two contrasting production sectors. We have managed to demonstrate existence of several types of interactions. To begin with, we could conclude that utilization of non-spatial models, such as OLS would, in our analysis, have let to biased parameters and overestimation of the effects among employed predictors.

Spatial dependencies were observed in both error term, the dependent and among independent predictors, suggesting that our models were spatially sensitive towards certain processes and attributes in their neighboring locations.

Furthermore, we could distinguish between direct and indirect spatial impacts of several predictors on the produced commodities. This enables us to apprehend positive spillover effects, as well as negative impacts that could be discerned as market competition.

Finally we could demonstrate that the inherit information in spatial data is important and valuable and beside helping us in estimation of unbiased and powerful models, it can enhance the models with information that in the area of regional economics is scarcely available.

1 Introduction

Econometric models of production and consumption are broadly employed in regional policy analysis. They aim to describe interaction between, and magnitude of, produced and consumed commodities and services. Within regional economic domain, three traditions are generally established and extensively practiced for modeling purposes, namely Computable General Equilibrium models (CGE), input-output models and micro economic production-consumption models.

These models are theoretically driven and are restricted to certain causal hypothesis. Despite their strength in resolving interactions between production, consumption and land-use, they are associated with certain weaknesses. Rickman (1992) for instant showed that the inherent structure of input-output models introduce bias in regional impact and policy assessments. Also Gillespie et al. (2001) showed that implicit assumption about fixed-price and perfect elastic supply that is regularly employed, lead to overestimation of net benefits.

Another common impediment faced by regional economic modelers is scarcity of sufficient representative data, which is one of the reasons for rareness of empirical studies. Correspondingly, employed models often share similar structure, same simplifying assumptions and suffer same weaknesses in describing economic behavior, Partridge & Rickman (2010). This leads to aggregated and simplified models that often are inadequate in representing the specifics of economic activities that are addressed.

Lack of details, concerning spatial relationships is yet another obstacle as employed models often are conducted in an aggregate manner with intention to enable proper feedback to and from national and international influences that may or may not include the so-called global spillover effects. As a consequence, these models often have weak receptivity towards less aggregate spatial dependencies such as spillover effects within local economies, see for instant Partridge & Rickman (1998).

This constitutes a genuine problem since one of primary aims in regional science is to understand and explain spatial spillovers, Partridge et al. (2012). In less aggregate models, increased spatial resolution expands the influence of proximity among economic entities/agents. The increased proximity amplifies richness of the studied details and results in increased modeling complexity.

Physical proximity such as distance may however have weak relation with the actual economic interaction process. This shortcoming is the main rationale behind the concept of *economic distance*. Fingleton & Le Gallo (2008) for instant argue that "the spillover between areas will not simply be a function of spatial propinquity, to the exclusion of other effects" and claims that it is more realistic to base it on relative economic distance.

It is within this context that spatial econometric models can be advantageous compared to traditional CGE and Input-output models. Utilization of spatial econometric approach has however been criticized for lacking theoretical justification. The approach has been argued to be data driven and applied in a mechanical manner rather than acknowledging the underlying economic interaction processes in a proper manner.

That claim is undeniably true in occasions where little care is taken to describe the theoretical underpinning processes. However, the same critique holds for all economic models where the theoretical basis for the models are carelessly handled. Partridge & Rickman (2010) for instant review various regional economic models and discuss aspects, within which they are vulnerable and identify a growing need for adequate empirical studies as input to better tailored models.

Nevertheless, there exists numerous spatial econometric applications, where the foundations of spatial interactions are designed in a theoretically sound manner and in accordance with valid economic theories, see for instant Fingleton (2003), Fingleton & López-Bazo (2006) or Barde (2010).

Partridge et al. (2012) discuss three contrasting approaches for evaluation of spillovers:

- abandon spatial econometrics and adopt the experimental route currently popular among urban and labor economists, Gibbons & Overman (2012),

- use standard spatial econometrics as a diagnostic tool to support more flexible nonparametric approaches, McMillen (2010),
- refine standard spatial econometrics with more careful theoretical treatment, constructing better spatial interaction matrices, and using hierarchical approaches to achieve better identification, Corrado & Fingleton (2012).

In this research we have followed the third path. The aim of this research is to demonstrate efficacy of spatial econometric approach in modeling spillover effects. The suggested approach is empirical in nature while much attention has been paid to ascertain that the model follows supported premises of regional economic theory. It advocates use of higher focus on spatial interactions in the economy and permits a better representation of spatial linkage between the demand and supply, while facilitating increased efficiency in data usage. The analysis are completed for production of commodities in two contrasting economic sectors within four neighboring counties in Southeastern Sweden.

The remainder of this paper is outlined as follows. Section 2 discuss various spatial econometric models that are relevant in this research such as models with endogenous spatial lag, models with spatially dependent errors(autoregressive or moving average), models with both exogenous dependent and explanatory variables and Generalized Nesting Spatial models. Section 3 describes the employed data for empirical studies, followed by analysis of the results of the employed models in section 4, "Empirical Analysis". Section 5 concludes this papers, highlighting major findings from the research.

2 Review of Spatial Econometric Models

Tobler (1970) first law of geography reveals that *everything is related to everything else, but near things are more related than distant things.* This property of space, probably is the most important foundation stone for all interaction models where proximity exists and matters. Distinction between activities that are *close* and those who are *closer* is probably one of the most important features of economic entities, which delineate contrasts between proximity cost and agglomerations benefits.

Generally, the term proximity is associated with costs, increasing accessibility. This is the case for practically all regional economics, as well as transportation related models. At the same time, spatial proximity/heterogeneity can be seen as level of industrial consolidation, deliberately arranged in the scope for the producers to leverage their skills across a diversified range of industries. This is generally accomplished using the same people and systems to market many different products. If the consolidations take form among several firms in collaboration, they manifest an agglomeration and testify existence of spillover effects.

In order to be able to recognize differences between spatial econometric models and non spatial models, lets start with a general linear regression model, also called Ordinary Least Square model (OLS)[1].

$$Y = \alpha \iota_N + \mathbf{X}\beta + \epsilon \, , \tag{1}$$

where Y is an $N \times 1$ vector of dependent observed samples in i, $i = 1, 2, ..., N$. ι_N is an $N \times 1$ vector of ones associated with the constant term α. X is a $N \times k$ matrix of predictors and β is a $k \times 1$ vector of associated parameters to predictors. Finally $\epsilon = (\epsilon_1, \epsilon_2, ..., \epsilon_N)$ is a vector of disturbances where ϵ_i are independently and identically distributed error terms (iid) with zero mean and σ^2 variance.

In context of studied empirical examples, variate vector, Y represents quantity of produced good, hear represented by total turnover of firms within a ceratian sector, while independent variables such as consumption of intermediary commodities and number of people involved in production are portrayed as predictors.

Considering that one or several unmeasured processes could exist that might alter the outcome, Y, we are interested in if those processes are manifested in space and if they are spatially correlated. If so, the simple regression model in 1 will have biased coefficients, exaggerated R^2 and most importantly, we might have made incorrect inferences. In order to prevent such problems, we will need to either:

- eliminate spatial dependencies,

[1] It is called OLS as the model is mathematically solved by using Ordinary Least Square method.

- and/or incorporate them with variables in the model, dependent and/or independent.

Regardless of how we may handle spatial interactions, we will need to integrate some measure of spatial proximity in equation 1 above. According to Ord (1975), the purpose of a spatial econometric model is to establish and describe the interaction between *neighboring* locations for the dependent variable. Neighborhood or contiguity is a concept that is utilized in all spatial econometric models and that allows for spatial interactions. Agglomeration/spillover effects are reproduced in the model by means of spatial contiguity matrix W.Contiguity includes

- in it's simplest form, an identification term in binary form who makes account for neighbors and non-neighbors,
- a measure of proximity between locations like distance between cities (in case of points data),
- a measure that represents degree of conjunction between neighboring areas like length of common border (in case of polygon data).

However, the foremost role of contiguity matrix is to describe cost of interaction, similar to role of accessibility, in the economic interaction between firmsthat also is the reason for describing contiguity as economic distance. This description is among others, considered by Fingleton & Le Gallo (2008). As locations may have several neighbors, a $N \times N$ contiguity matrix, W, can be assembled for representation of all potential interactions, where the value in cell w_{ij} in the matrix W represent economic distance/cost of interaction among firms in geography.

Spatial weights matrix however can not be estimated. Furhtermore, economic theory does not reveal any clear instructions on how they should be specified. Anselin & Bera (1998) explain that "a mismatch between the spatial unit of observation and the spatial extent of the phenomena under consideration will result in spatial measurement errors and spatial autocorrelation between these errors in adjoining locations". Therefore, it is conventional to examine robustness of estimated models against specification of W.

Spatial dependencies, can enter the model in different ways. They can for instant be manifested in the residual of the model, if the error term is spatially correlated ($\epsilon_i \overset{w_{ij}}{\longleftrightarrow} \epsilon_j$). The interaction can be modeled through incorporation of a spatial autoregressive process in the error term, resulting in a so called *spatial error model (SEM)*, see equation 2 below.

$$\begin{aligned} Y &= \iota_N + \mathbf{X}\beta + u \ , \\ u &= \lambda W u + \epsilon \end{aligned} \tag{2}$$

If there are no spatial correlations in the residuals then the resulting coefficient, $\lambda = 0$. A positive spatial error on the other hand reflects that a spatial pattern exists and that one or more spatially clustered independent variables, who potentially areexplaining that pattern, are omitted.

"Endogenous interaction effects are typically considered as the formal specification for the equilibrium outcome of a spatial or social interaction process, in which the value of the dependent variable for one agent is jointly determined with that of neighboring agents." Elhorst (2014). In spatial error models however, "observed[2]" spatial dependencies are disregarded as meaningful and are primarily perceived as nuisance.

This is a restrictive assumption and might lead to identification problem, see Corrado & Fingleton (2012) or Partridge et al. (2012). The problem can for instant be illustrates for neighbors with no economic interaction or when spillover is manifested through dependent x variables. In the first case the concept of neighborhood as source of spatial interaction would be redundant while assumption about existence of spatial interaction in the error term will become redundant in the second example.

In both cases however, statistical tests such as *Moran's I* or *Geary's C* may wrongfully display significant spatial interactions. It is therefore important to not become overenthusiastic in adoption of the spatial lag without giving sufficient consideration to the theoretical rationale that is to be embedded in the model.

When the spatial dependency is manifested through endogenous dependent variable, $y_i \overset{w_{ij}}{\longleftrightarrow} y_j$, the spatial interaction can be modeled by incorporation of an autoregressvie dependent term. Positive spatial

[2] Refers to observed spatial interactions in independent x variables.

autoregressivity is evidence of correlation of the dependent variable among adjacent areas. This model is generally referred to as *Spatial Autoregressive Model, SAR*.

$$Y = \rho WY + \alpha\iota_N + \mathbf{X}\beta + \epsilon \ , \tag{3}$$

Elhorst & Vega (2013) claim that theoreticians are mainly interested in endogenous spatial interactions and/or exogenous error terms, while predominant aim of practitioners is to measure spatial spill over effects. Models incorporating exogenous explanatory variables, $(y_i \overset{w_{ij}}{\longleftrightarrow} x_j)$ and $(y_j \overset{w_{ij}}{\longleftrightarrow} x_i)$,are often referred to as *Spatial Lagged eXogenous model, SLX*, see equation 4.

$$Y = \alpha\iota_N + \mathbf{X}\beta + WX\theta + \epsilon \ , \tag{4}$$

Before 2007, above mentioned models were generally employed by spatial econometricians. Chiefly thanks to ground pillar work by Anselin (1998) and testing procedures for spatial error and lagged models, developed by Anselin et al. (1996). After 2007 however, the interest for models with more than one spatial interaction effects has increased.

Use of models incorporating both endogenous and exogenous spatial interactions, or so called kelejian-Purcha type models (*SAC-model*), where for instant emphasized by Harry Kelejian during his keynote speech at the first World Conference of the Spatial Econometrics Association in 2007, see equation 5.

$$\begin{aligned} Y = \rho WY + \alpha\iota_N + \mathbf{X}\beta + u \ , \\ u = \lambda Wu + \epsilon \end{aligned} \tag{5}$$

James LeSage on the other hand[3] advocated for models with both exogenous dependent and explanatory variables, also called *spatial Durbin model, SDM*, see equation 6.

$$Y = \rho WY + \alpha\iota_N + \mathbf{X}\beta + W\mathbf{X}\theta + \epsilon \ , \tag{6}$$

A generalization, employing recommendations form both Kelejian and LeSage result in equation 7 below, even referred to as *Generalized Nesting Spatial model, GNS-model.*

$$\begin{aligned} Y = \rho WY + \alpha\iota_N + \mathbf{X}\beta + W\mathbf{X}\theta + u \ , \\ u = \lambda Wu + \epsilon \end{aligned} \tag{7}$$

[3] In his presidential address at the 54th North American Meeting of the Regional Science Association International in 2007

Demonstration of spatial spillover effects can be a complicated task, specially when spatial dependencies are, as in case of the Durbin and GNS-models, provoked from multiple spatial interactions. As been pointed out by LeSage & Pace (2009) any change in an explanatory variable, beside imposing direct impact on observed dependent variable in own location/region, may potentially influence all other locations/regions which could have indirect impact on the dependent variable.

The indirect influence of predicting variables on observed dependent variable are referred to as spillover effects, representing multi-regional interactions. Lets rewrite equation 7 as

$$Y = (I - \rho W)^{-1}(\mathbf{X}\beta + W\mathbf{X}\theta) + R \tag{8}$$

where R contains both intercept and error terms. The matrix of partial derivatives of expected value of Y with respect to the K:th predictor, X in location/region 1 up to N can then be written as

$$\begin{aligned}\left[\frac{\partial E(Y)}{\partial x_{1k}} \cdot \frac{\partial E(Y)}{\partial x_{Nk}}\right] &= \begin{bmatrix} \frac{\partial E(Y_1)}{\partial x_{1k}} & \cdots & \frac{\partial E(Y_1)}{\partial x_{Nk}} \\ \vdots & \ddots & \vdots \\ \frac{\partial E(Y_N)}{\partial x_{1k}} & \cdots & \frac{\partial E(Y_N)}{\partial x_{Nk}} \end{bmatrix} \\ &= (I - \rho W)^{-1} \begin{bmatrix} \beta_k & w_{12}\,\theta_k & \cdots & w_{1N}\,\theta_k \\ w_{21}\,\theta_k & \beta_k & \cdots & w_{2N}\,\theta_k \\ \vdots & \vdots & \ddots & \vdots \\ w_{N1}\,\theta_k & w_{N2}\,\theta_k & \cdots & \beta_k \end{bmatrix}\end{aligned} \tag{9}$$

Diagonal elements in matrix in equation 9 represent the direct effects of predictors on expected value of Y while off-diagonal elements represent indirect effects or spillover effects. It is worth noticing that spillover effects will not occur unless both $\rho \neq 0$ and $\theta \neq 0$.

The magnitude of direct effects, β_k, is different for different locations/regions since diagonal elements of matrix $(I_N - \rho W)^{-1}$ are different for different locations, given that $\rho \neq 0$. Same goes for indirect effects since both off-diagonal elements of the matrix $(I_N - \rho W)^{-1}$ and contiguity matrix, W, are different for different locations, given both $\rho \neq 0$ and $\theta \neq 0$.

Assuming a study area with N spatial units and for K predictors, the model will have K different $N \times N$ matrices of direct and indirect effects which will be difficult to interpret, even for small K and N. To make these effects more comprehensible, LeSage & Pace (2009) suggest one summary indicator for the direct effect and one for indirect effects.

The direct effects summary indicator is measured as the average of the diagonal elements of the matrix on the right-hand side of equation 9 and can be explained as direct change in a predictor on the dependent variable in own location/region.

The indicator for indirect effects, however is measured as average of either row sums or sums of the off-diagonal elements of that matrix[4]. The indirect effect should be interpreted as the impact of changing a particular element of a predictor on the dependent variable in all other locations/regions.

3 Data

The empirical analysis requires information on size and level of economic activity of firms within each economic sectors. It has not been possible to procure required data on firm level as such data is considered strategic and regarded as business secret by firms. We were therefore preconditioned to use aggregated data. Determination of convenient level of aggregation for the analysis is conditioned by:

- required resolution for analysis of made hypothesis, regarding spatial interactions among endogenous and exogenous variables,
- size and homogeneity of spatial entities (polygons in this case) in representing aimed interactions,
- and availability of data.

[4] Average of row and column sums of the off-diagonal elements in the matrix are equal which allows for use of either one of them.

In the Swedish national model for transport of commodities, produced goods are divided among thirty four industrial sectors in total. In this research we completed analysis for two contrasting sectors producing:

- products of agriculture, hunting, and related services (sector one),
- fabricated metal products except machinery and equipment (sector twenty eight).

The first sector is represented by firms, generally located in rural areas while the second sector regards firms that are mainly located in or close to cities. These contrasting sectors were chosen in order to demonstrate diversity in spatial spillover effects regarding contrasting spatial dependencies in different economical sectors.

Geographically, the studied area includes four neighboring counties in Southeastern Sweden. That is to say Jönköping, Kronoberg, Kalmar and Blekinge. As been discussed, choice of economic distance that is manifested through weight matrix W is dependent on choice of spatial resolution. Dimension of the spatial resolution[5], in other words is determined by dimension of spatial weight matrix while level of interaction between locations are determined by the functional form of the cells in the weight matrix, representing relative economic distance.

Finding data with convenient resolution is very difficult and most analysis are subjected to a few data source and. This study isn't exempted from the problem either. The most suitable that in this case is the most dissaggregate data we could find is based on so called *Small Areas Market Statistics, SAMS*[6] breakup. The demarcated area in our empirical study is divided into 933 parcels. Polygons in SAMS roughly represents areas with 1000 inhabitants but could differ greatly from a polygon to next and are not uniformly shaped.

Values of the cells in the weight matrix W are representing relative economic distance and are constructed through multiplication of first order binary contiguity matrix[7] with a distance decay function[8].

[5]Issues regarding spatial representativeness of data are not discussed here but are extensively discussed in litterateur. See for instant litteratur on *Modifiable Areal Unit Problem, MAUP* and on *spatial fallacy*.

[6]SAMS is a geographical classification designed by Statistics Sweden (SCB) and is widely employed for statistical modeling purposes.

[7]First order neighbors in this case are adjacent SAMS-parcels/polygons with common border to own parcel.

[8]For this calculation, an exponential decay function is used, $e^{\beta d_{ij}}$, where $\beta = 3.29$ x 10^{-3}, obtained from an earlier study.

Potential peculiarities and issues regarding use of spatial classification according to SAMS are however not discussed in this paper. Nevertheless we assume that spatial representation of geography according to SAMS can produce aimed spatial interactions between neighboring polygons. Figure 1 represents each location's standard deviation from

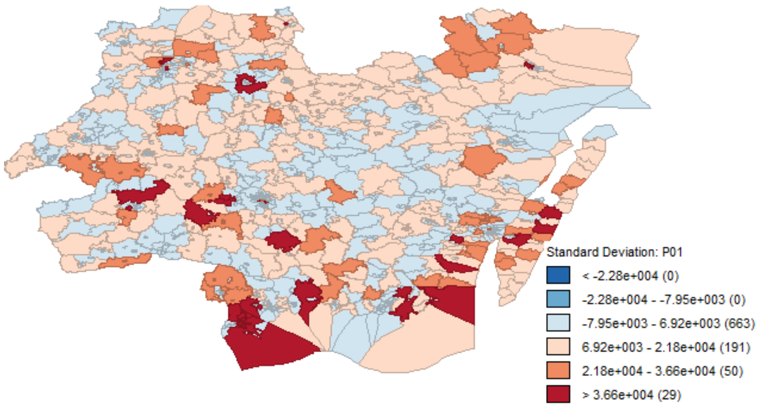

Figure 1: Standard deviation of produced agriculture and hunting related products in south-east Sweden in 2006.

average production in sector one. As it could be anticipated, production of agriculture and hunting related goods is more intensive in rural areas were producers have access to larger farmlands, while smaller urban areas show negative deviation form the average.

Figure 2 on the other hand represents deviation form average for fabricated metal products. We can see that the relation is almost the opposite of the case for sector one.

It is possible to evaluate the existence of clusters as possible source of spillover effects in spatial arrangements. This is done through means of a statistical measure called *local Moran's I*.

$$I_i = \frac{x_i - \bar{X}}{S_i^2} \sum_{j=1, j\neq i}^{n} w_{ij}(x_j - \bar{X}) \tag{10}$$

where x is the attribute of interest and $\bar{X}$ is the average, n is number of observed samples. and

$$S_i^2 = \frac{\sum_{j=1, j\neq i}^{n}(x_j - \bar{X})^2}{n-1} - \bar{X}^2 \tag{11}$$

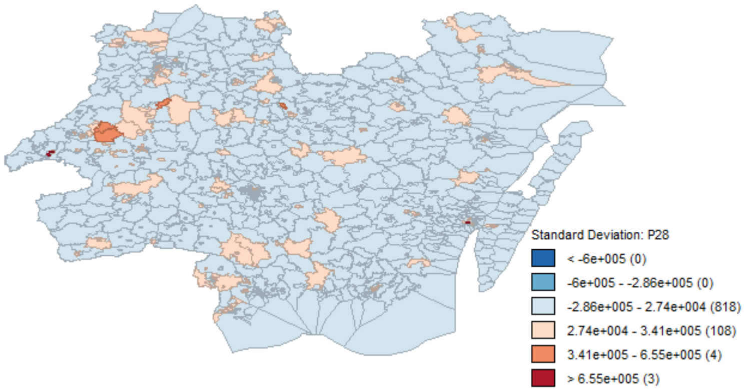

Figure 2: Standard deviation of fabricated metal products in south-east Sweden in 2006.

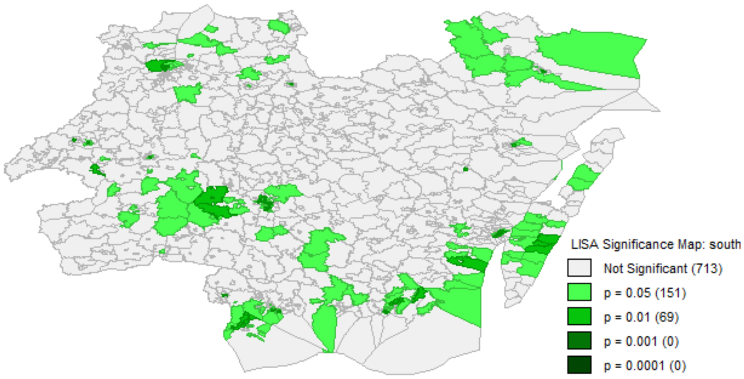

Figure 3: Map of local Moran's i for produced agriculture and hunting related products in south-east Sweden in 2006.

Figure 3 shows locations with significant Moran's I (p-value in map legend). Comparing this map with the map in figure 1, we can see that not all locations deviating with the average production in 1 are having significant Moran's I and that only a few of locations seems to be a part of a cluster. Corresponding map for production in sector twenty eight is represented in figure 4.

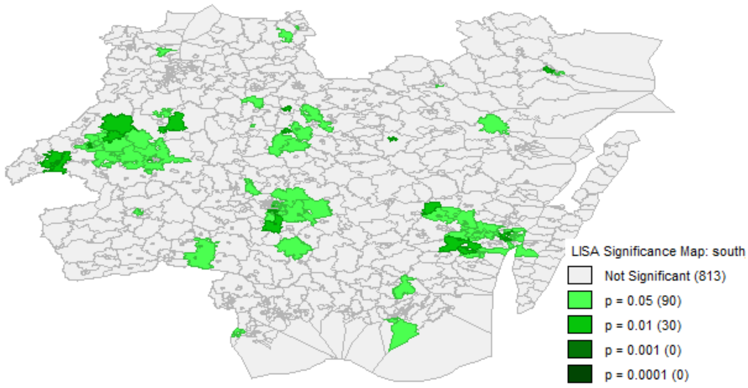

Figure 4: Map of local Moran's I for fabricated metal products in south-east Sweden in 2006.

4 Empirical analysis

Our aim is to examine performance of spatial econometric approach in modeling spatial spillover effects. We hypothesize that spillover effects potentially exist:

- among neighboring firms within same sector of economy,
- among workers in neighboring locations who work within same sector of economy,
- across interdependent industrial clusters who either deliver intermediary goods for production or clusters of industries who are consumers of the produced commodities.

Two general nesting spatial models (GNS) are constructed for production of goods in sector one and twenty eight. Both models employ turnover in own sector as dependent variable. Turnover in Swedish crowns has been employed as a proxy to actual production. Employed independent variables are divided in two categories. The first category of variables include independent predictors, representing attributes of the economical sector, modeled, such as:

1- number of firms in same producing sector and location,
2- number of firms in same producing sector but in neighboring locations,

3- number of people working in same producing sector and location,
4- number of people working in same producing sector but in neighboring locations,

The second category of independent variables include predictors related to other sectors of economy who either deliver intermediary goods for the production or are consumers of produced commodities. These sectors are chosen from an input-output matrix, available at Statistics Sweden and contain symmetric input-output terms for year 2006 in current prices. These tables are derived from the supply and use tables (annual GDP calculations) by Statistics Sweden.The hypothesis we are testing are that accessibility to intermediary goods, required for production, could potentially matter as well as consumers accessibility to produced commodities. These are introduced as mix regressive predictor terms in the GNS model. Following predictors are therefore tested:

5- total turnover among sectors, producing three largest intermediary goods required for own production, located in own polygon,
6- total turnover of three largest consumers of produced commodity in modeled sector thta are located in own polygon.

For each sector, accuracy of the generalized nesting specified model (GNS) is examined against OLS, SEM, SAR and mixed regressive effects using specification tests.

Table 1 shows estimated parameters and corresponding statistics for production in sector one, Products of agriculture, hunting and related services. $emp - S01$ represents number of employees involved in production in sector one for each location and $firms - S01$ represents number of firms producing in same sector and location.

$S02$ and $S23$ represent production (turnover in Swedish Kronor) for sector two (Products of forestry, logging and related services) and sector twenty three (Coke and refined petroleum products, chemical fertilizers, etc). Three further sectors, chosen from the input-output matrix, were also examined but rejected due to their weak significances in the models. Two further independent variables were significant (in case of GNS-model), namely number of employees at neighboring locations $w\,ln(emp - S01)$ and production in sector two among neighboring locations, $w\,ln(S02)$.

	GNS-model	direct impact	indirect impact
$ln(emp - S01)$	1.160 (.000)	0.584	0.513
$ln(firms - S01)$	0.525 (.000)	0.265	0.232
$ln(S02)$	0.416 (.000)	0.210	0.184
$ln(S23)$	0.241 (.039)	0.121	0.107
$w\,ln(emp - S01)$	-0.333 (.000)	-0.168	-0.147
$w\,ln(S02)$	-0.256 (.000)	-0.130	-0.114
ρ	.496 (.000)	-	-
observations	933	-	-
R^2	0.809	-	-
log-likeliehood	-1622.010	-	-
Morans I	8.3 (.000)	-	-
$LM - \epsilon$ (robust)	166.9 (.000)	-	-
$LM - wy$ (robust)	123.4 (.000)	-	-
LR-test, SDM vs. OLS $(\rho = 0)$	263.0 (.000)	-	-
LR-test, $(w\,X's = 0)$	124.7 (.000)	-	-

Table 1: Estimated parameters and statistics for spatial GNS-model and direct and indirect impacts, regarding production in sector one. Significance levels within parentheses.

We can, by inspecting table 1, see that all estimated parameters are significant. Number of employees in own sector of economy and location, $ln(emp-S01)$, have a positive sign as one might expect. Same goes for number of firms in own sector, $ln(firms - S01)$. Furthermore we can see that existence of firms producing products related to forestry and logging, $ln(S02)$, as well as refined petroleum products[9], $ln(S23)$, have positive correlation with production in sector one. It can also be seen that existence of firms and number of employees working in sector two among neighbors, $wln(emp - S02)$ and $wln(S02)$, have negative sign, indicating potential competition between sectors one and two.

Statistical test confirms existence of spatial dependencies compared to a general OLS model[10]. Lagrange Multiplier test for the lagged dependent variable, statistically demonstrates existence of spatial lagged dependencies as parameter for the autoregressive part of the GNS-model,

[9]Products in sector one are sometimes used for production of for instant methanol and oil is produced from rapeseed.

[10]significant lakeliehood-Ratio test which compares a mixed spatial Durbin-model with OLS-model, $(LR - test, SDM - vs. - OLS, (\rho = 0))$

ρ, is significant. Same is true for existence of spatial dependencies in error term as been established by the Lagrange Multiplier test, $LM - \epsilon$. The Laikeliehood ratio test also shows that significant spatial mixed dependencies are at work among independent predictors, $wln(emp - S02)$ and $wln(S02)$.

The third column in table 1 represent marginal direct impact of change of a predictor variable on production in sector one. The indirect effects, shown in fourth column in the table represents the marginal indirect impact or so called spillover effect and should be interpreted as the impact of changing a particular element of a predictor on the dependent variable in all other locations/regions. Here we can see that both direct and indirect impacts have same sign as estimated parameters. This however is not the standard behavior, as it will be demonstrated for the case of sector twenty eight. Figure 5 is representing a LISA-map

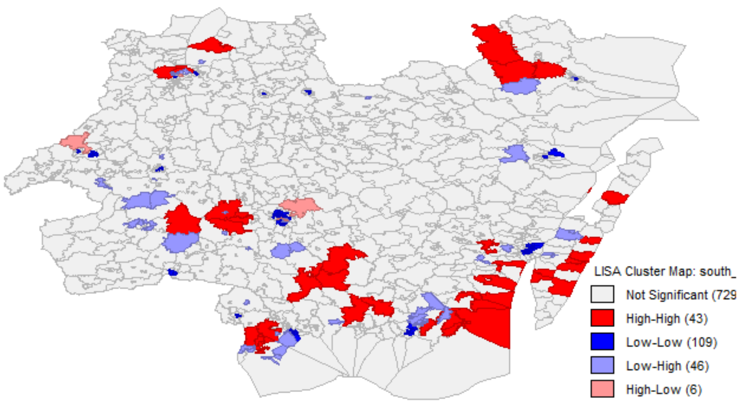

Figure 5: Map of local Moran's I for fabricated metal products in south-east Sweden in 2006.

(Local Indicators of Spatial Associations) and shows location and type of clusters. The so called *hot spots* (high-high) are presented by bright red color polygons where positive spatial associations are observed both in own and among neighboring locations. *Cold spots* (low-low) are presented by bright blue polygons, representing locations where spatial associations are low for both own and neighboring locations.

Areas with light red and light blue polygons represent *spatial outliers* and can be identified through their light red and blue colors. Because of their inverse orientation, such areas depict pockets of instationarity where areas with positive significant local Moran's I are surrounded by neighbors with negative significant Moran's I and vise verse.

Table 2 shows estimated parameters and related statistics for production in sector twenty eight, fabricated metal products (not machinery and equipment). The intermediary and consuming sectors that were also examined were, sector twenty four (chemicals products and man-made fibers), sector twenty five (rubber and plastic products), sector twenty nine (machinery and equipment) and sector thirty three(precision medical and optical instruments, watches and clocks).

	GNS-model	direct impact	indirect impact
$ln(emp - S28)$	1.593 (.000)	1.679	-0.087
$ln(firms - S28)$	0.379 (.000)	0.399	-0.021
$ln(area)$	0.345 (.000)	0.363	-0.019
$ln(S24)$	-0.111 (.000)	-0.117	0.006
$ln(S25)$	0.088 (.000)	0.092	-0.005
$ln(S29)$	0.051 (.000)	0.054	-0.003
$ln(S33)$	-0.090 (.000)	-0.095	0.005
$w\,ln(emp - S28)$	0.446 (.000)	0.470	-0.024
$w\,ln(firms - S28)$	-0.709 (0.001)	-0.748	0.039
$w\,ln(S25)$	-0.056 (.002)	-0.059	0.003
$w\,ln(S29)$	-0.032 (.064)	-0.034	0.002
$w\,ln(S33)$	0.162 (.000)	0.171	-0.009
ρ	-.0539 (.068)	-	-
observations	933	-	-
R^2	0.809	-	-
log-likeliehood	-3355.030	-	-
Morans I	0.042 (.046)	-	-
$LM - \epsilon$ (robust)	1.09e+06 (.000)	-	-
$LM - wy$ (robust)	1.09e+06 (.000)	-	-
LR-test, SDM vs. OLS $(\rho = 0)$	3.342 (.067)	-	-
LR-test, $(wx_i = 0)$	58.108 (.000)	-	-

Table 2: Estimated parameters and statistics for a spatial GNS-model, regarding production in sector twenty eight. Significance levels are within parentheses.

Here again we can see that number of employees in own sector and location, $ln(emp - S28)$, as well as number of firms in own sector and location, $ln(firms - S28)$ are positive and significant. The lagged predictors of same variables, $wln(emp - S28)$ and $wln(firms - S28)$, are also significant, suggesting existence of spatial correlation among neighboring locations.

However, the lagged parameter for number of employees among neighbors, $w\,ln(emp - S28)$ shows a positive correlation on production while the sign of number of neighboring firms $w\,ln(firms - S28)$ is negative. This can be interpreted as existence of similar firms in neighboring locations have negative impact on own production, suggesting the existence of competition. This hypothesis is confirmed by the parameter for the autoregressive element in the model, ρ, which also is negative and significant, which concludes existence of spatial autocorrelation.

Again, the third column in table 2 represent marginal direct impact of change of a predictor variable on production in sector one. The indirect effects, shown in forth column is representing the spillover effect and should be interpreted as the impact of changing a particular element of a predictor on the dependent variable in all other locations/regions.

Unlike the model for sector one, marginal direct and indirect impacts in this model, in several cases, have different signs witnessing their complex spatial dependencies. Most obvious is the negative indirect impact of number of employees and it's lagged variable ($emp - S28$ and $w\,ln(emp - S28)$), suggesting a negative marginal impact on production in sector twenty eight in neighboring locations, when number of employees increase in own location. This could be interpreted as production in sector twenty eight becomes saturated and an additional employee will impose negative impact on production in other locations. We can also see that despite the fact that indirect impacts are many times weaker than direct impacts, they are statistically significant and are not to be neglected.

Figure 6 is representing a LISA-map for sector twenty eight and shows location and type of clusters. As could be expected, location and type of clusters and outliers are very different from sector one. We can see a significant cluster of locations with high spatial dependencies (high high or bright red) exists in west, where city of Växjö is located, which was expected, considering the type of industry sector twent eight represents.

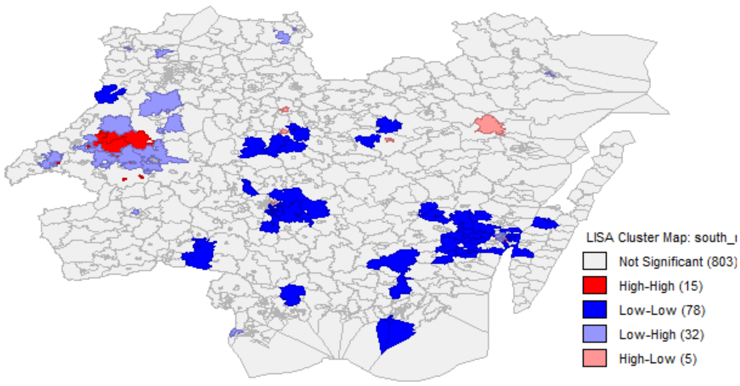

Figure 6: Map of local Moran's I for fabricated metal products in south-east Sweden in 2006.

5 Conclusions

Our aim was to assess capability of spatial interactions techniques in apprehending spatial dependencies. For two contrasting production sectors, we managed to demonstrate existence of several interaction effects.

To begin with, we could conclude that utilization of non-spatial models, such as OLS would, in our analysis, have let to biased parameters and overestimation of the effects among employed predictors.

Spatial dependencies were observed in both error term, the dependent and among independent predictors, suggesting that our models were spatially sensitive towards certain processes and attributes in their neighboring locations.

Furthermore, we could distinguish between direct and indirect spatial impacts of several predictors on the produced commodities. This enables us to understand and apprehend positive spillover effects, as well as negative impacts that could be discerned as market competition.

Finally we could demonstrate that the inherit information in spatial data is important and valuable and beside helping us in estimation of unbiased and powerful models, it can enhance the models with information that in the area of regional economics is scarcely available.

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